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

Luyu Liu 1, Adam Porr 2, Harvey J. Miller 1, \*[[1]](#footnote-1)

1 Department of Geography and Center for Urban and Regional Analysis, The Ohio State University, Columbus, OH, USA

2 Mid-Ohio Regional Planning Commission, Columbus, OH, USA

# 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 factors that affect people’s preference of a public transit system (*1*, *2*).

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 (*3*, *4*) 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 (*3*), 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 (*5*). 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.

# Background

We review relevant literature in this section.

## Resilience

Resilience is introduced as the capacity of a system to maintain its functions during a disruption (*6*, *7*). As climate change, pandemics, and energy crises increase the risk and frequency of disruptions, transport resilience becomes a new focus of transportation focus. However, the definition of transport resilience can be rather heterogenous and nuanced. Most prior research agree that resilience includes two core functions: Robustness and recoverability (*6*, *8*, *9*).

Robustness – some papers also use adaptability and reliability, or vulnerability and unreliability as antonyms – is the ability to maintain the disruption during a disruptive event. An ideal transport system should still maintain a minimum required performance when facing a disruptive event. Robustness is measured by the decline of a system performance index (*8*, *9*). Recoverability – some papers also use resilience or resiliency – is defined as the ability to return to its previous state in a timely manner (*8*). It is usually measured by the time from the disruptive event happens to the time when the performance recovers to pre-disruption level (*8*, *9*). 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 (*9*); however, its specific definition can be quite nuanced, depending on the performance the index measures. Most of the prior research investigated travel time reliability (*9*, *10*). Carrion and Levinson (*11*) categorized the concept of travel time reliability 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, depending on the standard for comparison.

Similarly, due to the direct link between travel time and accessibility, the reliability of accessibility can also be defined as the variation of accessibility. Gu et al. (*9*) discussed transport reliability associated with accessibility, i.e., the variation of accessibility. D’este and Taylor (*12*) and Taylor and D’este (*13*) first introduce reliability and vulnerability with the idea of accessibility. On the other hand, just like travel time reliability, accessibility reliability can also be defined as the variation between expected/scheduled accessibility and actual accessibility. Wessel, Allen, and Farber (*4*) and Wessel and Farber (*3*) investigated the accuracy of schedule-based accessibility by calculating the difference between delivered accessibility and scheduled accessibility. They retrospectively collected historical General Transit Feed Specification real-time (GTFS-RT) data to calculate actual delivered accessibility. They conclude that schedule-based accessibility is unreliable and cannot represent the actual experience of transit users. However, the retrospective measure assumes transit users know *a priori* the actual arrival time of vehicles, which is not attainable before the event happens. This also means the retrospective measure cannot be an accurate representation of users’ actual experienced accessibility.

To solve this issue, Liu, Porr, and Miller (*5*) introduced realizable real-time accessibility as a more realistic measure of transit users’ accessibility experience. The paper also introduced accessibility reliability as the difference between scheduled and realizable accessibility. The measure 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 can be measured by the decline of accessibility reliability or increase of accessibility unreliability during a disruption, while recoverability can be measured by the recovery period of accessibility reliability during a disruption. Note that unreliability as a system performance measure exists even without a disruption. We will use this theoretical framework in our following analysis.

## Disruptions and transit reliability

Depending on the effects, persistency, and frequency of the event, we can categorize all disruptions with multiple principles: 1) Short-term and long-term (*14*), 2) planned and unplanned (*15*), and 3) Recurring and non-recurring (*14*, *16*). 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) 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) 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 (*11*, *16*). Other examples include weather (e.g., disruptive rain) (*17*, *18*) and major social events (e.g., large social gatherings or even terrorist attack) (*19*). However, the research on this topic is still lacking. Due to the momentary nature of these events and lack of reliable high-resolution data, most prior studies did not measure the impact on accessibility and reliability.

