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Measuring the impacts of new public transit services on space-time accessibility: An analysis of transit system redesign and new bus rapid transit in Columbus, Ohio, USA

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ABSTRACT

The absence of effective access to opportunities and services is a key contributor to poor socio-economic and health outcomes in underserved neighborhoods in many cities. The city of Columbus, Ohio, USA is attempting to enhance residents' accessibility by providing new public transit services. These new services include a major Transit System Redesign (TSR) of the conventional bus network and the introduction of a new bus rapid transit, named CMAX. Using a high-resolution space-time accessibility measure, we analyze whether these new public transit services will change residents' accessibility to job and healthcare in an underserved neighborhood of Columbus. Also, we assess whether enhancing the CMAX service to reduce delays (e.g., reserved lane, off-board payment system) will improve accessibility. The high-resolution space-time accessibility measure in this study uses published public transit schedules via the General Transit Feed Specification (GTFS). We use multiple departure times during a day to account for the temporal fluctuations of accessibility based on the transit schedule changes. We also consider the operating hours of job opportunities and healthcare services. Results suggest that the TSR yields ambiguous benefits for accessibility to jobs and healthcare. However, the new CMAX service and its potential upgrades lead to a substantial increase in both job and healthcare accessibility. The results can be used for city officials and urban planners to evaluate the effectiveness of public transit innovations in improving accessibility.

1. Introduction

Accessibility provides opportunities for citizens to participate in vital activities and to reach necessary services (Handy & Niemeier, 1997; Hansen, 1959). Low levels of accessibility and accessibility inequalities can exacerbate socio-economic and health disadvantages. For example, the Linden neighborhood in Columbus, Ohio, USA faces many challenges because of the limited access to crucial resources such as job and health care services. The median household income of Linden is less than half of the broader city, and parts of the neighborhood's unemployment rate are over 15% (Bliss, 2016; Columbus, 2016a). Also, South Linden's infant mortality rate is close to 26 (per 1000 live birth) which is about four times higher than the national average (Bliss, 2016; CelebrateOne, 2015).

To improve accessibility to opportunities, the city of Columbus is providing new public transportation services in collaboration with Central Ohio Transit Authority (COTA), the main public transit agency in Columbus. The city's public transit innovation consists of two stages. The first stage is a major Transit System Redesign (TSR) which revamps the existing COTA bus system. TSR simplifies complex routes and offers more frequent and consistent service, with the intent of providing a simpler, more reliable system with better access to destinations (Central Ohio Transit Authority, 2017a). The second phase is constructing a new bus rapid transit (BRT) service called CMAX through the Linden neighborhood. CMAX is designed to enhance Linden residents' accessibility to job and healthcare by connecting major employment centers and hospitals with relatively short headway (Columbus, 2016a, 2016b, 2016c; Bliss, 2016; Central Ohio Transit Authority, 2017b).

In this study, we investigate whether the TSR and new BRT services will improve Linden residents' access to job and healthcare. Furthermore, we simulate changes in the CMAX operating speed to assess whether potential upgrades that minimize delays (e.g., off-board payment system, reserved bus lane) will further improve accessibility. We use a high-resolution space-time accessibility measures based on published and proposed transit schedules available via the General Transit Feed Specification (GTFS) and detailed street network data. The

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space-time accessibility measures capture multimodal accessibility, namely, walking to access and egress the transit system. We also consider the time of day and day of the week since transit travel times fluctuate due to the changes in service provision parameters such as headways (Boisjoly & El-Geneidy, 2016; Farber & Fu, 2017; Farber, Morang, & Widener, 2014; Owen & Levinson, 2014; Widener, 2017). We consider four departure times representing peak/off-peak hours to capture dynamics in accessibility due to the transit schedule changes. We also account for temporal availability at the destinations such as working hours and healthcare service hours. Results suggest that the TSR by itself yields ambiguous benefits for accessibility to jobs and healthcare in this neighborhood. However, the new CMAX service and its potential upgrades lead to a substantial increase in both job and healthcare accessibility.

