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Does ridesourcing respond to unplanned rail disruptions? A natural experiment analysis of mobility resilience and disparity

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ABSTRACT

Urban rail transit networks provide critical access to opportunities and livelihood in many urban systems. Ensuring that these services are resilient (that is, exhibiting efficient responses to and recovery from disruptions) is a key economic and social priority. Increasingly, the ability of urban rail systems to cope with disruptions is a function of a complex patchwork of mobility options, wherein alternative modes can complement and fill occurring service gaps. This study analyzes the role of ridesourcing in providing adaptive mobility capacity that could be leveraged to fill no-notice gaps in rail transit services, addressing the question of distributional impacts of resilience. Using a natural experiment, we systematically identify 28 major transit disruptions over the period of one year in Chicago and match them, both temporally and spatially, with ridesourcing trip data. Using multilevel mixed modeling, we quantify variation in the adaptive use of on-demand mobility across the racially and economically diverse city of Chicago. Our findings show that the gap-filling potential of adaptive ridesourcing during rail transit disruptions is significantly influenced by the station-, community-, and district-level factors. Specifically, greater shifts to ridesourcing occur during weekdays, nonholidays, and more severe disruptions, in community areas that have higher percentages of white residents and transit commuters, and in the more affluent North district of the city. These findings suggest that while ridesourcing appears to provide adaptive capacity during rail disruptions, its benefits do not appear to be equitable for lower-income communities of color that already experience limited mobility options. Research implications for mobility operator collaborations to support mobility as a service are discussed. This study builds a more comprehensive understanding of transit service resilience, variation in vulnerability, and the complementarity of ridesourcing to existing transport networks during disruptions.

1. Introduction

Urban livability refers to the quality of life in urban communities and the degree to which cities satisfy the needs and aspirations of their inhabitants by providing physical and social well-being and supporting meaningful existences (Kashef, 2016). One important component of urban livability is a resilient mobility system that provides reliable access to work, healthcare, food, recreation, and other life-sustaining services (Renne et al., 2022). Ensuring resilience is challenging, however, because transportation systems rely on a complex web of fixed assets and multiple dynamic components, including competing operators, fixed-schedule and on-demand modes, and operations across heterogeneous built and social environments. In some regions, rail transit serves as a backbone for urban mobility (Litman, 2007). As such, in complex urban mobility systems, the ability of alternative modes to fill no-notice gaps in transit services is of critical importance, and the interplay between rail transit with other modes in the transportation system is increasingly recognized as foundational to mobility resilience.

Unexpected disruptions, such as service interruptions due to accidents, infrastructure breakdowns, and passenger distress, are common occurrences in urban transit systems (Mo et al., 2022). The presence of ridesourcing services in mobility portfolios introduces a novel opportunity to bolster mobility response and recovery. Recent work has begun to highlight the need for more equitable resilience plans, noting that impacts can vary across population groups and be tied to existing vulnerability (Coleman et al., 2020; Dargin & Mostafavi, 2020). In this

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research, we consider the role of ridesourcing as an adaptive substitution strategy to fill gaps created by no-notice disruptions in fixed guideway systems, such as rail transit services. Moreover, we analyze socio-spatial variation in rail-to-ridesourcing substitution across communities. Therefore, our discussion of resilience focuses on the dimension of redundancy, as well as the distributional impacts of resilience. This is in line with other works that have emphasized the feature of redundancy across spatially heterogeneous urban transport systems to reduce the risk of service disruptions (e.g., Estévez-Mauriz et al., 2017).

Our research uses a natural experiment to study the resilience of urban transit in Chicago. The natural experiment approach unlocks the opportunity to study variation that naturally results from an event or intervention beyond the researchers' control (e.g., Lu et al., 2021; Wen et al., 2017). By jointly studying naturally occurring disruptions in the rail transit system with associated surges in ridesourcing demand, we empirically capture the substitutability among competing modes. We systematically identify 28 significant no-notice rail transit disruptions over the period of one year (November 2018 through October 2019). Then each event is temporally and spatially matched with ridesourcing trip data from the City of Chicago. We estimate a multilevel mixed (MLM) model to examine socio-spatial variation in ridesourcing demand surges that are associated with transit disruptions across stations, neighborhoods, and districts, while controlling for the time of day, day of the week, and disruption location. The research design thereby captures spontaneous mobility resilience as travelers use ridesourcing as an adaptation strategy to cope with disruptions to their travel.

The main contributions of this study are the insights it provides into: (1) whether ridesourcing is used as a gap-filling mechanism during unplanned rail transit disruptions in Chicago, (2) whether its utilization for this purpose is equitably distributed across the city, especially in terms of racial and economic representation, and (3) whether variation in adaptive ridesourcing demand during disruptions is primarily attributable to the station-, community-, or broader district-level factors. This study contributes to an improved understanding of how riders across different communities cope with disruptions. Furthermore, we discuss how our findings can guide more equitable communication strategies for transportation agencies and potential collaborations with private, on-demand mobility service operators to treat mobility as a service regardless of the specific transportation mode used.

Our research contributes to filling two main gaps in knowledge. First, considering the resilience concept of redundancy, we analyze how the complex multimodality of transportation systems contributes to mobility resilience in terms of the *interaction* between public transit and ridesourcing, rather than focusing on single-mode resilience. Second, acknowledging the growing interest in equitable resilience, we provide further insights on the socio-spatial variation in adaptive ridesourcing during unplanned transit disruptions. Our analysis suggests that transit riders in under-resourced areas may not be benefitting as much as more privileged transit users from the same ridesourcing-based, mobility gap-filling strategy.

The remainder of this paper is organized as follows. The next section reviews related studies on the relationships between transit disruptions, connections between rail transit and ridesourcing, and social equity. The third section discusses the data sources, variable definitions, and model specifications. The fourth section compares the results from the MLM models and discusses the empirical findings. Research implications are discussed in the fifth section. Finally, the conclusion is presented in the sixth section.

2. Literature review

2.1. Mobility resilience

To study mobility resilience, we must consider how transit agencies are preparing for, reacting to, and recovering from service disruptions that impact the daily lives of individuals and businesses. Resilience is currently a key priority in national policy agendas and discourse (National Academies of Sciences, Engineering, and Medicine, 2021a; U.S. Chamber of Commerce, 2022). Mobility resilience refers to the adaptive ability of a transportation system to maintain functionality despite a disturbance (Walker et al., 2002; Walker et al., 2004). da Mata Martins et al. (2019) define *mobility resilience* as the ability of travelers to maintain their mobility without compromising their quality of life, *adaptable resilience* as the possibility of adopting new mobility patterns to maintain quality of life, and *transformable resilience* as the ability to transform current mobility patterns into more adaptable ones. Current research on mobility resilience covers a broad range of subjects, from post-disaster recovery following extreme climate events (Chan & Schofer, 2016; Donovan & Work, 2017; Ji et al., 2022) to disruption preparation that takes into consideration network redundancies and impacts on links and nodes (Caprì et al., 2016; Fotouhi et al., 2017; King & Shalaby, 2016; Leu et al., 2010; Serulle et al., 2011).

Operationally, transportation resilience is difficult to define and measure (National Academies of Sciences, Engineering, and Medicine, 2021b), and many metrics have been proposed, often centering on the four Rs of resilience: *robustness* (i.e., maintaining operations while withstanding stresses), *resourcefulness* (e.g., supply chain management, communication, and mobilization of resources), *rapidity* (i.e., quickly returning to normal operations, containing losses, and preventing further degradation of the system), and *redundancy* (e.g., providing backup resources and substitutability) (Adams et al., 2012; DiPietro et al., 2014; Faturechi & Miller-Hooks, 2015; Gu et al., 2020; King et al., 2020). In this study, we focus on disruption recovery by applying the resilience dimension of *redundancy*, that is, the provision of backup urban mobility resources for modal substitution. Recently, resilience equity and its ties to vulnerability have attracted attention (Coleman et al., 2020; Dargin & Mostafavi, 2020). From a social equity perspective, it is important to consider how spatial and temporal differences in resilience can result in inequitable outcomes (Meerow & Newell, 2019). Specifically, in this paper we examine the variation of resilient mobility behavior across communities at three levels of aggregation to identify potential resilience inequities.

2.2. Recovering from mobility disruptions: what do we know?

Understanding mode substitution for disruption recovery requires us to ground our analysis in travel behavior surrounding transit disruptions more broadly, followed by a focus on no-notice disruptions. We also summarize the on-demand mobility literature in the context of disruptions and user profiles to build a fuller understanding of the connections between disruptions in fixed transit services and on-demand ridesourcing behaviors.

2.2.1. Recovery from planned rail transit disruptions: decisions of travelers

The duration of planned transit service disruptions can span from short-term (e.g., hours or days) to long-term (e.g., months or years) (Arslan Asim et al., 2021). Planned, long-term rail transit disruptions may include scheduled maintenance, infrastructure upgrades, and strikes. For planned and long-term rail line or station closures, riders have ample time to adjust their travel plans, whether temporarily or permanently, including choice of departure time, route, and mode. The impacts of long-term rail transit disruptions on travel behavior have been widely studied over the past decades (Marsden & Docherty, 2013; Pnevmatikou et al., 2015; Pu et al., 2017; Van Exel & Rietveld, 2001; Zhu et al., 2017). Across Europe and the United States, the effects of long-term transit disruptions have resulted in a permanent decline in transit ridership (Van Exel & Rietveld, 2001; Zhu et al., 2017). In Chicago, lengthy track operation disruptions have led to transit abandonment by an estimated 4 % of riders (Mojica, 2008).

