Measuring the Impacts of Disruptions on the Ability of Public Transit Systems to Deliver Reliable Accessibility

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# Introduction

As extreme weather, pandemics, and social unrest and other disruptions shake our world, public transit systems are operating in more unstable environments, challenging their ability to deliver reliable accessibility to their clientele. Therefore, the resilience of a public transit system – the ability to maintain its functions during after external socks and disruptions – should be a major focus for public transit research and planning. Accessibility is the primary indicator of a public transit system’s utility, as it determines people’s ability to reach opportunities and resources given the limited time available to conduct essential and discretionary activities (*1*). Gaps between scheduled and delivered service propagate downstream through routes and can spread through the system due to interconnections among equipment and operators (*2*). Delays degrade user experience and the usefulness of transit systems and has negative consequences for transit-dependent riders who may miss work, medical appointments and other time-critical events. This makes schedule reliability one of the most important factors that affect people’s preference and use of public transit (*3*, *4*).

Public transit faces both short-term and long-term disruptions. Short-term disruptions are temporary events that do not fundamentally alter the service and infrastructure. Prominent examples are traffic jams, weather events, major entertainment events such as concerts, sports events games and street festivals. Short-term disruptions affect accessibility primarily by influencing the on-time performance, in the form of delayed or sometimes early arrivals. Long-term disruptions have persistent impacts on the on the system; examples include pandemics, damaging weather events, and route and schedule changes caused by budget reductions that can be a consequence of these disruptions. Long-term disruptions can create more nuanced patterns of unreliability beyond direct and temporary impacts on on-time performance.

There are still large gaps in research on the reliability and resilience of public transit-based accessibility. First, prior studies focus on system resilience based on travel time, ridership, and capacity (*5*), rather than accessibility and accessibility reliability. Second, studies of short-term disruptions are lacking. The historical lack of reliable high-resolution data source made it hard to conduct empirical analysis on short-term disruptions. Finally, few papers discussed the recoverability of transit accessibility after a disruption; this is a major aspect of system resilience. Due to the availability of high-resolution real-time data, we now can address these gaps in this paper accordingly. In this paper, we use *realizable real-time accessibility* – a space-time prism-based measure (*6*, *7*) that conservatively measures the accessibility that can be achieved by users in a public transit system subject to delays (*8*). This measure uses both schedule and vehicle location data to simulate the decision-making process of users, acknowledging their inability to know actual arrival time *a priori* when planning their trips. The gap between scheduled accessibility and reliable accessibility is an indicator of the reliability of transit accessibility (*8*). We use the realizable accessibility and reliability measures to conduct two case studies of the impacts short-term and long terms disruptions on public transit: college football games that generate major impacts on traffic and therefore bus delays, and the COVID-19 pandemic that persistently altered the system’s schedules and routes. We conduct these case studies using data from Columbus, Ohio, USA and its bus-based public transit system, the Central Ohio Transit Authority (COTA).

# Background

We review relevant literature in this section. We first introduce the transportation resilience and its two core features. We then review the development of public transit reliability from travel time-based reliability to accessibility reliability. We finally assess disruptions and their impacts on public transit accessibility and reliability.

## Resilience

Resilience is the capacity of a system to maintain its functions during a disruption (*9*, *10*). As climate change, pandemics, and energy crises increase the risk and frequency of disruptions, transportation resilience becomes a new focus of transportation focus. However, the definition of transportation resilience can be heterogenous and nuanced. Most prior research agrees that resilience includes two core features: robustness and recoverability (*9*, *11*, *12*).

Robustness – some researchers also use the terms adaptability and reliability, or vulnerability and unreliability as antonyms – is the ability to maintain service during a disruptive event. An ideally robust transport system should still maintain a minimum required performance in the face of a disruptive event. Robustness is measured by the decline of a system performance (*11*, *12*). Recoverability – some researchers also use resilience or resiliency – is the ability for the system to return to its previous state in a timely manner (*11*). It is usually measured by the time from the disruptive event happens to the time when the performance recovers to pre-disruption level (*11*, *12*). The two aspects determine the transport system’s ability to resist, adapt to, and recover from the disruption.