**Long-term disruptions.**  We define long-term disruptions as the event that: 1) are longer in time span, which last from weeks to multiple years; 2) affect both the on-time performance and the timetable; 3) may land on a new normality, 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 (*20*). COVID-19’s significant negative impacts on public transit accessibility are reported by many papers. For example, Kar et al. (*21*) 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. (*22*) 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. Allen and Farber (*23*) found that newly opened food bank locations increase food accessibility by 10% in Toronto during the pandemic.

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. (*24*) simulated the potential effect of a 100-year pluvial flood on Shanghai Metro, China and found universal decrease in accessibility. He et al. (*25*) found flood disruptions lead to increase in headways and loss of job accessibility in Kinshasa, Democratic Republic of the Congo.

There are still huge gaps in this area. First, prior studies focus on the disruptions’ impact on travel time, ridership, and capacity (*26*), rather than accessibility and accessibility reliability. Second, the studies on short-term disruptions are lacking. Lack of reliable high-resolution data source made it very hard to conduct empirical analysis on short-term disruptions. Last, few papers discussed the recoverability of transit accessibility. It is noteworthy that most introduced studies above only investigate the robustness of the system. Due to the availability of high-resolution real-time data, we now can address these gaps in this paper accordingly.

# 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 (*27*, *28*). The data have two data standard, GTFS static and GTFS real-time data, which contain the schedule timetable and real-time timetable, respectively (*29*, *30*). 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 (*31*); 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 (*32*). In practice, we use implicit STP – the number of accessible stops from a stop give a time budget – as the accessibility measure (*5*). 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 .

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 (*33*, *34*). 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 (*35*, *36*). 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 (*5*) 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 (*5*). 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.

Like what we introduce 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 generally 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

Football is one of the most popular sports in the US; about 22 million viewers watch the final college football game in 2022 (*37*). 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 (*38*). Home games attract large amount of traffic to the Ohio Stadium, creating a short-term disruption to local public transit system. Away games are also popular but far less crowded than home games.

Football games are a good example of short-term disruption because: 1) most football games are around 3 hours, which is short in time span compared to other disruptive events; 2) transit systems recover from the disruption in a timely manner; 3) football games will not change the schedule of transit system in a fundamental way, despite some rerouting in small 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 some Saturdays without a home and away game in the same time period.

First, we will investigate the temporal trend of accessibility reliability before and after the event time to its impacts. Meanwhile, each game can have different start time, whose impacts can thus occur at different hour. There are three start time slots: 12:00pm, 3:30/4:00pm, and 7:30pm; we categorize games based on their start time. There are 9 home games at 12:00pm, 4 home games at 3:30/4:00 pm, and 1 home game at 7:30pm.

Also, the impacts of football games are spatially heterogenous. We map the spatial distribution of 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 (*39*), which resulted in immediate decline of the ridership (*20*). The plunge in ridership also leads to service cut and schedule changes to adapt to staff shortage and economic difficulties (*40*). 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

## Football games

We calculate accessibility unreliability of every hour from 8 am to 22 pm for every game day during 2018 to 2019. We also aggregate all games days based on their start time; Figure 1 shows the hourly profile of the average accessibility unreliability. All game days, except the one 7:30pm game (discussed later), have two unreliability peaks before and after the game, which represent the traffic to and from the stadium respectively.