In general, mode-shifting behavior during long-term transit disruptions has been shown to vary according to rider sociodemographics, disruption type, and city-specific factors. More specifically, transit disruption responses during strikes include individual-specific factors (i.e., car ownership, number of household members, available cars, driver's licenses, and income), context-specific factors (i.e., travel distance, travel time, travel cost, trip destination, and weather), and journey-specific factors (i.e., public transport station accessibility and trip purpose) (Nguyen-Phuoc et al., 2018). Li et al. (2020) found that the uncertainty surrounding disruptions split riders into two classes of behaviors, namely uncertainty pessimists and uncertainty optimists. Typically, during long-term disruptions, most travelers switch to personal vehicles (Van Exel & Rietveld, 2001; Zhu et al., 2017), but disruption outcomes are often inequitable. For example, those less likely to shift to a car during transit disruptions include women and lower-income individuals, as well as workers with more flexible schedules (Pnevmatikou et al., 2015). In Washington, D.C., long-term rail transit disruptions are associated with increased bus ridership (Pu et al., 2017), especially among lower-income riders (Zhu et al., 2017). In Chicago, planned maintenance resulted in a minor share of rail riders shifting to buses and the majority continuing to use rail transit (Mojica, 2008). More recent smart card data analysis suggests that Chicago travelers use a myriad of adaptation strategies (Mo et al., 2022).

Since 2020, the COVID-19 pandemic has resulted in long-term disruptions to transportation systems, including lasting reductions in public transit ridership (Soria et al., 2023). A national U.S. study found that locations with greater proportions of essential workers, African Americans, Hispanics, older adults, and females, maintained higher transit demand levels during COVID-19 (Liu, Miller, & Scheff, 2020; Liu, Palm, et al., 2020). Ongoing work is finding interesting relationships between pandemic transit disruptions and alternative mode use. During the pandemic, bikeshare ridership was shown to increase (Chen et al., 2022; Kim & Cho, 2022). Considering 'post-pandemic' travel (defined as "the period during which COVID-19 is no longer a public health threat"), Loa and Habib (2023) found a greater influence of sociodemographic factors and level-of-service attributes for mode choice decisions than perceptions of risk and other pandemic-related factors.

2.2.2. Recovery from unplanned, short-term rail transit disruptions

Compared to the extensive body of research on planned, long-term rail transit disruptions, research on the travel behavior effects of unplanned, short-term disruptions is scant (Sun et al., 2016). Unplanned service disruptions may be the result of extreme weather or natural disasters, infrastructure failures (e.g., related to power, signaling, and crossovers), vehicle breakdown (e.g., rolling stock issues), and service interruptions or delays due to intrusions on rail tracks or medical emergencies (e.g., debris, suicides, crossing incidents, etc.) (Arslan Asim et al., 2021; Pender et al., 2013). A probabilistic model using smart card data found five behavioral responses to unplanned rail transit disruptions: using a bus, changing rail route, not changing rail route, not using public transit, and not being affected (Mo et al., 2022). Important factors influencing behavioral responses to no-notice disruptions include user expertise, car availability, perception of service recovery time, available transport services, time constraints, and the timing and location at which communication about the disruption is received (Adelé et al., 2019). In response to short-term disruptions, riders are more likely to cancel their trips compared to long-term disruptions (Nguyen-Phuoc et al., 2018).

2.3. Unexplored capacity: on-demand ridesourcing for mobility resilience?

Ridesourcing offers a potential solution for urban passenger mobility in ordinary travel settings, and a large body of research has investigated its demographic and spatial use. However, little is known about the ability of on-demand modes like ridesourcing to provide urban mobility resilience during disruptions (Borowski & Stathopoulos, 2020). The following sections summarize what is known about user patterns and social inequities to guide the analysis of the role of ridesourcing platforms in providing mobility redundancy during disruptions.

2.3.1. Ridesourcing demand user and spatial profiles

Consistently, studies have shown that ridesourcing users tend to: have a higher income (Sikder, 2019), be younger (Clewlow & Mishra, 2017; Rayle et al., 2016; Young & Farber, 2019), highly educated (Alemi et al., 2018; Dias et al., 2017), full-time workers (Shamshiripour et al., 2020), male (Zhang & Zhang, 2018), own fewer vehicles per household, and live closer to transit stations (Deka & Fei, 2019). Looking at spatial use patterns, recent analyses of large-scale ridesourcing trip data reveal that several aggregate city-specific factors correlate with ridesourcing trip counts. Greater ridesourcing usage is shown to be positively correlated with the population density in Austin (Lavieri et al., 2018), Chicago (Ghaffar et al., 2020), and Los Angeles (Brown, 2019b), employment density in Austin (Lavieri et al., 2018), Chicago (Ghaffar et al., 2020), Los Angeles (Brown, 2019b), and New York City (Correa et al., 2017), and land-use diversity in Austin (Yu & Peng, 2019) and Chicago (Ghaffar et al., 2020), as well as lower household income in Los Angeles (Brown, 2019b) and zero-vehicle households and percentage transit commuters in Chicago (Ghaffar et al., 2020).

Relationships of ridesourcing with competing transport options, like public transit, are less clear. Some evidence suggests that public transport demand is reduced when competing with the door-to-door business model of ridesourcing (Clewlow & Mishra, 2017). In Chicago, Marquet (2020) finds that ridesourcing is used to travel between areas that are already highly accessible by transit, suggesting the potential to complement transit due to market density. Soria and Stathopoulos (2021) note that the link between ridesourcing and transit varies across cities and space and can be either competing or complementary, warranting continued research to pinpoint the evolving and location-specific mode connections. Overall, evidence indicates that ridesourcing is related to rider privilege and that most rides take place in the dense and accessible urban core (Lewis & MacKenzie, 2017; Soria & Stathopoulos, 2021).

2.3.2. Social inequity concerns related to on-demand mobility

The question of demographic or spatial exclusion related to on-demand mobility platforms has attracted significant attention (Pangbourne et al., 2020). The ridesourcing business model has been accused of providing limited accessibility to several rider groups, namely; rural populations, under-banked households, individuals without smartphones, individuals with disabilities, lower-income groups, or other historically marginalized communities (Daus Esq, 2016). Specifically, the reliance on smart-phone access and skills may generate accessibility inequalities (Shaheen et al., 2017). Ridesourcing companies continue to grapple with problems of the digital divide, rider discrimination, data privacy, and workers' rights (Jin et al., 2018).

Prior research has shown evidence that ridesourcing service quality differs according to race, ethnicity, and income, which raises important equity concerns. Ge et al. (2016) point to patterns of discrimination in ridesourcing practices. In Seattle, longer wait times for ridesourcing services at night were observed in areas with higher percentages of racial minorities (Hughes & MacKenzie, 2016). A similar trend of longer ridesourcing wait times has been observed for communities of color in Chicago (CNT, 2019). In New York City, ridesourcing pickup rates were lower in lower-income areas (Correa et al., 2017; Jin et al., 2019). By contrast, other recent research instead argues that ridesourcing is closer than traditional taxis to eradicating racial and ethnic inequities in service quality (Brown, 2019a). In Atlanta, the estimated wait times of UberX and UberBLACK were not significantly correlated with either race or income (Wang & Mu, 2018).

Looking at broad spatial ridership patterns for the case of Chicago, research confirms a greater concentration of rides in the more affluent North and Central districts of the city (Brown, 2019b; Ghaffar et al., 2020; Soria et al., 2020). Fewer ridesourcing trips are generated in areas that are predominantly Hispanic or African American, lower income, or have lower rates of car ownership (Marquet, 2020). Similarly, solo ridesourcing demand is lower in areas where socioeconomic disadvantage is concentrated (Soria & Stathopoulos, 2021). These findings mirror research on another on-demand mobility platform; Divvy bikeshare uptake is lower in the less affluent, majority African American, South district of Chicago (Biehl et al., 2018).

2.3.3. Linking on-demand mobility to disruptions

Only recently has research begun to consider the role of ridesourcing in addressing resilience in the context of no-notice transit service disruptions. Borowski and Stathopoulos (2020) found that ridesourcing may be used to connect with transit during no-notice urban evacuations. One study of ridesourcing during unplanned subway disruptions in Toronto suggests less frequent shifts to ridesourcing in disadvantaged neighborhoods and inequitable bus bridging services (Liu, Miller, & Scheff, 2020; Liu, Palm, et al., 2020). For Chicago, stated preference survey research on ridesourcing usage during transit disruptions shows that millennial status, higher level of education, smartphone access, and prior ridesourcing experience is associated with a shift to ridesourcing (Rahimi et al., 2020). Another stated preference investigation shows that the preference for on-demand ridesourcing during no-notice mobility disruptions is shaped by identity factors, such as the intersections of race, gender, and class identities (Borowski & Stathopoulos, 2020).

The present study builds on earlier work investigating the role of bikesharing as a gap-filling mechanism during longer-term transit disruptions wherein a temporary increase in bikeshare demand during transit strikes and maintenance projects was noted, suggesting the ability of on-demand transportation modes to improve mobility resilience (Fuller et al., 2012; Kaviti et al., 2020; Pu et al., 2017; Saberi et al., 2018). In this study, we focus on shifts to ridesourcing during unplanned, short-term transit service disruptions. While similar research has been conducted in Toronto (Liu, Miller, & Scheff, 2020; Liu, Palm, et al., 2020), our work is among the first to investigate mobility resilience in the context of Chicago with its unique transit and sociodemographic patterns.

2.4. Literature takeaways

Acute shocks and chronic stressors are likely to continue to worsen in urban areas due to climate change and aging infrastructure. In this context, transit agencies face the risk of exacerbated ridership abandonment following unplanned service disruptions. This study examines an untapped potential of emergent, on-demand modes to mitigate the negative impacts of no-notice transportation system shocks, thereby boosting mobility resilience. However, this potential is not without shortcomings. Although the interest in equity is growing, its relationship with mobility resilience remains understudied (Mattsson & Jenelius, 2015). Here we carefully consider the equity context of on-demand mobility usage to guide our selection and interpretation of station-, community-, and district-level predictor variables. We use an MLM modeling analysis to examine spatially determined variation in resilience across the city. This research fills current gaps in the literature related to the question of "resilience for whom" while considering multimodal aspects of resilience. In this study, which is among the first to use a natural experiment to examine ridesourcing behavioral responses to no-notice, short-term transit disruptions, we hypothesize that adaptive ridesourcing will be associated with traditionally privileged sociodemographics and resource access.