## Accessibility Reliability of Public Transit systems

Reliability can be defined as the variation of a public transit system’s performance (*12*); however, its specific definition can be nuanced, depending on the performance measures. Most of the prior research investigated travel time reliability (*12*, *13*). Carrion and Levinson (*14*) categorized this concept into three categories: 1) centrality-dispersion, which measures the variation of travel time around the mean value; 2) scheduling delays, which measures the difference between preferred travel time and actual travel time; 3) average delays, which measures the difference between scheduled time and actual time, i.e., on-time performance of a public transit system. Travel time reliability represents the fidelity of the transit service; higher reliability means that a user can expect their incoming trips to abide by the scheduled or average performance.

Due to the direct link between travel time and accessibility, the reliability of accessibility can also be defined as its variation over time. However, depending on the standard of comparison, i.e., average accessibility or scheduled/expected accessibility, the definition can still vary. D’este and Taylor (*15*) and Taylor and D’este (*16*) first introduce reliability and vulnerability with the idea of accessibility. Conversely, just like travel time reliability, accessibility reliability can also be defined as the variation between expected/scheduled accessibility and actual accessibility delivered by the system based on its performance. Wessel, Allen, and Farber (*17*) and Wessel and Farber (*18*) investigated the accuracy of schedule-based accessibility by calculating the difference between delivered accessibility and scheduled accessibility. They use retrospective General Transit Feed Specification real-time (GTFS-RT) data to estimate the delivered accessibility in a public transit system based on vehicle location data. They show that schedule-based accessibility overestimates delivered accessibility. However, their retrospective accessibility measure assumes transit users have complete *a priori* knowledge of actual arrival time of vehicles; this requires clairvoyance or a perfect, idealistic real-time bus information system. In practice, real-time bus information has more complex impacts on waiting and travel times: it can increase waiting and travel times due to the temporal granularity of updates combined with bus operators attempting to make up for delays (*19*). This implies that the retrospective measure is also an overestimate of delivered accessibility.

To resolve this issue, Liu, Porr, and Miller (*8*) introduce realizable real-time accessibility as a more conservative measure of transit-based accessibility. They compare this measure to scheduled accessibility as a measure of accessibility reliability – the difference between scheduled and realizable accessibility. This represents the degree to which expected measure overestimate actual accessibility, as well as the fidelity of public transit systems to deliver an accurate and reliable service.

Reliability can also be used to measure resilience, namely robustness and recoverability of a transit system. Robustness as the increase of accessibility unreliability during a disruption, while recoverability can be measured by the recovery period of accessibility reliability after the disruption to a previous baseline. We will use this theoretical framework in our analysis.

## Disruptions and transit reliability

A major factor in the reliability of accessibility delivered by a public transit system are both chronic and occasional disruptive events. Depending on the effects, persistency, and frequency of the event, we can categorize disruptions by: 1) Short-term and long-term (*20*), 2) planned and unplanned (*21*), and 3) Recurring and non-recurring (*2*, *20*). These three categorizations are highly correlated with each other but not the same. In this paper, we adopt the short/long-term categorization based on the dimension of recoverability as we discussed above; we review the factors affecting public transit reliability in following paragraphs.

**Short-term disruption.** We define short-term disruption as the event that: 1) are short in time span: typically not exceeding a single day, which is the time unit of the operation of most transit systems; 2) do 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 many public transit systems use buses and trams that share roads with other vehicles, traffic on roads can significantly impact the on-time performance (*2*, *14*). Other examples include weather (e.g., heavy rain) (*22*, *23*) and major social events (e.g., concerts, sporting events, festivals, protests) (*24*). However, due to the ephemeral nature of these events and a previous lack of reliable high-resolution data, the research on this topic is still lagging.

**Long-term disruptions.**  We define long-term disruptions as events that: 1) are longer in time span, which can last from weeks to months and years; 2) affect both the on-time performance and the schedule; 3) may result in a new normal, rather than returning to the pre-disruption state. The studies and data on long-term disruptions are more abundant due to their more profound and persistent effects compared to short-term disruptions.

The COVID-19 pandemic is a major long-term disruption, if not the most important one in this century, that has huge impacts on the public transit systems in the entire world (*25*). COVID-19’s significant negative impacts on public transit accessibility are reported by many papers. For example, Kar et al. (*26*) studied the public transit accessibility to essential services in 22 US cities and found significant declines; the paper also pointed out that the pandemic-related decline primarily impacts marginalized communities. In response to the disruption, transit authorities and government also enacted policies and system adjustments to resist the negative impacts. For example, Singh et al. (*27*) found COVID-19 pandemic has negative impact on the transit accessibility in Winnipeg, Canada but a new BRT system helps to increase the accessibility for underprivileged populations.