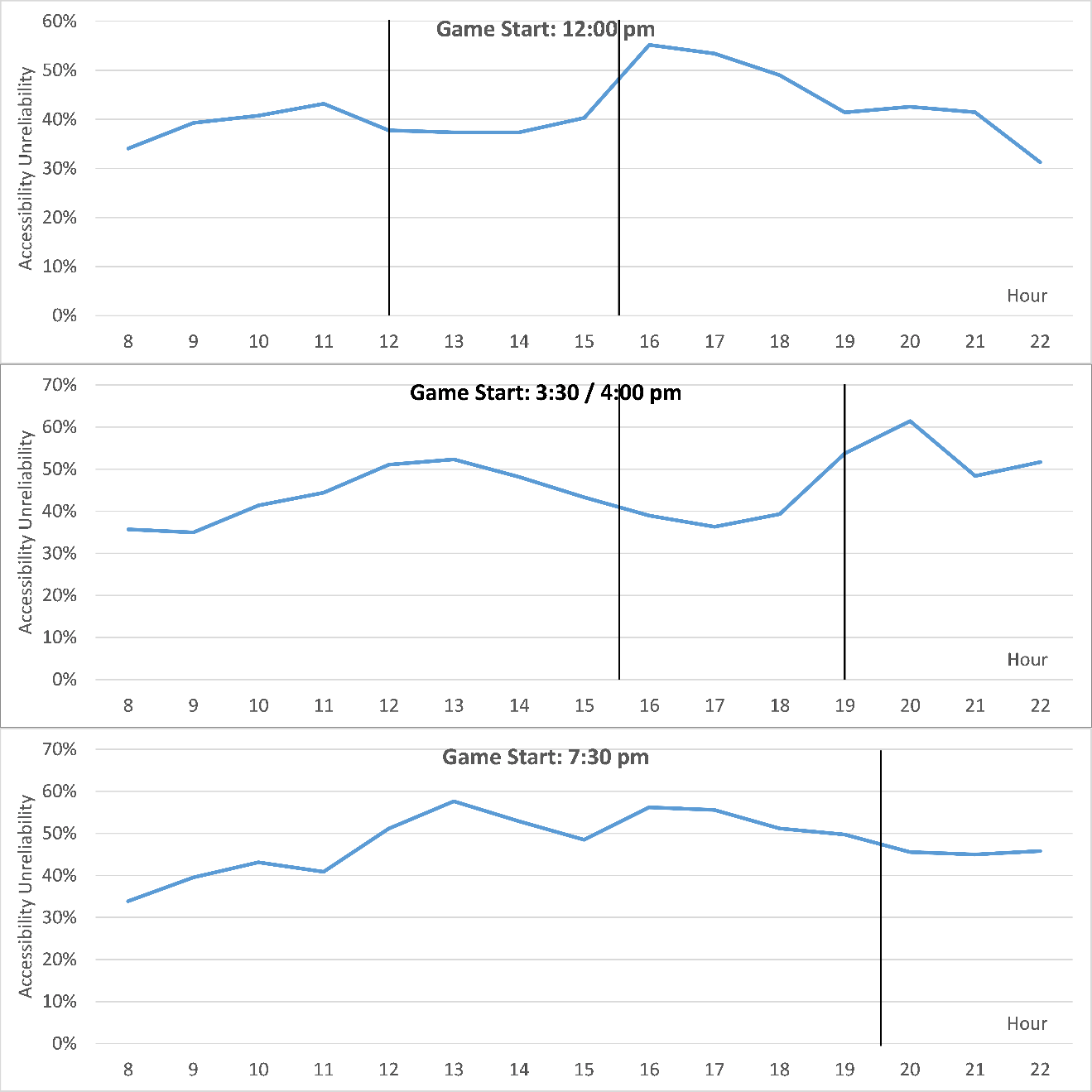


Figure : average hourly profile of accessibility unreliability in three different game start time slots. Black line indicates game start and end time.

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 also shows the hourly profile of accessibility unreliability for away game days and non-game days in the same time period. Note that the peak unreliability values do not exceed 45%, while peak values in game days easily exceed 50% or even 60%. This, moreover, shows that the unreliability levels in game days are abnormal and different from 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. With the average gap, the after-game peak would have been after 23:00, which is out of the main 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.

Chart, line chart

Description automatically generated

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

Moreover, we would like to 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. This, together with the evidence we present above, proves 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 4: before-game and after-game peaks’ unreliability value and hour