3. Data and model

3.1. Case study context

In this study, we analyze the equity of ridesourcing for mobility resilience in Chicago. Notably, Chicago is home to the second largest transit network in the U.S. with the Chicago Transit Authority (CTA) serving 3.5 million riders (CTA, 2020a) with nearly 16 million rail transit rides each month (CTA, 2020b). While unequal access to essential resources is common in many U.S. cities, Chicago contends with historically rigid, spatially defined, social and economic inequality that is frequently linked to race. For example, the income disparity between white households and racial minority households is wider in Chicago than it is across the nation (Asante-Muhammed, 2017). Additionally, urban mobility systems typically contend with multiple layers of inequality in mobility investments and service access that determine service quality for different population segments (Lowe, 2014). Chicago is subject to urban mobility inequities both in terms of inferior service provisions (e.g., poor mobility accessibility or lack of pedestrian-friendly infrastructure) and disproportionate negative impacts (e.g., biased policing) in low-income communities (Barajas, 2021; Krapp, 2020).

Fig. 1 shows the spatial distributions in 2019 for Chicago's 77 community areas of: (a) median household income, (b) percentage of people of color, (c) percentage of transit commuters, (d) population density, (e) total ridesourcing trips, and (f) percentage of active mode commuters. These heatmaps confirm the following three observations. First, there is a narrowly concentrated demand for ridesourcing and active mobility commuting in the Central district of the city, representing the urban core from which the rail transit network expands radially (e and f). Second, there is a greater concentration of population and transit commuting in the North district (c and d). Third, the distribution of income is largely opposite of the majority non-white racial breakdown (a and b). Fig. 2 shows the layout of the Chicago Transit Authority rail network with community area boundaries for comparison.

3.2. Data and variable description

This analysis draws on data fusion of six data sources. The ridesourcing dataset obtained from the City of Chicago data portal is freely available for download and consists of over 152 million trips by Uber, Lyft, and Via spanning the period of November 2018 through October 2019 (Chicago Data Portal, 2019). This dataset provided our "Number of ridesourcing trips" variable. Five additional datasets were used to extract explanatory variables for our analysis, including seven sociodemographic variables from the Community Data Snapshot (CMAP, 2019), 11 variables related to service quality, ridership, location, and timing extracted from the Chicago Transit Authority (CTA, 2019), one station count variable from the bikesharing Station Map and Data (Divvy, 2020), three disruption source variables from Google News for Chicago, IL (Google, 2019), and two weather variables from Iowa Environmental Mesonet (ISU, 2019). Table 1 lists all the variables resulting from this data fusion. Variables are grouped by station level when available or community level and further grouped by discrete or continuous nature.

3.2.1. Community area sociodemographics

The City of Chicago comprises 77 community areas that can be further aggregated into four districts (i.e., North, Central, South, and West). For reasons of privacy, individual-level data on ridesourcing tripmakers, such as sociodemographics and residential locations of rail and ridesourcing riders, are not publicly available (City of Chicago, 2020). Therefore, we follow the practice of using aggregated measurements of community sociodemographics to represent sociodemographic variables of interest (Liu, Miller, & Scheff, 2020; Liu, Palm, et al., 2020). While this practice can mask variation in rider characteristics, it is currently the best option available to researchers.

3.2.2. Disruption-based ridesourcing demand

Twenty-eight CTA rail transit disruptions lasting a minimum of 1 h are identified as having occurred from November 2018 through October 2019 using a Google News search for the phrase "CTA disruption". The timespan for our study was truncated to a single year due to the major impacts of the COVID-19 pandemic on public transit and ridesourcing

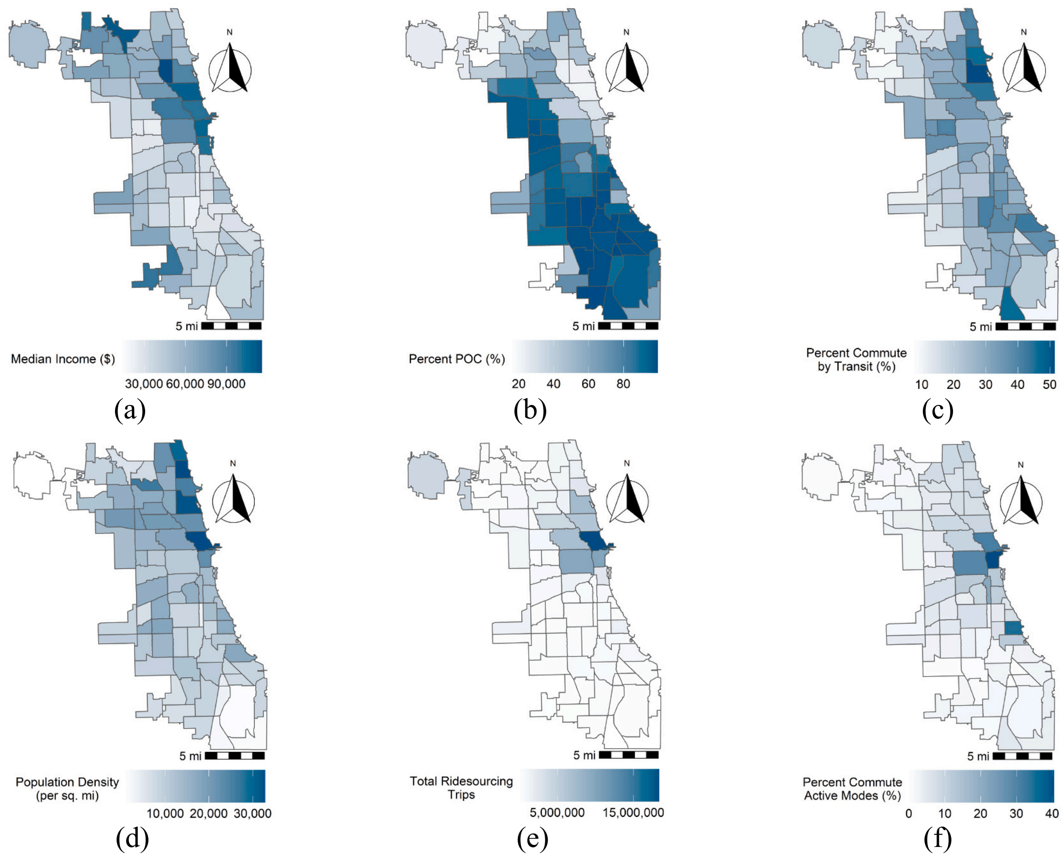

Fig. 1. Heatmaps showing the spatial distribution by Chicago community area (2019) of: (a) median household income, (b) percent population of color, (c) percent commute by transit, (d) population density, (e) total ridesourcing trips, and (f) percent commute by active (walk and bike) modes.

ridership beginning in early 2020. Fig. 3 highlights the locations of these transit disruption sources at the station, community, and district levels, and it can be observed that all CTA lines experienced disruptions during this period. Table 2 lists the disruption events and identifies their locations, impacted stations, whether the disruption occurred during peak travel hours, and whether a shuttle bus was deployed by CTA to assist riders according to the associated report.

3.2.3. *Baseline ridesourcing demand*

To generate a robust four-day ridesourcing demand baseline, trip counts during the disruption period are averaged across the same day of the week and the time of day (i.e., the specified disruption period) as the disruption for two weeks prior to the event and two weeks following, as in Liu, Miller, and Scheff (2020), and Liu, Palm, et al. (2020). This was done to account for station accessibility and seasonality. Each ridesourcing trip is included in the analysis if the starting location is within a 0.25-mile radius of a disrupted transit station. This frequently used walking estimate (Younes et al., 2019; Zhao et al., 2003) is applied to account for riders who source rides on their way to or from the impacted transit station, such as to facilitate ridesourcing pick-up by avoiding the potential crowds surrounding the disrupted station.

3.3. *Multilevel mixed model specification*

To address the research question of ridesourcing surges prompted by transit disruptions, we control not only for the immediate station attributes where the disruption occurs, but also for community area and district-level factors in an MLM structure as shown in Fig. 4. MLM models provide a mechanism for analyzing datasets where events (in this case, station disruptions) are nested within higher-order spatial contexts and correctly account for the hierarchical nesting of data and effects happening at different levels (Goldstein, 2003; Julian, 2001; Wampold & Serlin, 2000). In the past, MLM or hierarchical models have been used to represent the structure of social relations within personal networks (Carrasco & Miller, 2009), temporal changes in bikeshare trips (El-Assi et al., 2017), and transit demand between origin-destination station pairs (Iseki et al., 2018). Here we use the multilevel analysis to identify the factors associated with systematic variations in ridesourcing demand during transit disruptions at the station, community area, and city district levels. We can thereby examine explanatory variables at each level of the data hierarchy, and in doing so, control for the community area effects on station ridership variations.

The advantage of using the multilevel structure is the ability to estimate the variability in results that can be attributed to the neighborhood (e.g., community area) effects rather than only to the individual station effects. By carefully controlling variable inclusion at the appropriate level, the model considers the correlations between observations within the same group (i.e., a given community area) as distinct from the correlations between groups (Jones & Duncan, 1996). In contrast, a standard one-level regression model would ignore group-level distinctions (e.g., different commuting patterns in different communities) and group-level correlations (e.g., similar patterns of use among stations in the same community related to the income level of riders). A useful way to think of MLM models is as a structure positioned between two modeling extremes when groupings are known: fully pooled and fully unpooled specification (Gelman & Hill, 2007). A fully pooled model treats group-level variables as individual variables, thereby ignoring group-level distinctions. The opposite extreme, a fully unpooled model, asserts that the groups are so completely different that they cannot be associated in the same model. The MLM model offers a compromise between these perspectives by modeling individual-level fixed effects as well as distributional assumptions on the random effects.