Extreme weather events can also incur persistent disruption to public transit and transit accessibility. A prime example is flood and sea level rising caused by climate change. Li et al. (*28*) simulated the potential effect of a 100-year pluvial flood on Shanghai Metro, China and found universal decrease in accessibility. He et al. (*29*) found flood disruptions lead to increase in headways and loss of job accessibility in Kinshasa, Democratic Republic of the Congo. Despite many existing discussions, very few papers focus on the impacts on accessibility and reliability.

# Method

## 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 (*30*, *31*). The data have two data standard, GTFS static and GTFS real-time data, which contain the schedule timetable and real-time timetable, respectively (*32*, *33*). Based on the two datasets, 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 until January 2022.

## Accessibility Measure

Accessibility is a diverse concept that can measure different aspects of mobility (*34*); in this paper, we focus on the measure of physical accessibility in a transit system. Physical accessibility measures the upper limits on the reachability of locations by a transit user given a time budget; in other words, how far a user can go by using transit service given a travel time limit such as 30 minutes.

We use a well-established time geography concept – the space-time prism (STP) – to quantify the physical accessibility (*6*, *35*). It represents the envelope of all possible space-time paths in three possible scenarios: i) travel from an origin to all possible destination; travel from all possible origins to a destination, or; iii) travel between an origin destination pair, given departure and/or arrival times, a time budget and the speed afforded by the mobility modes, including multimodal trips such as walking and public transit (*6*). In our analysis, we treat bus stops as single origins and calculate the prisms from each single origin with a departure time to all possible destination We calculate the implicit STP based on public transit stops – this is the number of accessible stops from an origin stop given a time budget (*8*). First, we introduce a decision variable to determine if a user can arrive at a stop within the time budget.

|  |  |  |
| --- | --- | --- |
|  |  | (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 . 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.

Note that the travel times in the transit network are also determined by the arrival time at the origin stops. This is due to the time-dependent nature of transit networks (*36*, *37*). 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 static Dijkstra algorithm compatible to a transit network with dynamic costs (*38*, *39*). The rule assumes a public transit vehicle leaving an origin stop will never arrive later at the destination stop than a public transit vehicle on the same route that is scheduled later. Vehicle overtaking in violation of the FIFO restriction is a rare event: we estimate from COTA data that 95% of the buses meet this restriction.

## Unreliability measures

We define unreliability of transit accessibility as the gap between the schedule-based accessibility and the delivered 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 achieve in practice without clairvoyance or a perfect real-time bus information system. Liu, Porr, & Miller (*8*) introduce a realizable real-time accessibility measure that assumes no real-time information as the system operates and deviations from schedules occur. It is calculated in two steps – planning and implementation. 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 (*8*).

We measure accessibility unreliability as the normalized difference between scheduled and realizable accessibility:

|  |  |  |
| --- | --- | --- |
|  |  | (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.

As discussed in the background section, there are two major aspects of resilience, namely robustness and recoverability. We implement the two concepts with accessibility unreliability. We can define robustness as the change of accessibility unreliability before and during the disruption and recoverability as the duration of the disruption’s impact. We introduce specific definition and analyses in flowing sections with each case study.

## Short-term Disruption: College Football Games

Ohio Stadium hosts college football games from September to December every one or two weeks, which attract more than a hundred thousand viewers to the stadium before the pandemic (*41*). Home games attract large amounts of traffic to and from the Ohio Stadium before and after the game, creating short-term disruptions to both private and public transportation. Away games (hosted by another university) are also popular near campus due to the concertation of bars and restaurants showing the game on their televisions, but these do not attract the high concentrations of people as a home game

Football games are a good example of short-term disruption because: 1) most football games last around 3 hours, which is short in time span compared to other disruptive events; 2) transit systems recover from the disruption relatively quickly as crowds and traffic disperse; 3) football games do not change the schedule of transit system in a fundamental way, despite some short-term rerouting in some areas. Therefore, we choose Ohio State football games as our case study for short-term disruptions. We select all home and away game days in 2018 and 2019 from September to December and calculate the accessibility unreliability respectively. We also choose other Saturdays without a home and away game in the same time period for comparison.