## 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 (*41*), 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.

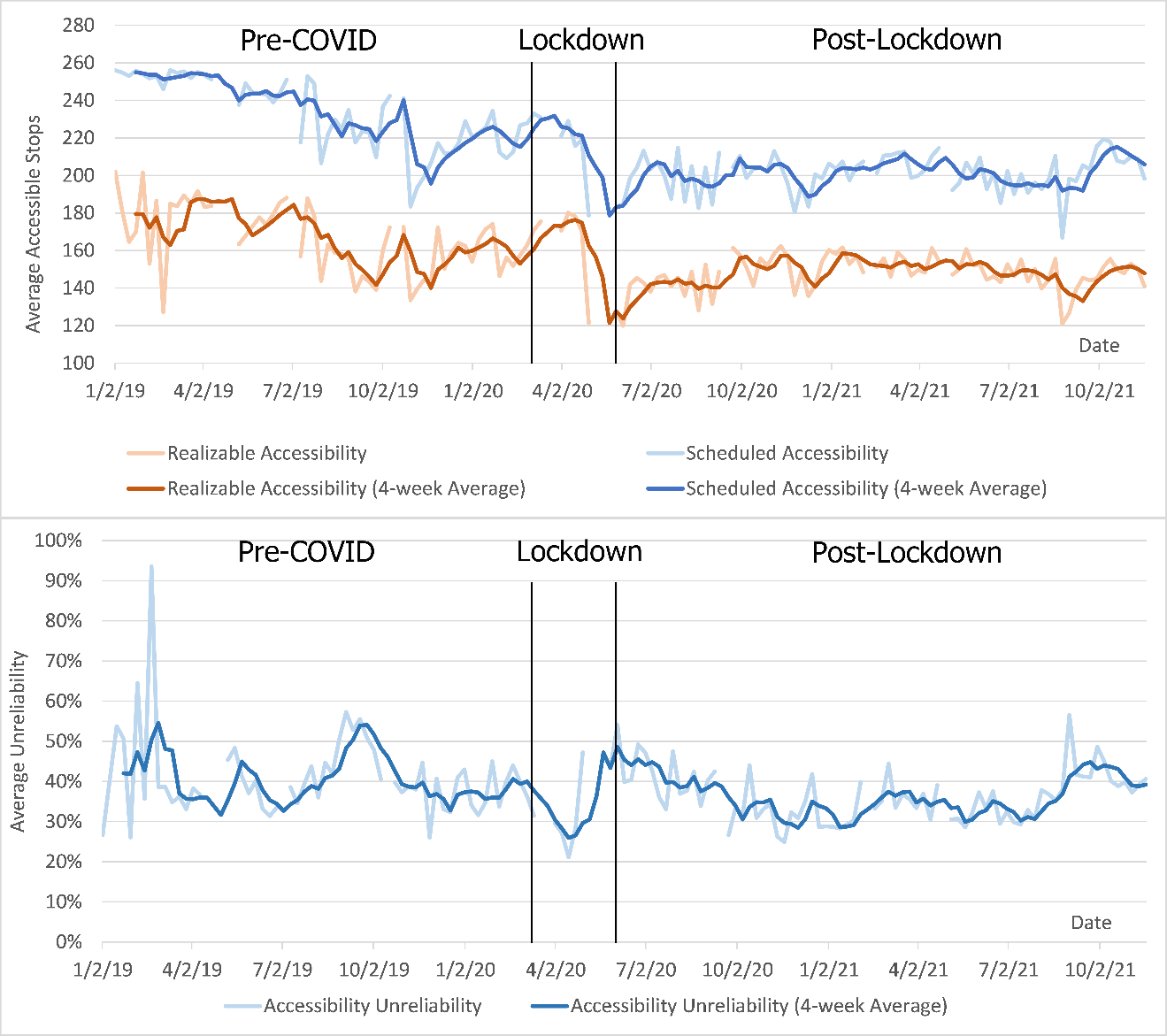


Figure : Temporal pattern of accessibility and unreliability

Meanwhile, 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 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 (*42*) 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.