The next section of this paper provides background about space-time accessibility measures for public transit. Section 3 provides detail on the new public transit services implemented in Columbus, Ohio and describes Linden, an underserved neighborhood in the city. Section 4 describes data used in this analysis and Section 5 describes the methodology. Section 6 describes the study design and scenario analysis. Section 7 provides the results, and Section 8 concludes with some comments on the study's contributions, limitations, and future steps.

2. Background

Recently, there has been growing interest from transportation researchers and practitioners in understanding accessibility by public transit within urban areas. Among the four major accessibility measurement approaches, opportunity-based, gravity-type, utility-based and space-time measures (Benenson, Ben-Elia, Rofé, & Geyzersky, 2016; Geurs & van Wee, 2004; Kwan, 1998; Liu & Zhu, 2004), space-time measures based on the time geographic framework are increasingly popular since they capture heterogeneous social constraints (e.g., gender, socioeconomic status) on human activities in space and time (Hägerstrand, 1970; Kwan, 1998, 1999; Lenntorp, 1978; Miller, 2005, 2017; Neutens, Witlox, & Demaeyer, 2007), as well as integrate spatial and temporal constraints imposed by public transport as well as the location and timing of opportunities (Djurhuus, Sten Hansen, Aadahl, & Glümer, 2016; Tasic, Zhou, & Zlatkovic, 2014). Also, space-time accessibility measures allow the analyst to simulate the changes in public transit performance using speed, time budgets, travel origins/destinations, and activity locations as parameters. Finally, data required to measure space-time accessibility at a high temporal and spatial resolution are increasingly available; these include detailed road networks, transit routes, and schedules, including the widely used GTFS data format for publishing transit schedules to services such as Google Transit (Salonen & Toivonen, 2013).

O'Sullivan, Morrison, and Shearer (2000) is the first attempt to investigate transit-based space-time accessibility using the time geographic framework. The researchers reconcile two accessibility measures: opportunity-based measures and space-time measures. They use isochrones delineating accessible areas given specified time budgets to combine those two measures using a geographic information system (GIS). In computing accessibility, O'Sullivan et al. (2000) account for various temporal elements of a trip, including walking time, waiting time, and in-vehicle travel time. Horner and Mefford (2005) conduct a similar isochrone-based study evaluating the spatial and social variation in job accessibility by bus service in Austin, Texas, USA. However, due to the unavailability of detailed transit schedule and the limitation of the conventional GIS network model, both of these studies above simplified the travel environment. For instance, they assume that bus speeds are constant along the whole routes, ignoring the differences between downtown and suburban roads. Also, they assume every traveler waits the same amount of time (one-half of the headway) at the initial bus stop. These simplifying assumptions result in less accurate travel time calculations and consequently misrepresent accessibility (Djurhuus et al., 2016; O'Sullivan et al., 2000; Salonen & Toivonen, 2013).

With the advent of GTFS data and techniques for combining the data with multimodal networks via GIS, more recent studies of space-time accessibility using transit account more fully for temporal elements of the transit-based trip, allowing more realistic calculations of transit-based accessibility (Benenson et al., 2016; Djurhuus et al., 2016; Farber et al., 2014; Ma & Jan-Knaap, 2014; Salonen & Toivonen, 2013; Tasic et al., 2014; Widener, 2017; Widener, Farber, Neutens, & Horner, 2015). A good example is the analysis of accessibility to healthy food options in Cincinnati, Ohio, USA by Widener et al. (2015). The authors construct a multimodal network capturing bus and walking using GTFS and sidewalk data. They apply a single departure time, 5 p.m. on Monday, to calculate and compare accessibility with different origins. However, using one departure time cannot reveal fluctuations in accessibility subject to transit schedule changes.