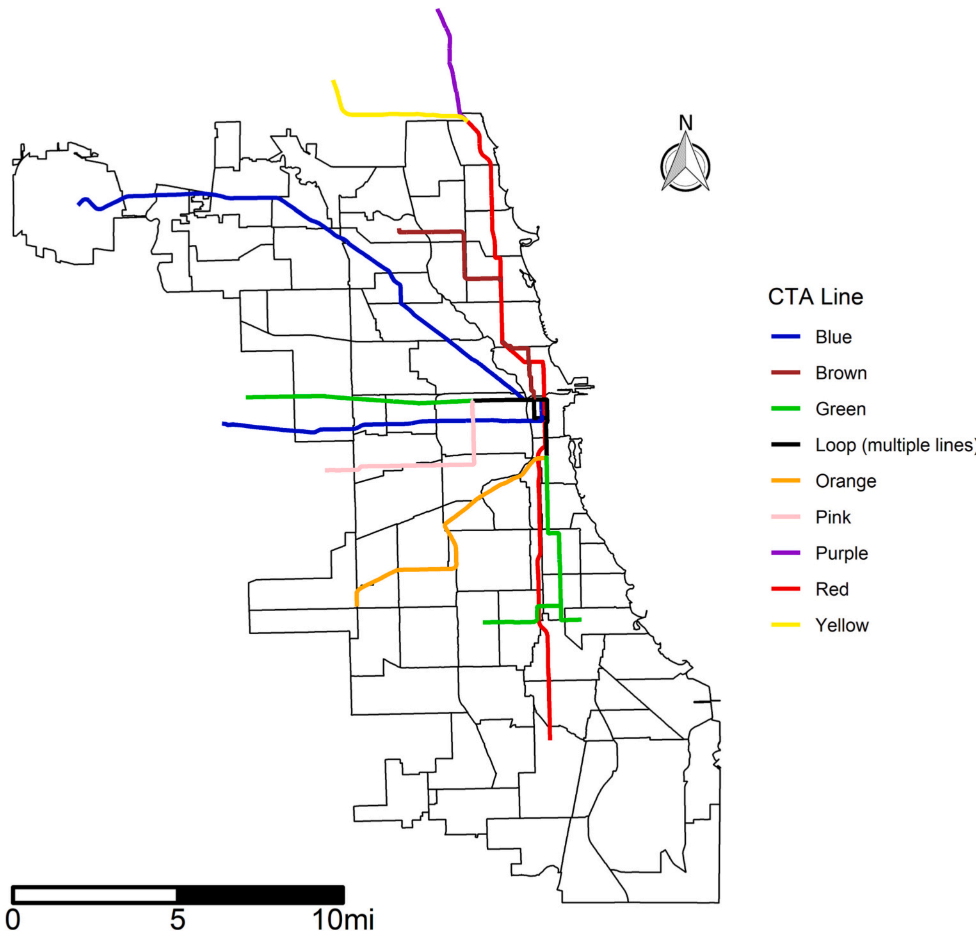

Fig. 2. Map of the Chicago Transit Authority rail network and community area boundaries.

Fig. 5 highlights each variable tested in the modeling along with the inclusion strategy for each level of analysis. The dependent variable is the number of ridesourcing trips compared to the baseline demand two weeks prior and two weeks following the disruption (i.e., individual station observations). Covariates related to the disruption cause, context, and timing are included as explanatory variables at the station level, in line with Mojica (2008) and Pu et al. (2017). Some variables were tested in the model at multiple levels. For example, during model development, the temperature and precipitation variables (measured for the city at weather stations) were included at various levels, but they were only significant at the station level. This makes sense given the expectation that weather impacts station-level decision-making (Chan & Schofer, 2014). The slight discrepancy that weather data is aggregated at the city level and included in the model at the station level does not present any major issue given the lack of micro-climates in the city of Chicago, and thus, the weather is not a unique characteristic of a community area or district. Future micro-climate studies using localized forecasts are encouraged, but the weather in Chicago lacks variation at the station level.

We further investigate whether the fact that stations are nested within community areas and major districts plays a role in ridesourcing demand shifts. A comparable disruption can likely generate different mode-shifting effects depending on where it is located, owing to the different composition of travelers and the availability of alternative modes. Specifically, the broader context is controlled for by including sociodemographic and mobility factors measured at the community level, which are then in turn aggregated to the district level of analysis. We apply group mean centering for community area variables (Enders & Tofighi, 2007) to facilitate the interpretation of the cross-level interactions. It is worth noting that since the disruptions we measure result from a natural experiment, we are unable to control exhaustively for all combinations of factors that are at play within and between community areas. Therefore, we include random intercept effects at each of the lower-nested group levels to partition the unexplained variability effects on the dependent variable.

Conceptually, the model can be articulated as regression equations occurring at different levels where each group-level coefficient has its own regression equation. Following Gill and Womack (2013), the general three-level structure is defined in Eq. (1) as:

$$y_{ijk} = \beta_{0jk} + \beta_{1jk}x_{1ijk} + \varepsilon_{ijk} \tag{1}$$

where i represents the station, j represents the community area, and k represents the district. β_{0jk} is the (random) intercept measuring average ridesourcing use (defined in Eq. (2) when $i = 0$), and x_{1ijk} is a predictor, such as the average daily transit use measured at the station level, while β_{1jk} is the (random) slope depicting the relationship between the station-level variables and the change in ridesourcing demand (as defined in Eq. (2) when $i = 1$). The error term ε_{ijk} relates to station-level effects.

By including Level 2 and 3 explanatory variables in the model, we uncover broader area effects. The Level 2 formulation includes variables aggregated at the community area level. This can be thought of as being equivalent to how student educational performance may be affected by their classroom teacher in a way that is distinct from the effects of their individual factors or from more aggregate school-level effects. At Level 2, the general regression equation is defined as:

$$\beta_{ijk} = \gamma_{i0k} + \gamma_{i1k}x_{2jk} + u_{ijk} \tag{2}$$

Table 1
Descriptive statistics of the variables considered in this study.

Variable name (unit)	Minimum	Maximum	Mean	Standard deviation	Data source
Station-level factors[a] (continuous)					
Air temperature (degrees Fahrenheit)	11.00	85.45	53.83	18.10	(ISU, 2019)
Disruption duration (hours)	1.00	7.00	2.49	1.52	(CTA, 2019)
Number of bus stations	0.00	129.00	36.17	28.83	(CTA, 2019)
Number of Divvy stations	0.00	30.00	4.02	5.54	(Divvy, 2020)
Number of ridesourcing trips	0.00	5581.00	635.57	1001.46	(Chicago Data Portal, 2019)
Number of stations impacted	1.00	15.00	8.46	4.16	(CTA, 2019)
Precipitation (inches)	0.00	0.04	0.00	0.01	(ISU, 2019)
Station ridership (in thousands of riders)	0.65	58.05	12.26	11.39	(CTA, 2019)
Community area factors (continuous)					
Area (miles squared)	0.71	32.47	3.83	6.31	(CMAP, 2019)
Median household income (in thousands of U.S. dollars)	19.80	104.35	55.44	28.40	(CMAP, 2019)
Percentage of commuters taking transit	10.80	54.20	34.26	11.78	(CMAP, 2019)
Percentage of residents who self-identify as white non-Hispanic	0.70	81.50	38.06	30.65	(CMAP, 2019)
Percentage of zero-vehicle households	8.60	57.40	33.50	12.06	(CMAP, 2019)
Population (in thousands of people)	2.44	100.47	40.57	25.64	(CMAP, 2019)
Population density (in thousands of people per square mile)	0.38	32.73	16.52	9.64	(CMAP, 2019)

Variable name (binary)	Number of 1's	Percentage of 1's	Data source
Station-level factors[a] (discrete)			
Deployment of shuttle bus: 1 if yes; 0 otherwise	71	63 %	(CTA, 2019)
Disruption cause: Medical emergency: 1 if yes; 0 otherwise	65	58 %	(CTA, 2019)
Disruption source: same station. 1 if direct effect (i.e., occurring at the same station)	30	27 %	(Google, 2019)
Disruption source: different station. 0 if indirect effect (i.e., occurring at a different station)	81	73 %	(Google, 2019)
Holiday occurrence: 1 if yes; 0 otherwise	8	7 %	(CTA, 2019)
Late night (after 10 PM): 1 if yes; 0 otherwise	6	5 %	(CTA, 2019)
Peak hour indicator: 1 if yes; 0 otherwise	24	21 %	(CTA, 2019)
Weekday indicator: 1 if yes; 0 otherwise	71	63 %	(CTA, 2019)
District-level factors (discrete)			
Airport: 1 if present; 0 otherwise	7	6 %	(Google, 2019)
District: North side: 1 if yes; 0 otherwise	50	45 %	(CTA, 2019)

[a] Station-level variables are for the affected stations considering the 28 disruptions.

where $i = 0, 1$ and the random intercept β_{0jk} is a function of γ_{00k}, which is the grand mean of the ridesourcing demand surges across the stations in the community (defined below in Eq. (3)). The subscript jk denotes the distinct community area impacts. The γ random effects coefficient has numbered subscripts; the first denotes the intercept (0) or slope (1), while the second subscript denotes the independent variable. Departures from this average intercept represented by x_{2jk} are the community-level predictors with γ_{01k} denoting the random slope for the community-level predictors (Eq. (4)), and u_{0jk} is the unique effect associated with the communities assumed to have a multivariate normal distribution. The random slope β_{1jk} is a function of γ_{10k} representing the average effect of the station-level predictors (i.e., the slope over all stations shown in (Eq. (5))). Departures from the slope (i.e., random effects) over the station predictors are represented by the γ_{11k} coefficient (Eq. (6)) that would be removed in the case of a random intercept-only model (as in the current analysis).