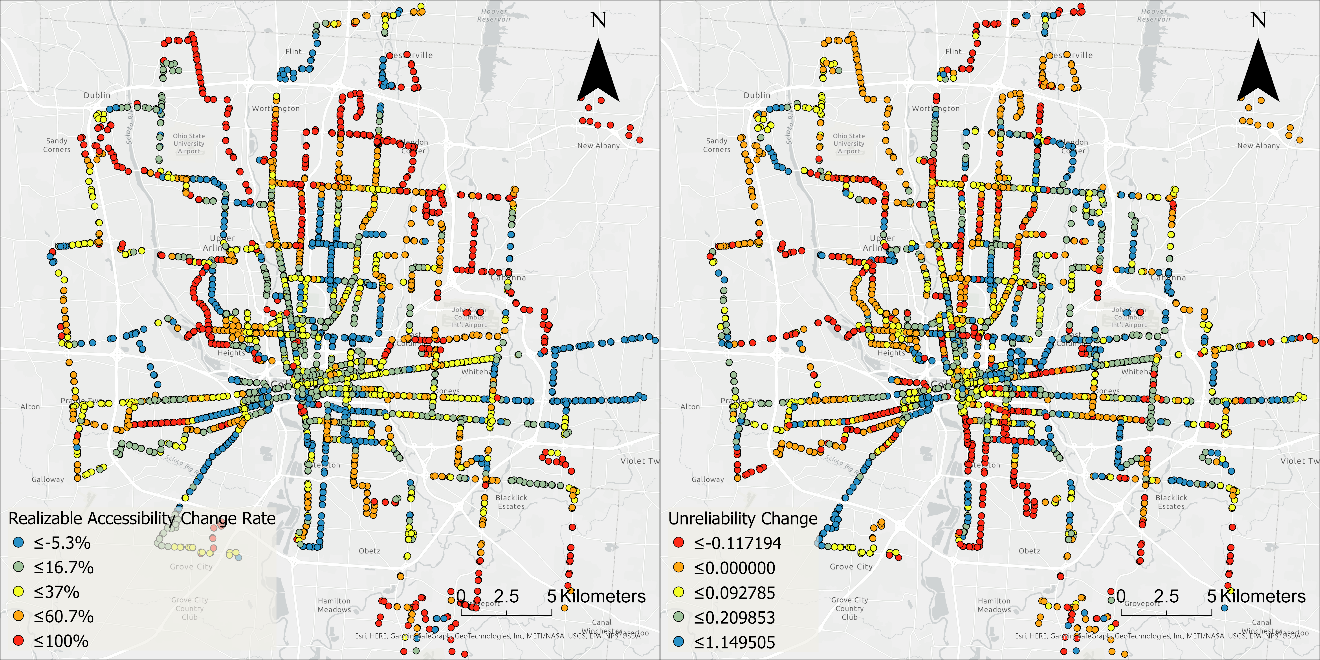


Figure : the change rate of realizable accessibility and unreliability after COVID-19.

# Conclusion

Reference:

1. Chakrabarti, S., and G. Giuliano. Does Service Reliability Determine Transit Patronage? Insights from the Los Angeles Metro Bus System. *Transport policy*, Vol. 42, 2015, pp. 12–20.

2. Erhardt, G. D., J. M. Hoque, V. Goyal, S. Berrebi, C. Brakewood, and K. E. Watkins. Why Has Public Transit Ridership Declined in the United States? *Transportation Research Part A: Policy and Practice*, Vol. 161, 2022, pp. 68–87.

3. Wessel, N., and S. Farber. On the Accuracy of Schedule-Based GTFS for Measuring Accessibility. *Journal of Transport and Land Use*, Vol. 12, No. 1, 2019, pp. 475–500.

4. Wessel, N., J. Allen, and S. Farber. Constructing a Routable Retrospective Transit Timetable from a Real-Time Vehicle Location Feed and GTFS. *Journal of Transport Geography*, Vol. 62, 2017, pp. 92–97.

5. Liu, L., A. Porr, and H. J. Miller. Realizable Accessibility: Evaluating the Reliability of Public Transit Accessibility Using High-Resolution Real-Time Data. *Journal of Geographical Systems*, 2022. https://doi.org/10.1007/s10109-022-00382-w.

6. Azolin, L. G., A. N. R. da Silva, and N. Pinto. Incorporating Public Transport in a Methodology for Assessing Resilience in Urban Mobility. *Transportation research part d: transport and environment*, Vol. 85, 2020, p. 102386.

7. Holling, C. S. Resilience and Stability of Ecological Systems. *Annual review of ecology and systematics*, 1973, pp. 1–23.