To fill this gap, researchers have developed dynamic accessibility analysis using multiple departure times (Boisjoly & El-Geneidy, 2016; Farber & Fu, 2017; Farber et al., 2014; Owen & Levinson, 2014; Widener, 2017). While these studies capture the temporal dynamics in accessibility in transit schedules, they fail to consider the temporal variations in the travel destinations such as working and operating hours. Assuming the opportunities such as jobs and healthcare are available at all times can lead to a serious over-estimation of accessibility (Boisjoly & El-Geneidy, 2016). To address this limitation, Legrain, Buliung, and El-Geneidy (2015) combines variations in both job availability and transit schedule for their accessibility computation. Further, researchers utilize a big spatio-temporal database including opening/closing hours as well as locations of various resources to model and simulate urban accessibility (Fosset et al., 2016).

3. New public transit services in Columbus

This section describes the new public transit services being deployed in Columbus, Ohio, USA. The first is a Transit System Redesign (TSR) that simplifies the existing bus network and offers more frequent and consistent service along the new routes. The TSR is a region-wide change. In contrast, a new bus rapid transit (BRT) service called CMAX explicitly targets northeast Columbus, in particular, the Linden neighborhood that is underserved by job opportunities and healthcare (Bliss, 2016). Fig. 1 provides a map of the study area, the Linden neighborhood, and the proposed CMAX route.

3.1. Transit System Redesign (TSR)

TSR is the first major rerouting of COTA bus network since its inception in 1974. During the past 40 years, the urban form has changed, and new employment clusters have emerged in suburban areas. However, COTA had maintained its routes the same as designed by the former transit agency, Columbus Transit Company (CTC), when jobs were centralized in downtown. As a result, the old bus network increasingly failed to satisfy customers' needs to access their destinations.

To meet new ridership needs, COTA developed a new bus network and implemented this system overnight on May 1, 2017. Fig. 2 shows the maps of former (Fig. 2a) and TSR (Fig. 2b) bus systems. The TSR bus network is more straightforward compared to the traditional bus network. TSR has three major advantages compared to the conventional bus operation. First, TSR saves travel time by simplifying bus routes and making services more direct. Second, TSR provides more frequent service (maximum 15 min headway) by reducing the number of bus lines (from 74 to 48) and allocating 70% of service to high-ridership routes. The total sum of bus routes' lengths decreases from 2297.44 km to 1640.81 km, accordingly. Third, TSR operates with the consistent schedule regardless of weekdays or weekends. COTA expects TSR will connect customers to more jobs and other opportunities (Central Ohio Transit Authority, 2017a).