First, we investigate the temporal trend of accessibility reliability before and after the event time. Meanwhile, each game can have different start time, whose impacts can thus occur at different hour. There are three start time slots: 12:00 pm, 3:30/4:00 pm, and 7:30 pm; we categorize games based on their start time. There are 9 home games at 12:00 pm, 4 home games at 3:30/4:00 pm, and 1 home game at 7:30 pm. Also, since the impacts of football games are spatially heterogenous, we map the accessibility unreliability at each stop across the whole city of Columbus.

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

Since Jan 2020, the COVID-19 pandemic has persistent and significant impacts on transit systems across the whole United States. For this case study, we choose the COVID-19 pandemic as an example of long-term disruptive event and the city of Columbus and COTA as our study area.

The city of Columbus reported its first three cases on March 9, 2020; local authorities declared the state of emergency on March 11, 2020, and enacted lockdown and curfew shortly after the date (*42*), which resulted in immediate decline of the ridership (*25*). The plunge in ridership also leads to service cut and schedule changes to adapt to staff shortage and economic difficulties (*43*). To investigate the distinctive impacts of different stages of the pandemic, we select all the Wednesdays during March 2019, to Jan 2022. We first calculate the average realizable accessibility, i.e., the average number of accessible stops, and accessibility reliability for each date.

To measure the robustness of the system with respect to COVID, we calculate the changing rate of realizable accessibility and the difference of accessibility unreliability between the first year of COVID (March 1, 2020 – March 1, 2021) and the year before COVID (March 1, 2019 – March 1, 2020). The two measures gauge the disruption’s impacts on accessibility and unreliability, which represent the extent and quality of the public transit service respectively. We map the two measures for every stop in the city of Columbus and explore their spatial pattern.

# Result

## Short-term Disruption: Football games

We calculate accessibility unreliability of every stop and every hour from 8 am to 22 pm for every game day during 2018 to 2019. We aggregate all games days based on their start time; Figure 1 shows the hourly profile of the average accessibility unreliability. Higher unreliability means that the deviation of realizable accessibility from the scheduled accessibility is larger; for example, unreliability of 100% means that system users can actually only access half of the stops in the scheduled scenario. All game days, except the 7:30pm game (discussed later), have two unreliability peaks before and after the game, which represent the traffic to and from the stadium respectively.