8. Wan, C., Z. Yang, D. Zhang, X. Yan, and S. Fan. Resilience in Transportation Systems: A Systematic Review and Future Directions. *Transport reviews*, Vol. 38, No. 4, 2018, pp. 479–498.

9. Gu, Y., X. Fu, Z. Liu, X. Xu, and A. Chen. Performance of Transportation Network under Perturbations: Reliability, Vulnerability, and Resilience. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 133, 2020, p. 101809.

10. Kathuria, A., M. Parida, and C. Sekhar. A Review of Service Reliability Measures for Public Transportation Systems. *International Journal of Intelligent Transportation Systems Research*, Vol. 18, No. 2, 2020, pp. 243–255.

11. Carrion, C., and D. Levinson. Value of Travel Time Reliability: A Review of Current Evidence. *Transportation research part A: policy and practice*, Vol. 46, No. 4, 2012, pp. 720–741.

12. D’este, G. and, and M. A. Taylor. Network Vulnerability: An Approach to Reliability Analysis at the Level of National Strategic Transport Networks. In *The network reliability of transport*, Emerald Group Publishing Limited.

13. Taylor, M. A., and G. M. D’Este. Transport Network Vulnerability: A Method for Diagnosis of Critical Locations in Transport Infrastructure Systems. In *Critical infrastructure*, Springer, pp. 9–30.

14. Lin, T., A. Shalaby, and E. Miller. Transit User Behaviour in Response to Service Disruption: State of Knowledge. 2016.

15. Zhu, S., and D. M. Levinson. Disruptions to Transportation Networks: A Review. *Network reliability in practice*, 2012, pp. 5–20.

16. Park, Y., J. Mount, L. Liu, N. Xiao, and H. J. Miller. Assessing Public Transit Performance Using Real-Time Data: Spatiotemporal Patterns of Bus Operation Delays in Columbus, Ohio, USA. *International Journal of Geographical Information Science*, Vol. 34, No. 2, 2020, pp. 367–392. https://doi.org/10.1080/13658816.2019.1608997.

17. Mesbah, M., M. Luy, and G. Currie. Investigating the Lagged Effect of Weather Parameters on Travel Time Reliability. *WIT Transactions on Ecology and the Environment*, Vol. 191, 2014, pp. 795–801.

18. Pender, B., G. Currie, A. Delbosc, and N. Shiwakoti. Social Media Use during Unplanned Transit Network Disruptions: A Review of Literature. *Transport Reviews*, Vol. 34, No. 4, 2014, pp. 501–521.

19. Berche, B., C. Von Ferber, T. Holovatch, and Y. Holovatch. Resilience of Public Transport Networks against Attacks. *The European Physical Journal B*, Vol. 71, No. 1, 2009, pp. 125–137.

20. Liu, L., H. J. Miller, and J. Scheff. The Impacts of COVID-19 Pandemic on Public Transit Demand in the United States. *Plos one*, Vol. 15, No. 11, 2020, p. e0242476.

21. Kar, A., A. L. Carrel, H. J. Miller, and H. T. Le. Reducing Public Transit Compounds Social Vulnerabilities during COVID-19. 2021.

22. Singh, S. S., R. Javanmard, J. Lee, J. Kim, and E. Diab. Evaluating the Accessibility Benefits of the New BRT System during the COVID-19 Pandemic in Winnipeg, Canada. *Journal of Urban Mobility*, Vol. 2, 2022, p. 100016.

23. Allen, J., and S. Farber. Changes in Transit Accessibility to Food Banks in Toronto during COVID-19. *Findings*, 2021, p. 24072.

24. Li, M., M.-P. Kwan, J. Yin, D. Yu, and J. Wang. The Potential Effect of a 100-Year Pluvial Flood Event on Metro Accessibility and Ridership: A Case Study of Central Shanghai, China. *Applied geography*, Vol. 100, 2018, pp. 21–29.

25. He, Y., S. Thies, P. Avner, and J. Rentschler. Flood Impacts on Urban Transit and Accessibility—A Case Study of Kinshasa. *Transportation research part D: transport and environment*, Vol. 96, 2021, p. 102889.