At Level 3, the variables vary by district and apply to all individual cases and community areas assigned to this group. Therefore, they contain the subscript k as opposed to ijk or jk. At Level 3, the separate regression equations for the intercepts and slopes are defined as:

$$\gamma_{00k} = \delta_0 + \delta_4 x_{3k} + u_{00k} \tag{3}$$

$$\gamma_{01k} = \delta_2 + \delta_5 x_{3k} + u_{01k} \tag{4}$$

$$\gamma_{10k} = \delta_1 + \delta_6 x_{3k} + u_{10k} \tag{5}$$

$$\gamma_{11k} = \delta_3 + \delta_7 x_{3k} + u_{11k} \tag{6}$$

where δ_0 is the intercept shared by all individual cases; δ_1, δ_2, and δ_3 are the main effects; δ_4, δ_5, and δ_6 are two-way interactions; and δ_7 is a three-way interaction.

In our specific modeling, the outcome variable of the three-level hierarchy y_{ijk} is defined as the change in the ridership over the baseline. After the specification testing, the final model takes the specific form as shown in Eqs. (7)–(15). The model includes a random intercept β_{0jk} and two main effects ($non\_holiday_{ijk}$ and $peak\_hour_{ijk}$) at Level 1, shown in Eq. (7). Level 2 brings in contextual variables used to explain variability in ridesourcing demand via cross-level interactions. That is, we model the intercept and slopes explicitly and include Level 1 and Level 2 independent variables interacted to describe variation in the intercept. Eqs. (8)–(10) show the random intercept γ_{00k} and the cross-level interaction terms ($percent\_white_{jk} \times peak\_hour_{ijk}$ and $percent\_transit_{jk} \times disruption\_source_{ijk}$). Level 2 also specifies β_{1jk} and β_{2jk} which represent the parameter slopes with γ_{10k} and γ_{20k}. Level 3 includes the random intercept δ_0 and one district-level interaction ($north\_quad_k \times shuttle_{ijk}$) that is found to generate variability in ridesourcing (Eq. (11)), with the remaining parameters δ_1 and δ_2 denoting the fixed slope coefficients. The disturbance parameters are included at the community u_{0jk} and district levels u_{00k} (Eqs. (14)–(15)).

Level 1 Model: station effects

$$y_{ijk} = \beta_{0jk} + \beta_{01k,non\_holiday}\, non\_holiday_{ijk} + \beta_{peak\_hour} peak\_hour_{ijk} + \varepsilon_{ijk} \tag{7}$$

Level 2 Model: random intercept & cross-level interactions at community level

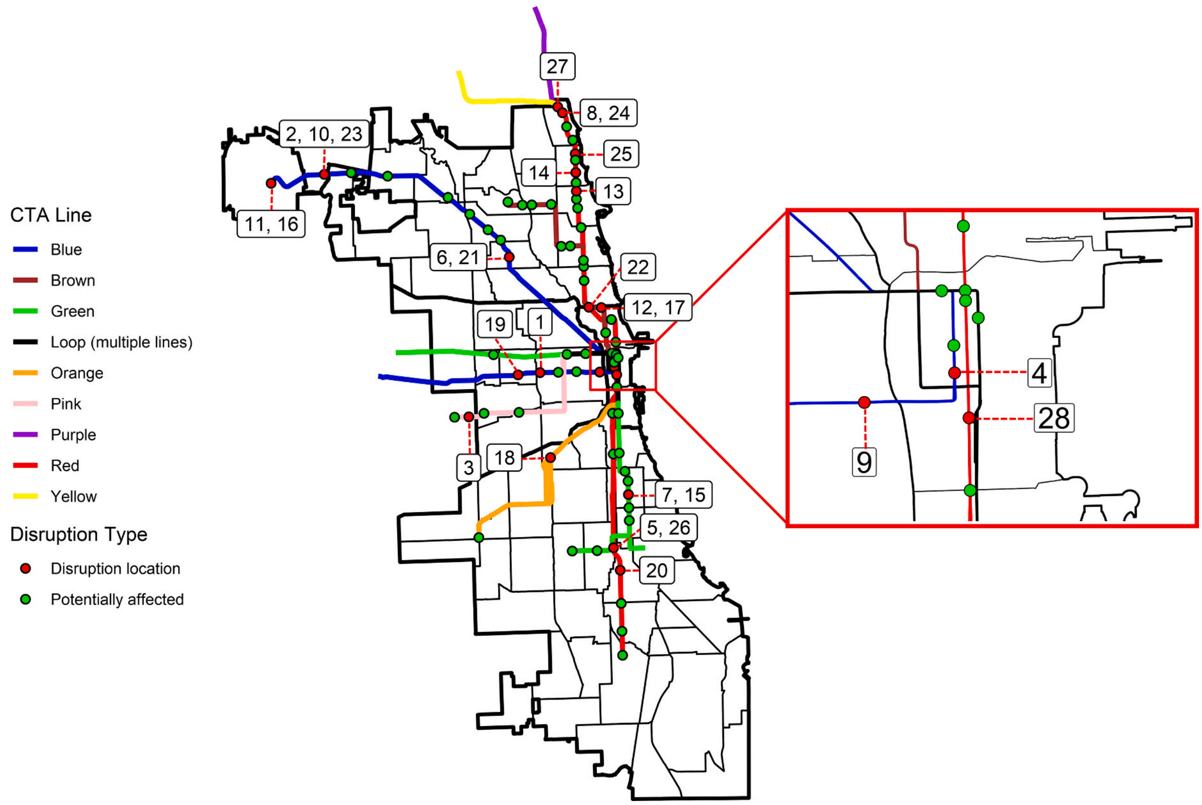

Fig. 3. Map of Chicago showing rail transit lines and disruption events within community area and district boundaries. Insert represents the Loop (i.e., the central business district).

$$\beta_{0jk} = \gamma_{00k} + \gamma_{01k} x_{percent\_white,jk} \times x_{peak\_hour,ijk} + \gamma_{02,}\ x_{percent\_transit,jk} \times x_{disruption\_source_{ijk}} + u_{0jk} \tag{8}$$

$$\beta_{1jk} = \gamma_{10k} \tag{9}$$

$$\beta_{2jk} = \gamma_{20k} \tag{10}$$

Level 3 Model: random intercept & cross-level interaction at district level

$$\gamma_{00k} = \delta_0 + \delta_{NorthShuttle} north\_district_k \times shuttle_{ijk} + u_{00k} \tag{11}$$

$$\gamma_{10k} = \delta_1 \tag{12}$$

$$\gamma_{20k} = \delta_2 \tag{13}$$

$$u_{0jk} \sim \mathcal{N}\left(0, \sigma_d^2\right) \tag{14}$$

$$u_{00k} \sim \mathcal{N}\left(0, \sigma_e^2\right) \tag{15}$$

It is important to note that the cross-level interactions explain a significant amount of variance of ridesourcing demand changes in addition to that already explained by the station-level equations.

3.4. Equity analysis

A social equity perspective is applied in the interpretation of the model findings to examine the question of "mobility resilience for whom?" This is achieved through population segmentation and the identification of statistically significant determinants related to spatial differences in socioeconomic characteristics like race and income, which is in line with the research methodologies of many scholars in the field of mobility inequity (Biehl et al., 2018; Brown, 2019a,b; Ghaffar et al., 2020; Hughes & MacKenzie, 2016; Marquet, 2020; Soria & Stathopoulos, 2021; Wang & Mu, 2018). Although this study does not include alternative ways of considering distributional effects through a synthetic estimator, like the Gini Index, this would be a valuable area of research for the future that would support practical application and policy design.

4. Results and discussion

4.1. Neighborhood differences in adaptive ridesourcing during disruptions: descriptive analysis

Exploratory analysis shows that adaptive ridesourcing response is not uniform across the city. Two different poles are exemplified in Fig. 6. Fig. 6.a shows a significant surge in the use of ridesourcing following a no-notice rail transit disruption. This high-impact North district case in Lakeview at the Belmont station (i.e., the source location of the disruption) occurred on a Monday in December during morning peak hours and was caused by a train striking a person. The baseline ride-sourcing demand for this time and location is 807 rides, meaning the disruption is associated with a statistically significant surge in ride-sourcing trips totaling 2883, which corresponds to a 257 % increase.

Fig. 6.b shows a similar disruption event occurring in an under-resourced West district neighborhood with limited shifting to on-demand services. This low-impact disruption in East Garfield Park at the Kedzie station (i.e., the source location) resembles the Belmont disruption in that it occurred during weekday morning peak hours and was caused by a person on the tracks. However, the baseline ride-sourcing demand for this time and location is a fraction of that at Belmont: only 89 rides. The number of ridesourcing rides during the disruption event is lower than the baseline of 76 (an insignificant decrease of 15 %). This observed difference in the disruption response is likely related to more pervasive racial and economic inequities, along with differences in transit accessibility. Specifically, Lakeview has a

Table 2
Twenty-eight unplanned rail transit disruptions in Chicago (Nov. 2018–Oct. 2019).