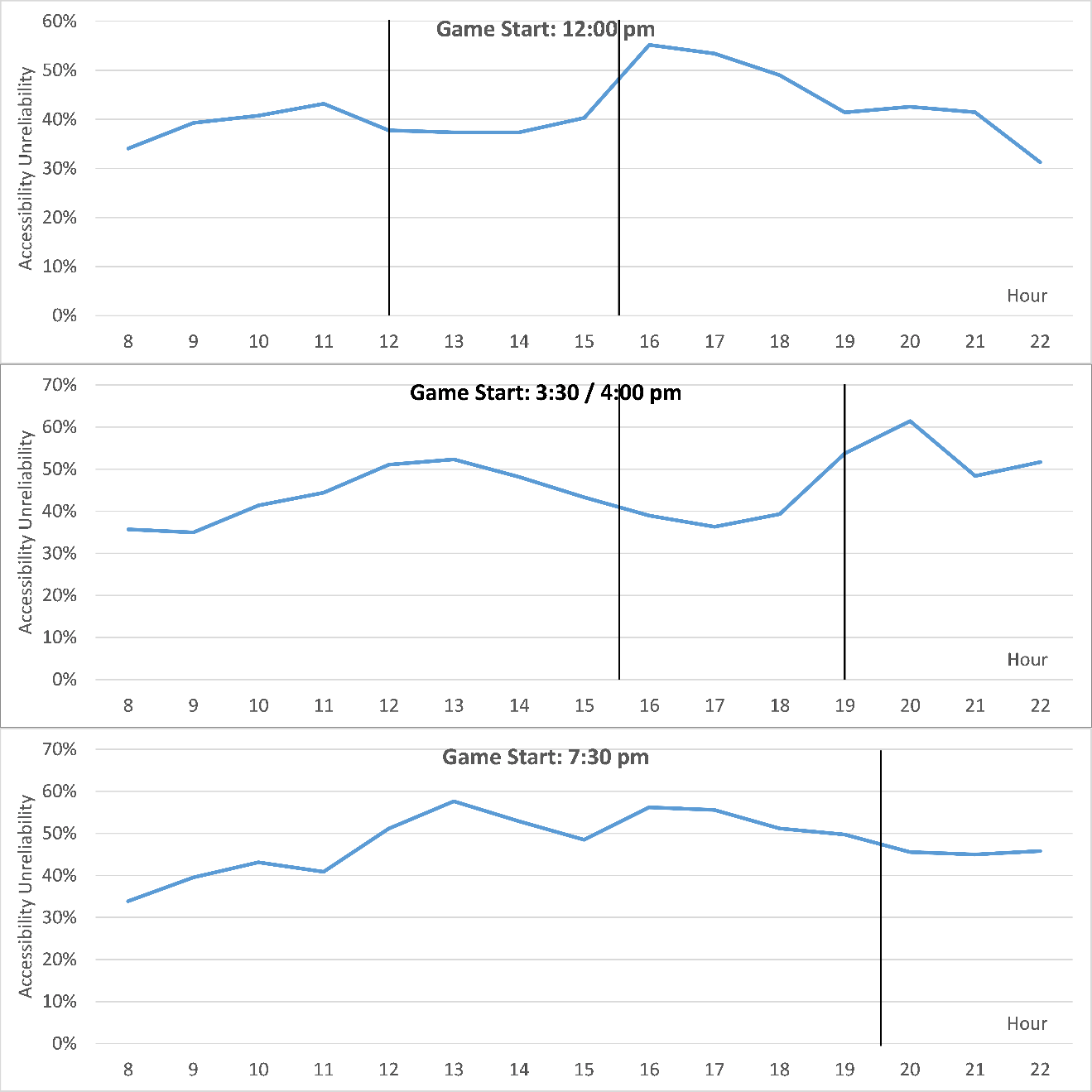


Figure : average hourly profile of accessibility unreliability in three different game start time slots. Black line indicates game start and end time. Note that the 7:30 pm game ended at 11:03 pm, which is outside the scale of the graph and normal operation hours.

Several phenomena prove that the peaks in game days are not random or caused by ordinary commuting traffic. Figure 2 visualizes the relationship between the positions of the two peaks and the game start and end time. We can clearly witness that the positions of the peaks are shifting along with the changing game start time. The consistency strongly suggests that the peaks are caused by the football games. Figure 3, moreover, reaffirm this correlation between football games and high unreliability. The graph shows the hourly profile of accessibility unreliability for home game, away game, and non-game days in the same time period. The unreliability in home game days is higher than away game days and non-game days, while away game days are higher than non-game days.

We also measure the two factors of resilience as we introduce in the background and method section, namely robustness and recoverability. In term of robustness, unreliability at the before-game peak is 8.7% higher than the average, while unreliability at the after-game peak is 25.4% higher than the average, showing football games’ great impacts on transit service’s reliability. In term of recoverability, the duration of football games’ impact, i.e., the gap between before- and after-game peaks, is 6.8 hours. We can also divide the whole period into three sections: 1) before-game gap, i.e., the gap between the before-game peak and the game start, 2) game duration, and 3) after-game gap, i.e., the gap between the game end and the after-game peak. The average before-game gap is 2.2 hours, and average after-game gap is 1.1 hours. Note that there is no after-game peak in Oct 5, 2019 from the third graph in Figure 1 and Figure 2, which started at 7:30 pm. The game ended at 11:03 pm, which is beyond the scale of the graph. With the average after-game gap, the after-game peak would have been at the midnight, which is outside the normal operating hours of COTA buses.

We can see the before-game impacts have longer duration but less disruptive effects, while after-game impacts have shorter duration but larger disruptive effects. This suggests that people can arrive at different time, but most people will leave the stadium at the same time, creating a more intense but less extensive disruption.



Figure : the relationship between positions of before-game peak, game start time, game end time, and after-game peak.



Figure : the average hourly profile of accessibility unreliability for home game, away game and non-game days in the same time period.

Moreover, we investigate the spatial heterogeneity of the unreliability pattern. Figure 4 visualizes the unreliability value at each stop – i.e., the highest accessibility unreliability value during the game day – of the before-game and after-game peaks for all 9 games that started from 12:00 pm. Public transit unreliability shows a strong clustering pattern. Both before-game and after-game peaks values are clustered around the Ohio Stadium, which is the main site of the football games. We also conduct same analysis for away game days and non-game days, and we find no high clusters around the stadium. This, together with the evidence we present above, strongly suggests the causality between football home games and high public transit unreliability.