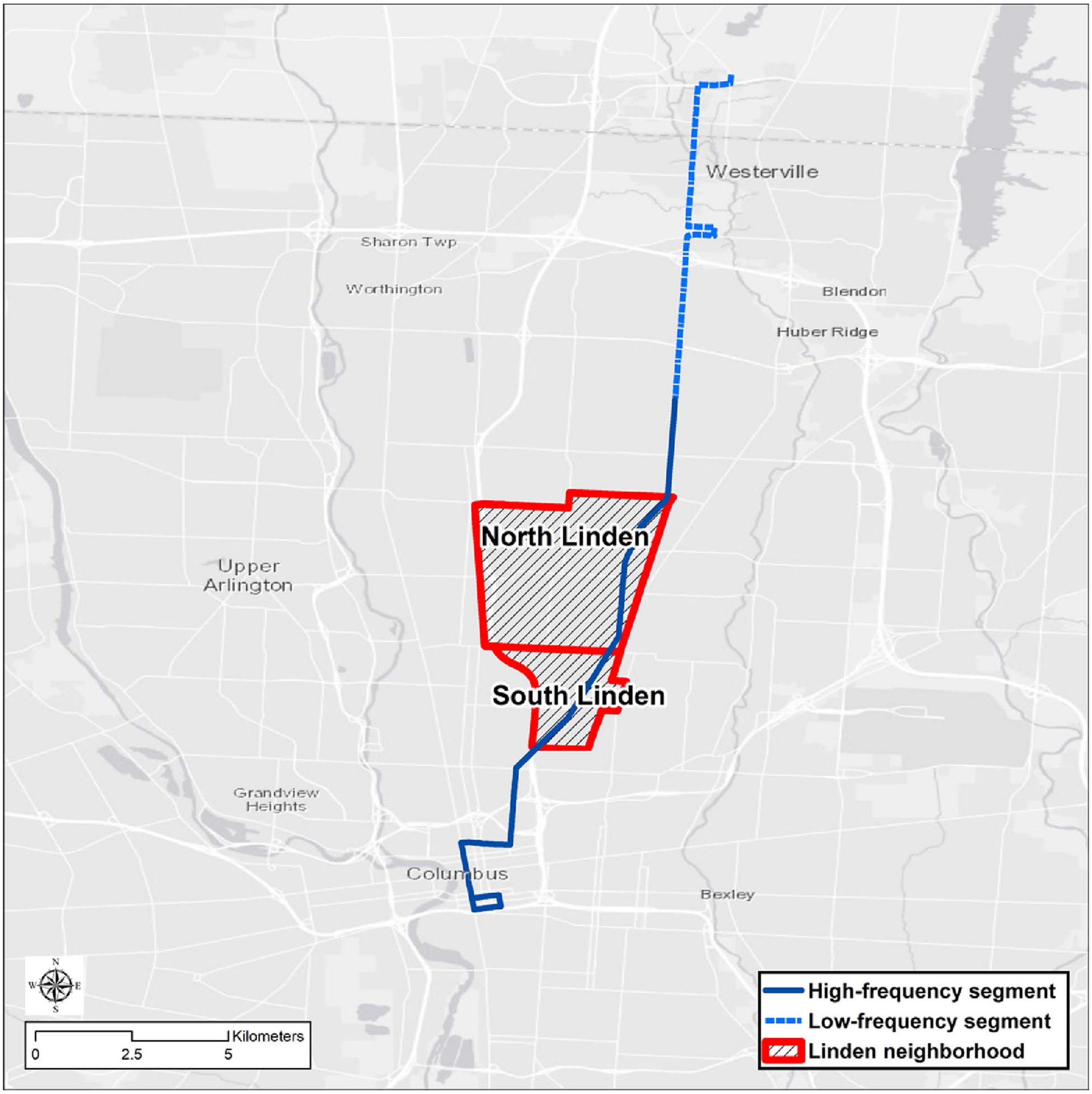


Fig. 1. Study area (Linden neighborhood) and CMAX route.

3.2. Bus rapid transit: CMAX

CMAX is a new BRT system in Columbus running along Cleveland Avenue, the main street of the Linden community and a major road connecting downtown with new concentrations of jobs, healthcare and other opportunities in the northeastern suburbs. As shown in Fig. 1, CMAX service consists of two sections: a high-frequency segment (between downtown and State Route 161) and a low-frequency segment (from State Route 161 to Polaris Parkway). CMAX service shares its route with the Line 6 regular bus. Table 1 describes the CMAX headway variation subject to the segment type and different time zones. In peak times, CMAX arrives every 10 min at stations in the high-frequency segment. In the low-frequency segment, buses arrive every 30 min.

Although CMAX was originally planned to be constructed before the Columbus' winning of the U.S. Department of Transportation (USDOT) Smart City Challenge (U.S. Department of Transportation, 2015), the city is using this opportunity to enhance CMAX project so it can play a key role in implementing Smart Columbus plan for improving Linden people's access to job and healthcare. Located in Linden and along the CMAX corridor are ten Neighborhood Hubs; these are stations for facilitating access to CMAX by supporting various first/last mile transport options (e.g., car sharing, bike sharing). Planned Wi-Fi infrastructure installed at the Neighborhood Hubs will help Linden residents' trip planning such as requesting ride sharing (e.g., Uber, Lyft) or getting real-time transit information. To encourage potential new transit riders in Linden, COTA will provide free CMAX service in the neighborhood during the initial stage of operation (Columbus, 2016a, 2016b, 2016c; Bliss, 2016; Central Ohio Transit Authority, 2017b).