Number	Date	Day	Start time	End time	District	Disruption source: station name	Impacted span	Stations impacted	Peak hour	Shuttle bus
1	11/06/18	Tuesday	5:00	6:00	West	Western	Pulaski to Racine	5		✓
2	11/12/18	Monday	13:30	16:30	North	Rosemont	Harlem to O'Hare	4		✓
3	11/26/18	Monday	9:00	12:15	West	Cicero	54th/Cermak to Pulaski	2	✓	
4	12/06/18	Thursday	17:00	18:00	Central	Jackson	Jackson	1	✓	
5	12/12/18	Wednesday	5:00	8:30	South	63rd	47th to 95th/Dan Ryan	7		✓
6	12/17/18	Monday	8:00	10:00	North	Belmont	Addison to Fullerton	5	✓	✓
7	01/12/19	Saturday	12:30	14:00	South	47th	63rd to Sox-35th	4		✓
8	01/20/19	Sunday	9:00	10:30	North	Jarvis	Belmont to Howard	14		✓
9	02/14/19	Thursday	13:00	16:00	West	Clinton	Ashland to Washington/Wabash	6		✓
10	03/12/19	Thursday	21:00	3:00	North	Rosemont	Jefferson Park to O'Hare	5		✓
11	04/10/19	Wednesday	19:00	2:00	North	O'Hare	O'Hare to Rosemont	2	✓	✓
12	05/01/19	Wednesday	7:20	8:20	North	North/Clybourn	Cermak-Chinatown to Fullerton	5	✓	
13	05/06/19	Monday	16:00	18:00	North	Argyle	Argyle	1	✓	
14	05/12/19	Sunday	14:00	16:00	North	Bryn Mawr	Addison to Howard	14		
15	06/06/19	Thursday	11:00	16:30	South	47th	Ashland/63rd to Roosevelt	10		✓
16	06/10/19	Monday	9:00	10:00	North	O'Hare	O'Hare to Rosemont	2	✓	
17	06/12/19	Wednesday	19:20	20:20	North	North/Clybourn	Cermak-Chinatown to Fullerton	11	✓	
18	06/20/19	Thursday	10:15	13:30	South	35th/Archer	Halsted to Midway	7		✓
19	06/25/19	Tuesday	7:30	8:45	West	Kedzie-Homan	Kedzie-Homan	1	✓	
20	06/27/19	Thursday	12:30	15:00	South	69th	63rd to 95th/Dan Ryan	5		✓
21	09/07/19	Saturday	14:00	15:15	North	Belmont	Fullerton to Kimball	15		
22	09/24/19	Tuesday	9:00	10:30	North	Sedgwick	Sedgwick	1	✓	
23	09/26/19	Thursday	1:00	4:00	North	Rosemont	Harlem to O'Hare	4		
24	09/26/19	Thursday	17:45	22:00	North	Jarvis	Belmont to Howard	14	✓	
25	10/05/19	Saturday	22:45	2:15	North	Granville	Belmont to Howard	14		
26	10/08/19	Tuesday	15:15	16:15	South	63rd	Roosevelt to 95th/Dan Ryan	10		✓
27	10/30/19	Wednesday	15:00	16:00	North	Howard	Belmont to Howard	14		
28	10/31/19	Thursday	16:15	18:30	Central	Harrison	Cermak-Chinatown to Fullerton	11		✓

median household income of $86,119, and 79 % of its residents are white, while East Garfield Park has a median household income of $23,116 and 5.6 % of its residents are white. To systematically examine different patterns of ridesourcing demand shifts prompted by transit disruptions across Chicago, we turn to our MLM model results.

4.2. Empirical model specification

Preliminary model exploration was done using standard regression models. Pitfalls of using ordinary least squares (OLS) regression to analyze group-level effects with clustered data have been documented (Moulton, 1990). Specifically, standard errors will tend to be too low, resulting in Type 1 errors of spurious significant effects (Maas & Hox, 2004). For this analysis, the MLM model was chosen as it is better suited to answer our research questions about partitioning variance at different levels and exploring (clustered) community variance in ridesourcing substitution. Three MLM models are estimated: (1) a basic intercept model, (2) a station-level analysis, and (3) a model accounting for cross-level effects. For model building, each of the hypothesized predictors measured at the station level are tested first independently and then jointly.

To model explanatory variables, we follow the block entry approach consisting of the gradual addition of covariates level by level (Cohen et al., 2014), following the plan outlined in Fig. 5. Data preparation and merging were done using R 3.5.0 (R Core Team, 2021), with modeling done in Stata using the *mixed* function for multilevel mixed-effects linear regression (StataCorp, 2019).

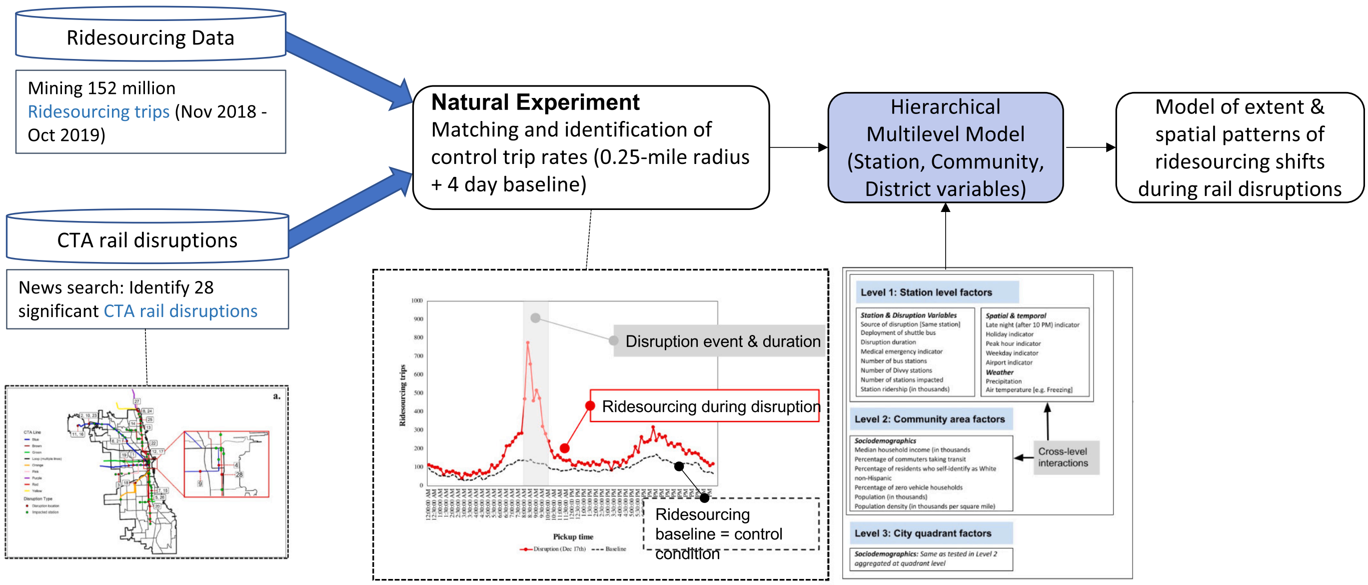

Fig. 4. Overview of analysis framework for the hierarchical multilevel mixed model of ridesourcing shifts during transit disruptions. Station-level disruptions are nested within community areas, which in turn are nested within districts.

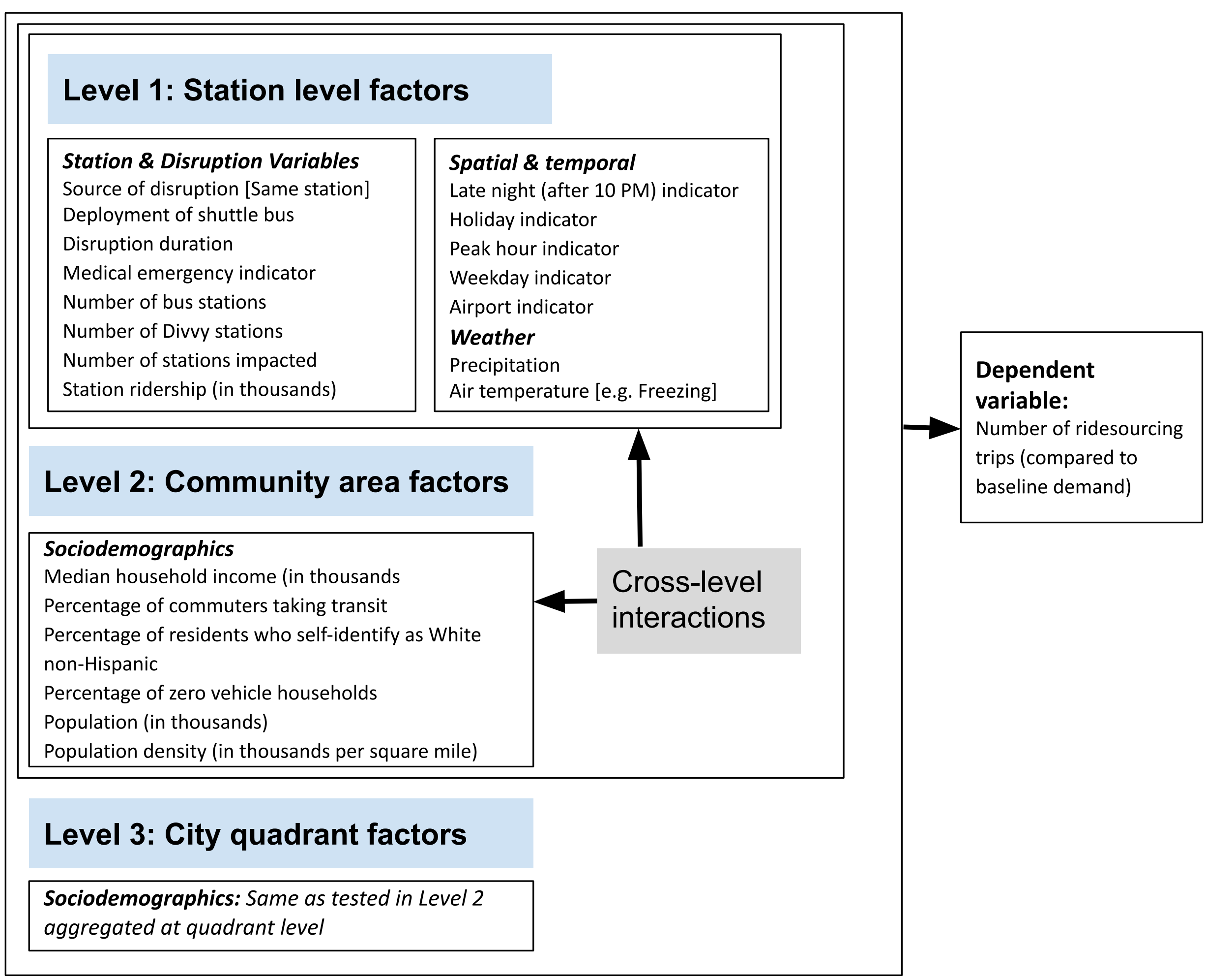

Fig. 5. Multilevel model variables. Considered variables are listed for each level.