Figure 4 also presents the hour of the peaks at each stop when the unreliability reaches its maximum. The stops near the stadium reach their maximum later compared to other stops before the game but reach their maximum earlier after the game. This also reflects a shockwave-like pattern of football games. Before the game, as viewers and most traffic are coming to the site, the event’s impacts would spread from the perimeter to the center; as soon as the football game ends, the impacts would spread from the center and reach neighboring stops first and spread to the perimeter.

Map

Description automatically generated

Figure : before-game and after-game peaks’ unreliability value and hour

## Long-term Disruption: COVID-19

COVID-19 has persistent negative impacts on public transit accessibility and accessibility reliability. Figure 5 (up) visualizes the temporal pattern of schedule-based accessibility and realizable accessibility; both significantly declined during the lockdown (March – June 2020) and kept lower than the pre-COVID level during the post-lockdown era. Note that the rapid decline of accessibility is not perfectly synchronous with the start of the pandemic. The major schedule change made by transit authority, which aims to adapt to the plunged ridership and financial difficulties, were enacted in May 2020, rather than immediately after the outbreak.

As we introduced in the background section, long-term disruption can impact unreliability by affecting both the on-time performance and the schedule. This means that these two factors can be conflicting with each other and produce nuanced patterns. For example, accessibility unreliability during the lockdown first declined and then increased as Figure 5 (bottom) shows. The decline can be because the lockdown eliminated all commuting travel and made roads empty (*44*), which makes the on-time performance better. Meanwhile, the schedule for the first few weeks stayed unchanged, resulting in less unreliability. However, following the service cut since May 2020, both accessibility measure rapidly declined but scheduled accessibility declined faster, resulting higher unreliability than usual. However, we do not observe major change in the global average of unreliability later after the lockdown.