Like many public transit services, especially those that share an existing road network, there are three main sources of possible delay during CMAX operation: signal delay, traffic delay, and passenger-stop delay. Stopping at signals cause signal delay. Traffic delay occurs when other vehicles interrupt bus operation. Passenger boarding/alighting and fee collection cause a passenger-stop delay (Walker, 2012). COTA will employ Transit Signal Priority (TSP), a system that triggers green lights to minimize signal delay (Central Ohio Transit Authority, 2017b).

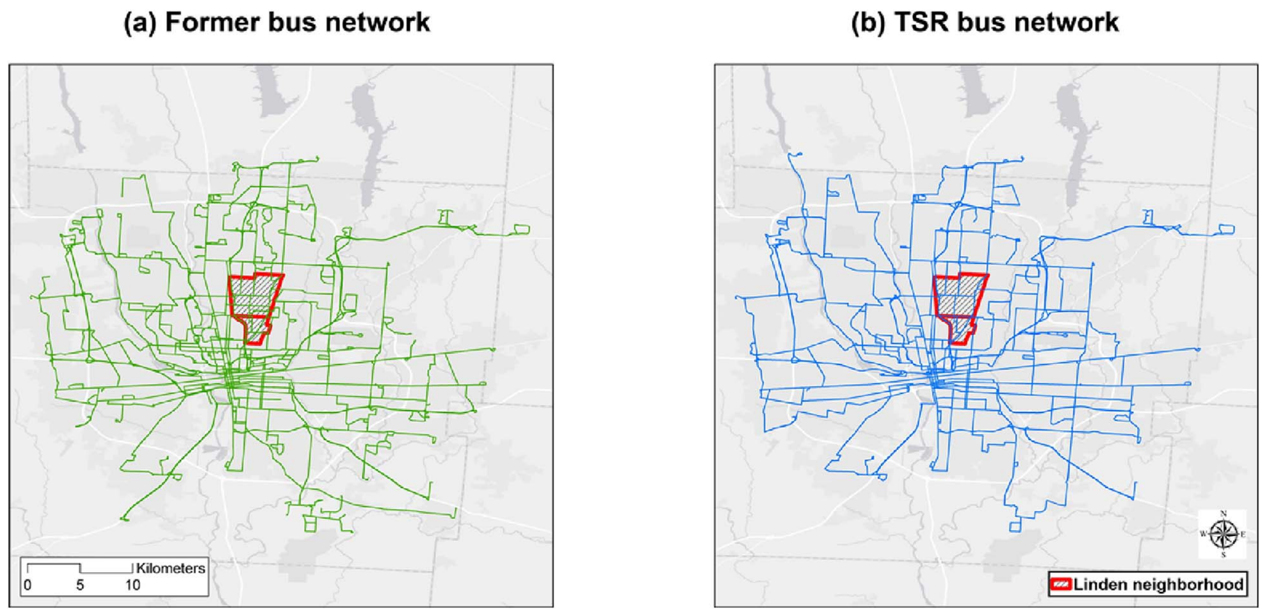


Fig. 2. Former and TSR bus networks in Columbus Ohio, USA.

Table 1
CMAX headway information.

	Peak (6:30–9 a.m. & 3–6 p.m.)	Midday	Evening	Weekend
High-frequency segment (Downtown to SR-161)	10 min	15 min	15 min	30 min
Low-frequency segment (SR-161 to Polaris Parkway)	30 min	30 min	30 min	30 min

However, COTA has no plan for alleviating other two delay sources. With this understanding, in this study, we identify a dedicated bus lane and an off-board payment system as possible new technologies for CMAX to minimize traffic delay and passenger-stop delay, respectively. We assess the impacts of these two potential upgrades on space-time accessibility.