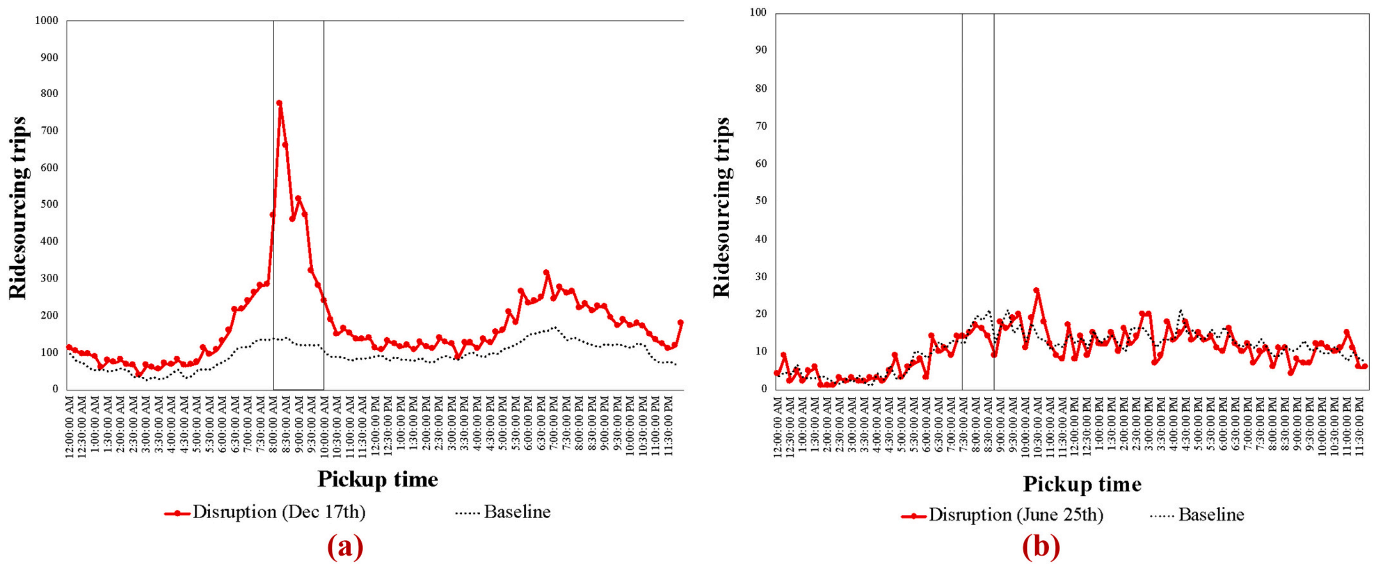

Fig. 6. Ridesourcing trips during disruptions (solid line) compared to baseline (dotted line) at (a) the Belmont station in the North district and (b) the Kedzie station in the West district. Disruption duration is indicated by a border. The y-axes are scaled according to baseline ridesourcing trips (10:1).

Table 3
Multilevel mixed model results.

	Model 1			Model 2			Model 3		
Fixed part	Coef.	z value	P > |z|	Coef.	z value	P > |z|	Coef.	z value	P > |z|
Non-holiday				541	2.97	0.003	599	3.58	0.000
Peak hour				408	4.11	0.000	353	4.22	0.000
Constant	−53.2	−0.39	0.700	54.1	0.97	0.332	91.8	1.53	0.125
Cross-level interactions									
Peak hour * Percent white							12.3	2.69	0.007
Disruption source: same station * Percent transit commuters							18.4	2.54	0.011
District-level interactions									
North district * Shuttle							321	3.66	0.000
Fit statistics									
Log-likelihood	−836.991			−822.099			−809.572		
LR test	12.170			7.150			17.100		
Prob > χ2	0.002			0.028			0.000		
AIC	1681.983			1672.508			1637.144		
Pseudo R^2				0.340			0.330		
Intraclass correlation									
Level 3: District	20 %			0 %			0 %		
Level 2: Community area	43 %			56 %			73 %		
Level 1: Station	37 %			44 %			27 %		

4.2.1. *Basic model specification*

The results of three MLM models are shown in Table 3. These models include significant fixed effects and explanatory features, and all parameters are significant to a 98.9 % level of confidence or greater except for the model constants. Station-level (Level 1) fixed effects (i.e., *non-holiday disruption* and *peak hours disruption*) have some resemblance with the standard regression parameter for *non-holiday* while *peak hours* (which is also included in cross-level interactions) has the opposite sign. Three explanatory features reflect the context surrounding the station, namely two cross-level (station- and community-level) random effects (i.e., *percent white during peak hours* and *percent transit commuters at the source of disruption*) and one district-level effect (i.e., *shuttle deployment in the North district*).

The empty reference MLM model (Model 1) partitions the variance at each aggregation level without including any explanatory variables. This null model is used to calculate the intraclass correlation (ICC), also known as the variance partition coefficient, for the three levels of analysis (Snijders & Bosker, 1999). Thereby, Model 1 provides an estimate of a baseline variance of the ridesourcing demand shifts attributed to factors beyond the immediate station (i.e., community- and district-level factors). The intra-community correlation reveals that the largest share of variation in ridesourcing demand (43 %) is related to community-level factors while the station level explains 37 % of the variance.

4.2.2. *Model with station effects*

In Model 2, with station-level variables, the *district* random intercept (and thereby ICC) is insignificant, while the variance is partitioned between the station (44 %) and community area levels (56 %). Owing to high variable collinearity, only two fixed-effect explanatory variables related to the timing of the disruption and a constant are included in Model 2. These statistically significant effects result in a significant improvement in the model fit as measured by the deviance difference (836.99–822.10 = 14.89, exceeding the critical χ2 of 5.99 with alpha set at 0.05) and AIC reduction.

4.2.3. *Model with community effects*

Along the same lines, in Model 3, when adding cross-level effects by including variables measured at the community area level, the variance explained clearly shifts toward the community area variables. Despite the Level 3 district random intercept collapsing to zero, removing this variance component from the analysis causes a significant reduction in overall model fit.

The main takeaway from the variance controls is that factors occurring across different *community areas* are the most decisive in shaping ridesourcing demand shifts during rail transit disruptions. In other words, the ICC calculation shows the community area context is the main source of differences in ridership-shifting strategies. We interpret this to mean that significant latent neighborhood effects are influencing adaptive ridesourcing behavior. These neighborhood effects likely vary as a function of community culture related to car, transit, and ridesourcing ridership, socioeconomic and political factors, and transportation agency strategies.

4.3. Model results

4.3.1. Station-level analysis: local effects of disruptions

The model constant suggests a moderate average increase of 54 ridesourcing trips (or 15.6 %) during a transit disruption, compared to the baseline. To contextualize this finding, the average baseline ridesourcing ridership is 347 trips across the Chicago community areas covered in the disruption analysis. This value represents the ridesourcing demand that would occur for the same station and timespan without the disruption. With this baseline in mind, the timing of the disruption is revealed to be highly impactful. On average, when a disruption occurs on a *weekday* (excluding holidays), ridesourcing trips increase by 541 from baseline (a 156 % increase). When a transit disruption occurs during *peak hours*, ridesourcing demand increases by 408 rides from baseline (a 118 % surge).

These observed citywide trends are likely related to the less flexible trips that occur during peak hours and weekdays. This is not surprising considering that business and commuting trips are more likely to be shifted to another mode than canceled, as shown for planned disruptions (Van Exel & Rietveld, 2009) and unreliable metro services (Pnevmatikou et al., 2015). Furthermore, peak hour disruptions have been shown to enhance perceptions of uncertainty (Li et al., 2020). Our findings for on-demand ridesourcing shifts are novel given that previous research in this area has been dominated by car substitution and bus replacement.

4.3.2. Community context effects

In Model 3, we examine the role that the disrupted station's surrounding context plays in determining the transfer of ridership from transit to ridesourcing during no-notice disruptions. Model 3 reveals a significant impact of two community area level factors: *racial composition* and *percent transit commuters*. The addition of these cross-level factors leads to significant improvements in goodness-of-fit measured by the deviance difference and AIC. The positive effect on the interaction term for the *percentage of white residents* in the community area with a dummy variable for *peak-hour travel* (a coefficient of 12.3 additional trips) suggests an added effect of racial composition in the local area on the previous peak-hour effect findings. Namely, the peak-hour impact (353 added trips) is amplified when disruptions occur in communities with higher shares of white residents. The implied effect is that a disruption occurring in a community area with a 1 % higher share of white residents would result in a boost of 120 (or 3.46 %) ridesourcing trips compared to the average peak-hour baseline. This finding adds to existing evidence that ridesourcing provides greater benefits to privileged user groups (Zhang & Zhang, 2018). Given that communities of color in Chicago are more likely to be underserved in job accessibility, transit supply, and on-demand mobility access, we believe this finding is likely a reflection of gaps in access to resources in areas with lower shares of white residents rather than of a lower willingness to use ridesourcing during disruptions, but further research is warranted to gain a deeper understanding.

Additionally, a novel effect is found related to the *proportion of transit commuters* in the community area and the *disruption source: same station*. Overall, every percentage unit increase in transit commuting in the community area results in 18 additional ridesourcing trips (or a 5.2 % increase). However, this effect is only observed at the station where the incident causing the disruption occurred. We speculate that transit commuters more readily shift to ridesourcing services when they experience and receive information about the disruption *directly*. In other words, riders at the source of the disruption are likely to have more information regarding the nature of the disruptive event (e.g., from official sources and other riders), which will likely factor into their travel adaptation strategy. In areas with less transit commuting, we speculate that there is presumably less *collective* experience with transit disruptions and therefore a higher likelihood of shifting to private modes due to limited opportunities for word-of-mouth information sharing and social influence and thereby greater individualization of adaptive mobility strategies.