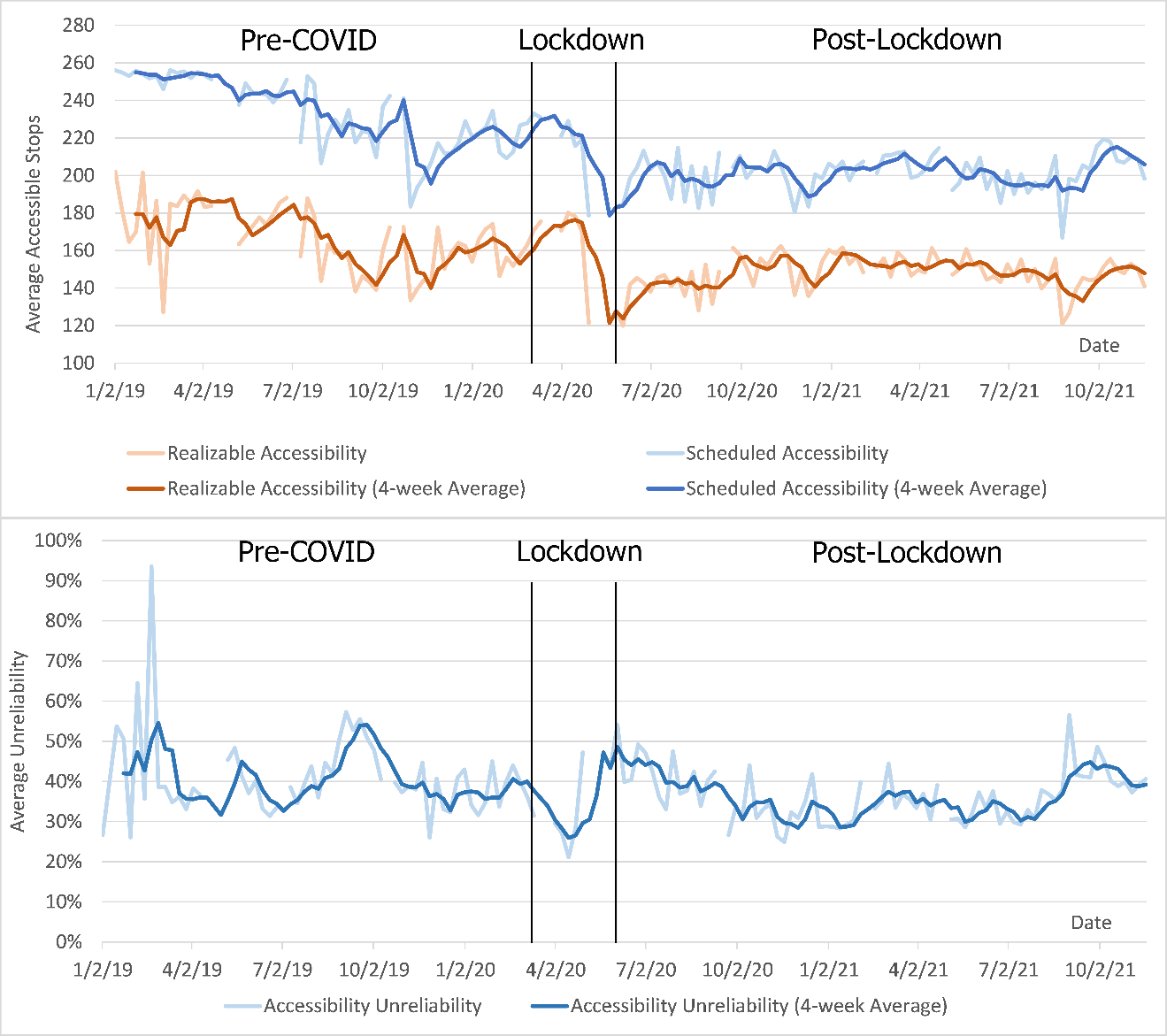


Figure : Temporal pattern of accessibility and unreliability

COVID-19’s impacts are also spatially heterogeneous. Figure 6 shows the changing rate of realizable accessibility (left) and the difference of accessibility unreliability (right) between the year before and after the COVID-19 outbreak. Red color means more system performance loss, and blue color means less performance loss. The two measures’ spatial patterns are very similar: both are highly clustered. The downtown area, which accounts for most ridership in the system (*45*) and experienced least service cut, has less accessibility and reliability loss. The decline of unreliability can also be explained by the reduction of general traffic. However, for urban perimeters and suburban areas, there are more unreliability and more accessibility loss due to service cuts.

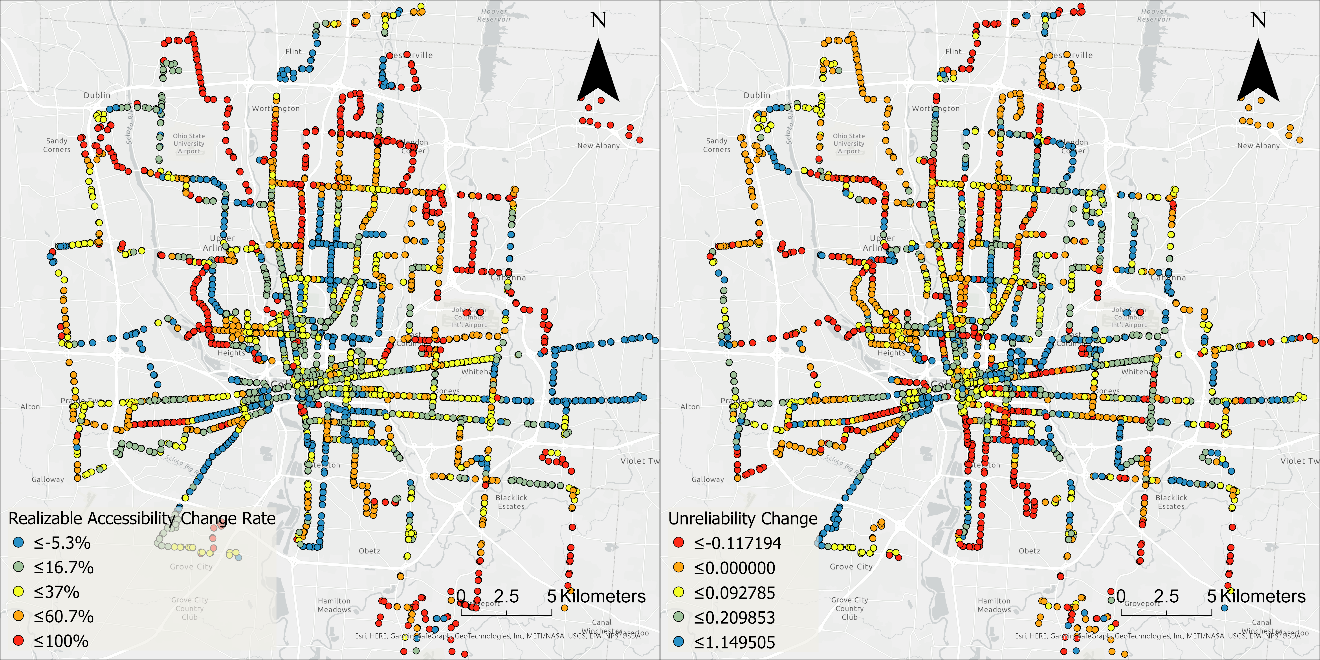


Figure : the change rate of realizable accessibility and unreliability after COVID-19.