4. Data

4.1. Transportation data

In this study, we use a multimodal transport network comprising two components: a transit network and a walking network. Depending on the scenario, we use two transit networks: a regular bus network and the BRT network. We obtained GTFS data from COTA to create regular bus space-time networks. Specifically, we use GTFS data as of January 11, 2017 and May 17, 2017 for pre-TSR and post-TSR bus networks, respectively. January 11 and May 17 were the dates when the GTFS data were published. GTFS data contains a series of text files regarding transit travel information (e.g., routes, stops, and arrival/departure times) as well as operation information (e.g., fare, bike/wheelchair allowed) (Google, 2016).

At the time of this research, the GTFS data for CMAX is currently not available because CMAX did not operate until January 2018. Instead, we create pseudo-GTFS data for CMAX based on the proposed route, stops, and headways (Central Ohio Transit Authority, 2017b). A GTFS builder provided by the USDOT and National Rural Transit Assistance Program (NRTAP) generates CMAX GTFS data. We acquired walking network data from the Mid-Ohio Regional Planning Commission (MORPC), the local metropolitan planning organization.

4.2. Job and healthcare data

We examine two types of opportunities in our analysis, namely, job and healthcare, due to the clear need for better access to these opportunities in Linden. We obtained job opportunity data at census tract level[1] from the Longitudinal Employer-Household Dynamics (LEHD) survey by the U.S. Census Bureau in 2014. In addition to the total job count data, we classified employment data by two educational attainment levels: low-skill jobs (less than high school, high school or equivalent) and high-skill jobs (some college or associate degree, bachelor's degree or advanced degree).

We obtained healthcare data from Infogroup business data by selecting all businesses with North American Industry Classification System (NAICS) code 62 (healthcare and social assistance). We excluded social assistance businesses (e.g., child day care service) because this study's focus is healthcare services. Since reducing infant mortality by increasing healthcare access is a key objective identified by COTA and Smart Columbus, we focus on two access to pediatrics and obstetrics/gynecology. We geocoded the selected healthcare businesses using their address information and aggregated these data to census tracts for comparability. Due to the lack of data, we did not include the healthcare facilities' capacity information.