Despite a lack of *unexplained* systematic differences related to the district level beyond Model 1, a model search was conducted to explore additional impactful cross-level interactions that incorporate indicator variables for the four districts of the city. The resultant model suggests an unexpected finding. In the *North* district, when a *shuttle bus* is deployed, ridesourcing trips increase by 321 instances (or 92.5 %) from baseline. The deployment of replacement bus services for added transit capacity to assist riders during rail disruptions is a common agency response (Pender et al., 2013), but there appears to be an unanticipated (although not surprising) effect of this strategy: a *boost* in ridesourcing requests. We interpret this unexpected increase in ridesourcing to be related to the signaling effect of this action, namely, riders could perceive bus deployment as a strong cue for the severity of the disruption and thus its expected duration. For context, the North district is home to the largest share of disruptions in our dataset (16 of 28 or 57 %). The North district maintains heavy transit demand by commuters (shown previously in Fig. 1.d), as well as higher income levels among these commuters (Fig. 1.b), factors which likely contribute to a greater shift toward ridesourcing in this area.

5. Discussion and implications: enhancing collaborations for resilient mobility

The findings in this analysis show that sudden disruptions in urban rail transit are often accompanied by a surge in demand for ridesourcing. This spontaneous mode-shifting behavior invites more organized support of collaborations to enhance mobility resilience. Specifically, this discovery presents opportunities for transit operators to establish more formal, a priori arrangements with ridesourcing services to invoke quick phase-in of the latter to fill short-term gaps resulting from transit disruptions.

Bringing these two transportation service competitors to the table to facilitate the integration of services can be challenging given the adversarial relationship often observed (Monahan & Lamb, 2022). However, it is not without precedent, such as for special needs riders or low-density markets and feeder services where traditional transit services may not be cost-effective. Deakin et al. (2020) describe several such cases, among which is the 2015 RIDE collaboration between Boston Massachusetts Bay Transportation Authority (MBTA) and ridesourcing companies to provide paratransit, as well as Livermore-Amador Valley Transportation Authority's Go Dublin! collaboration with ridesourcing agencies to replace low-volume, fixed-route bus services. Yet, in cases of short-term disruptions to mainline services, it may be a more complex management decision to divert passengers to ridesourcing.

5.1. Opportunities

If transit operators like the CTA were to envision their task as supporting *mobility* rather than stop-to-stop service, the objective would become to find the best way to get travelers to their destinations efficiently, whether that is letting the market work untouched, providing shuttle services, or inviting ridesourcing operators to help fill gaps. By actively communicating the nature of the disruption and anticipated needs, transit agencies could engage – and even support – ridesourcing companies in providing adaptive, gap-filling services to address no-notice disruptions and thereby reduce the delays experienced by transit riders. The flexibility of ridesourcing services offers on-call availability to provide extra capacity by replacing or supplementing shuttle buses, depending on the nature of the disruption.

Advance agreements between the transit operator and ridesourcing services would make the transition between the two when a disruption occurs quicker and more efficient for transit passengers. As an example, the LA Metro in the Los Angeles region was able to leverage a preexisting collaboration with the ridesourcing company Via by expanding their role from providing first- and last-mile services to private, point-to-point trips to accommodate essential travel during the COVID-19 pandemic (Grossman, 2020). Agreements should define the circumstances that will activate collaboration, as well as standards for messaging about disruptions, such as including information like location, expected duration, and passenger volumes based on train loadings. This exemplifies the ability of public-private partnerships to increase mobility resilience to unplanned disruptions.

5.2. Challenges

A first potential challenge is the existence of surge pricing when demand spikes, which is likely to occur in the case of a peak period transit disruption. This would be particularly burdensome for low-income transit riders. Incident-specific subsidies for these fill-in ridesourcing trips might offer a solution, but several issues need to be resolved to make this work. First, such subsidies would need to apply to all riders, since there is no means of testing at the farebox (or point of sale) to know who really needs them. Second, the level of subsidy would need to be scaled to the circumstance (e.g., how widespread is the disruption?). Lastly, a way to isolate the subsidy in time and space needs to be defined, and a mechanism for linking passengers experiencing the disruption (who should be subsidized) to the ridesourcing trip would be needed. All these capabilities would be required to assure the fair and efficient use of public resources and to make ridesourcing subsidies palatable to transit agency leadership. Ultimately, these important details would provide the basis for formal agreements between transit providers and ridesourcing companies. An additional challenge relates to the different standards of operation. Notably, transit providers are required to ensure fair service to all individuals in accordance with Title VI and the Americans with Disabilities Act, while ridesourcing services are not currently held to the same standards.

In sum, while collaborations between transit providers and ridesourcing companies may provide a way to decrease disruption response time and assist a greater number of affected travelers, these collaborations are not without challenges. A summary of the advantages and challenges related to the multimodal integration of transit agencies and ridesourcing companies for seamless adaptation is provided in Table 4.

Table 4
Summary of advantages and challenges of transit-ridesourcing integration.

Transit ridesourcing integration	Advantages	Challenges
Collaboration	Increases coordination and communication between operators	Contrasting expectations and standards of operators; Conflicting operator goals
Performance	Provides more seamless service integration	Differences in regulation and standards for operators
User experience	Improves the user experience for riders; Speeds up disruption recovery	User barriers, including difficulty for less tech-savvy demographics to navigate integrated mobility systems (Butler et al., 2020)

6. Conclusions

6.1. Summary of findings

Given the current climate crisis and urbanization, both acute shocks and chronic stressors of all kinds are multiplying in cities, and disruptions are occurring with increased frequency and severity. This study examines the effects of no-notice rail transit disruptions on mode-shifting strategies. Specifically, we examine the role of ridesourcing as an adaptive substitution strategy to fill gaps created by rail disruptions. This study uses a natural experiment to systematically identify and then temporally and spatially match 28 major transit disruptions with ridesourcing trip data for the City of Chicago. An MLM model is used, where the multilevel structure is designed to account for variation in rail-to-ridesourcing shifts and to identify whether determinants are local or occurring due to neighborhood differences.

The analysis yields the following main findings and implications:

(1) There is evidence of significant localized surges in ridesourcing demand following sudden rail transit disruptions, highlighting that there is spontaneous mobility resilience in the system. The observed demand substitution is strongest during peak-hour and weekday travel, suggesting that ridesourcing provides selective mobility redundancy in relation to mandatory and time-sensitive travel.
(2) Characteristics of the community area where the transit disruption is located are responsible for most of the variation in observed ridesourcing substitution. Greater shifts to ridesourcing occur in community areas that have higher percentages of white residents, especially during peak-hour disruptions, suggesting potential spatial inequities in the capacity for mobility adaptiveness and thus community resilience.
(3) To address the negative impacts of transit disruptions on ridership, transit agencies may consider investing in partnerships oriented toward mobility as a service. If transit operators like the CTA were to adopt a policy of delivering end-to-end service despite unplanned disruptions, they would maintain responsibility for providing transportation alternatives when service disruptions occur. Our research suggests a potential role for on-demand ridesourcing to address no-notice transit service disruptions.

6.2. Limitations

Some caveats warrant discussion. First, modeling was based on the identification of transit disruptions and shuttle bus deployment gathered from a systematic search of local news sources. As such, these data were aggregated at the station level, and it was assumed that a given disruption lasted the same duration at every impacted station. Second, our approach to analyzing mode-switching behavior was based on a spatial delimitation of a 0.25-mile radius around each impacted station, but mode-shifting behaviors may have occurred across a broader time-space domain, including travelers who learned of the disruption prior to departure. Third, sociodemographics were spatially aggregated, which may mask individual-level rider characteristics. Since individual ridership data were not available, we could not analyze multimodal adaptive strategies for individual travelers.

Despite these limitations, based on conversations with a CTA rail transit agency professional and considering the challenges of data availability and accessibility, our method of data aggregation was the best option available to us. Acknowledging the limitations associated with the use of a natural experiment, our research contributes new insights that would be difficult to gauge using small-scale stated response data. Specifically, we capture the circumstances of the disruptions that lead to real-world shifts to ridesourcing. Thereby the findings of this study shed light on which communities effectively shift to adaptive on-demand mobility during a disruption and which communities must rely on other alternatives.

6.3. Future work

Based on our findings, we suggest two main avenues for future research. First, to address the outlined limitations of spatiotemporal data, further collaborative research should aim for a more nuanced analysis of transit riders' behavioral adaptations to better understand socioeconomic determinants of mobility resilience. For example, matching individual-level ridership data by ridesourcing pickup locations with spatiotemporal bus and rail ridership data would reveal more detailed insights into individual user multimodal adaptive mobility strategies. Related to this, an interesting area of future research is to examine the potential impacts of rail transit disruptions on ridesourcing demand in neighboring areas to explore spatial and temporal spillover effects, perhaps by applying a methodology similar to that seen in Soria and Stathopoulos (2021). Such an investigation would provide insights into what happens to service quality and pricing when disruptions are publicized and ridesourcing drivers are pulled to the source of a disruption. This could have important implications for already-underserved areas where existing gaps in service may be exacerbated.

Second, we encourage the expansion of this investigation using more qualitative analysis. There is a need for further understanding of the adaptative decision-making process that riders use to cope with unplanned travel disruptions. This includes more precise identification of risk perceptions, communication about disruptions, circumstances of travel, and attitudes related to emerging ridesourcing options. One potential recommendation is to use latent variable modeling to better capture rider perceptions surrounding the use of ridesourcing as an adaptive mobility strategy and enable more tailored transportation policies to foster equitable disruption recovery.

CRediT authorship contribution statement

Borowski: Writing - Original draft preparation, Borowski, Stathopoulos, Soria, Schofer: Writing - Reviewing and Editing, Borowski, Soria: Visualization. Stathopoulos: Conceptualization, Stathopoulos, Borowski: Methodology, Borowski: Data curation, Stathopoulos: Supervision, Stathopoulos: Funding acquisition.

Declaration of competing interest

We have no conflicts of interest to disclose.

Data availability

All data used in the analysis is publicly available and referenced. Model code is available upon request from the main author.

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