# Conclusion

Public transit systems are facing higher risks of system failure caused by disruptions, such as climate change and pandemics. Despite myriad discussions on transit accessibility, reliability, and resilience, few papers integrate accessibility and its reliability into the study of resilience of public transit systems against disruptions. To fill in the gaps, we use two measures in this paper: *realizable accessibility*, which represents the accessibility that can be actually achieved by a transit user (*8*), and scheduled accessibility, which represents the expected useability of the transit system. Based on the two measures, we define accessibility reliability as the difference between delivered accessibility and scheduled accessibility to measure the variation of transit system’s performance. The paper provides a new way for future research and planning to understand public transit system’s resilience against different types of disruptions. The method uses the change of realizable accessibility – i.e., the delivered service, and accessibility reliability – i.e., quality of delivered service – during a disruptive event as two measures of system resilience. We choose two examples, namely the Ohio State football games and the COVID-19 pandemic, to exemplify short-term and long-term disruption, respectively.

We find that football games are correlated with exceptional high unreliability in local public transit system. Days with Ohio State home game days have significantly higher unreliability than away game and non-game days, while days with away games have higher unreliability than non-game days. There were two peaks of unreliability before and after each game, and the position of both peaks moved with the game time in a consistent manner. Spatial analysis also shows that Ohio Stadium was the very center of the high unreliability cluster, while other days did not show similar patterns. All evidence strongly suggests that the high unreliability was caused by the football games, rather than random fluctuations or daily commuting.

Analyses on COVID-19 and subsequent service cut also show that it incurred universal decline in realizable accessibility for transit users. However, improved traffic condition caused by the lockdown during the early stages of the pandemic helped to reduce unreliability, but unreliability later increased after the service cut. The shrinking service schedule and improved traffic condition, as two contradicting forces, created a subtle pattern of unreliability. Our spatial analysis also reveals that the city center, which has most ridership and accessibility, experienced least accessibility and reliability loss, while most of the urban perimeters and suburbs witnessed massive decline in system performance and service quality.

The contribution of proposed methods and results is threefold. First, both case studies show the effectiveness of realizable accessibility and accessibility unreliability to detect system disturbances, and it works on both short- and long-term disruptions with high spatial and temporal resolution. More public transit systems should use real-time data to monitor system performance and guide future system operation and planning. Second, the results on football games reveal crucial patterns of large social events’ impacts on public transit accessibility and reliability. For example, transit authorities can plan and broadcast rerouting in advance according to average before- and after-game peak hours, while keep normal schedule for other hours. Finally, major long-term disruptions, such as COVID-19, had effects on both on-time performance and schedule; despite the increase in unreliability, which can indeed be advantageous for some passengers, the impacts of COVID-19 are still devastating when factoring major decline in accessibility. This also shows that unreliability alone cannot show the whole picture of transit experience; instead, realizable accessibility together with accessibility reliability is a more holistic way to understand system performance, just like mean and variance.

The paper also has limitations. First, despite strong indications of causality, we cannot make definite conclusions on the causality between high unreliability and the disruptive events; there can be other dominating factors that we do not know of. In other words, despite revealing many *patterns* of the impacts, i.e., how much, where, and when are the disruptive event’s impacts, we still have very few information on the *process*, i.e., how and by what did the disruptive event impact the system [citation needed]. Archived real-time information is perfect media to reveal the patterns and reconstruct the process. Second, we do not address the implications of the disruptions on social equity and specific individual experience. Third, the paper does not address the heterogeneity of accessibility to different opportunities; we only measure accessibility with the number of accessible stops. The paper also points out several open topics for future research. For example, the method can be applied to any cities with corresponding real-time and schedule GTFS data. We would like to see more case studies on accessibility reliability in different settings in the future.

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