26. Mudigonda, S., K. Ozbay, and B. Bartin. Evaluating the Resilience and Recovery of Public Transit System Using Big Data: Case Study from New Jersey. *Journal of Transportation Safety & Security*, Vol. 11, No. 5, 2019, pp. 491–519.

27. Antrim, A., and S. J. Barbeau. *Opening the Door to Multimodal Applications: Creation, Maintenance and Application of GTFS Data*. 2017.

28. Liu, L., and H. J. Miller. Measuring Risk of Missing Transfers in Public Transit Systems Using High-Resolution Schedule and Real-Time Bus Location Data. *Urban Studies*, 2020, p. 0042098020919323. https://doi.org/10.1177/0042098020919323.

29. Google. GTFS Realtime Overview. https://developers.google.com/transit/gtfs-realtime. Accessed Jun. 27, 2021.

30. Google Developers. GTFS Static Overview | Static Transit | Google Developers. https://developers.google.com/transit/gtfs/. Accessed May 26, 2021.

31. Miller, E. J. Accessibility: Measurement and Application in Transportation Planning. *Transport Reviews*. 5. Volume 38, 551–555.

32. Miller, H. J. Time Geography and Space-Time Prism. *International encyclopedia of geography: People, the earth, environment and technology*, 2017, pp. 1–19.

33. Gendreau, M., G. Ghiani, and E. Guerriero. Time-Dependent Routing Problems: A Review. *Computers & operations research*, Vol. 64, 2015, pp. 189–197.

34. Wang, Y., Y. Yuan, Y. Ma, and G. Wang. Time-Dependent Graphs: Definitions, Applications, and Algorithms. *Data Science and Engineering*, Vol. 4, No. 4, 2019, pp. 352–366.

35. Ahn, B.-H., and J.-Y. Shin. Vehicle-Routeing with Time Windows and Time-Varying Congestion. *Journal of the Operational Research Society*, Vol. 42, No. 5, 1991, pp. 393–400.

36. Ichoua, S., M. Gendreau, and J.-Y. Potvin. Vehicle Dispatching with Time-Dependent Travel Times. *European journal of operational research*, Vol. 144, No. 2, 2003, pp. 379–396.

37. Saul, D. Viewership For College Football Playoff Championship Up From Record Low 2021 — But Still Below NFL’s Ratings. *Forbes*. https://www.forbes.com/sites/dereksaul/2022/01/11/viewership-for-college-football-playoff-championship-up-from-record-low-2021---but-still-below-nfls-ratings/. Accessed Jul. 1, 2022.

38. Kaufman, J. Ohio State Football Draws Crowd of Only 76,540 in Win over Tulsa, Smallest since 1971. *The Columbus Dispatch*. https://www.dispatch.com/story/sports/2021/09/18/ohio-stadium-crowd-osu-ohio-state-tulsa-football-game-76-540/8407755002/. Accessed Jul. 1, 2022.

39. Chow, A. Ohio Confirms First Cases Of Coronavirus. *The Statehouse News Bureau*. https://www.statenews.org/government-politics/2020-03-09/ohio-confirms-first-cases-of-coronavirus. Accessed Jul. 19, 2022.

40. Van Niel, L. COTA Faces Driver Shortages, Adjusts Services. *The Lantern*. https://www.thelantern.com/2021/09/cota-faces-driver-shortages-adjusts-services/. Accessed Jul. 19, 2022.

41. Lee, J., A. Porr, and H. J. Miller. Evidence of Increased Vehicle Speeding in Ohio’s Major Cities during the COVID-19 Pandemic. 2020.

42. Liu, L., A. Kar, A. I. Tokey, H. T. Le, and H. J. Miller. *Disparities in Public Transit Accessibility and Usage by People with Mobility Disabilities: An Evaluation Using High-Resolution Transit Data*.

1. \* Corresponding author, email: miller.81@osu.edu

   ORCID: Luyu Liu (0000-0002-6684-5570), Adam Porr (0000-0002-4776-5575), Harvey J. Miller (0000-0001-5480-3421) [↑](#footnote-ref-1)