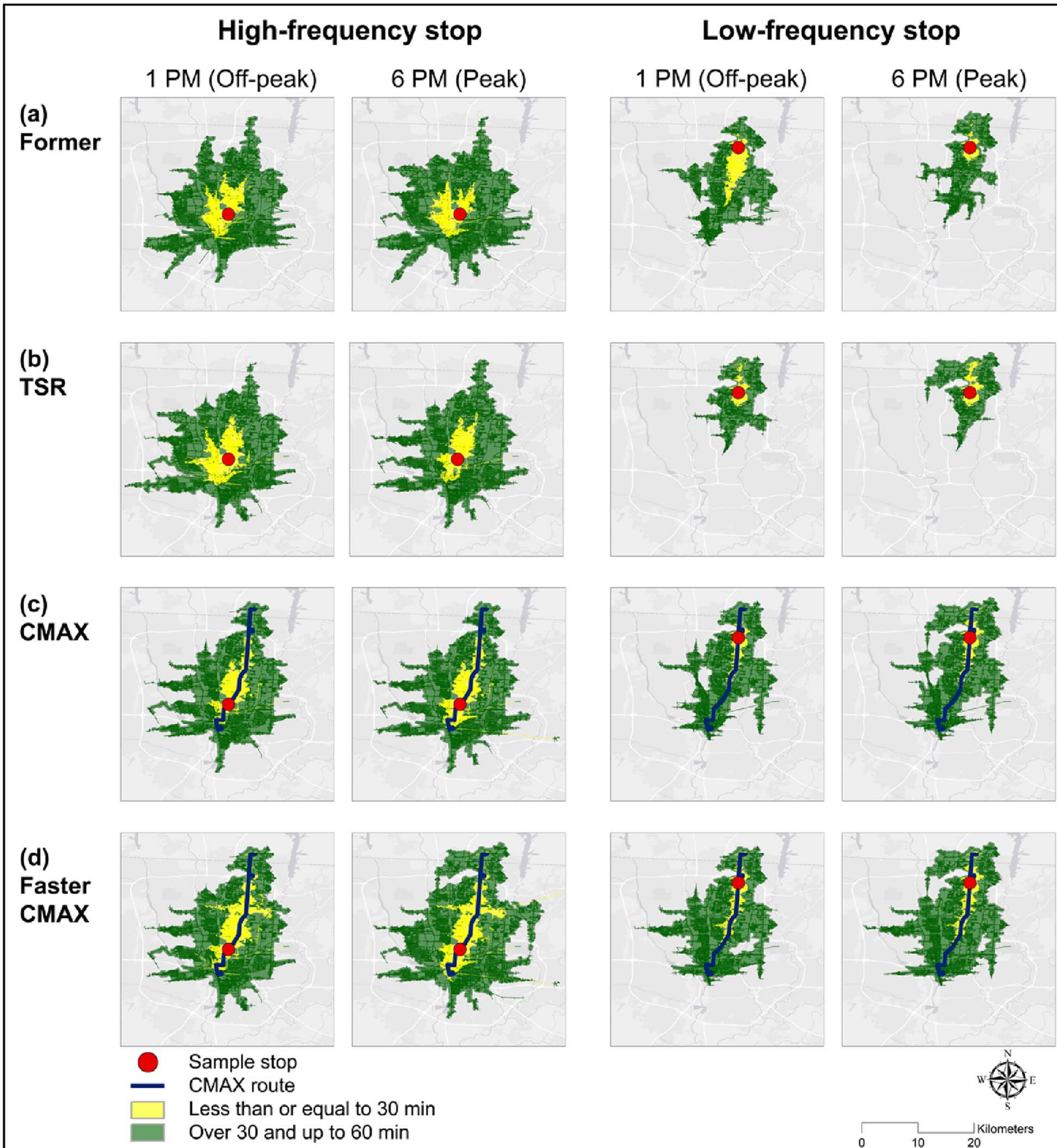
5. Methods

5.1. Constructing a multimodal transport network and estimating travel times

We use the *Add GTFS to a Network Dataset* tools provided by Morang (2015) to construct transit networks based on GTFS files and integrate them with the walking network to create a multimodal network dataset. The GIS scripts and toolkits have been used in previous public transit accessibility research (e.g., Farber & Fu, 2017; Farber et al., 2014; Widener, 2017; Widener et al., 2015).

The *TransitEvaluator* in the toolkit estimates travel time from trip origins (CMAX stops) to undefined destinations using the Network Analyst OD Cost Matrix Solver in ArcGIS which employs Dijkstra's algorithm to find the shortest (travel time) path in the network. The

[1] According to the U.S. Census Bureau (U.S. Census Bureau, 2018), the population size of a census tract varies from 1200 to 8000 people, with an optimum size of 4000 people.



Note: Lines in isochrone polygons are PMNAs indicating all possible routes that can be traveled in given time budgets. The labels on the vertical sides refer to: Former = the former transit network, TSR = TSR transit network, CMAX = the network of TSR with CMAX, Faster CMAX = the network of TSR with 20% faster CMAX.

Fig. 3. Space-time accessibility maps for weekday times.

estimation algorithm accounts for waiting, transfer, and in-vehicle time subject to the GTFS schedules as well as last mile walking time. The trip time calculation also considers transit boarding and alighting time (15 s). We compute walking time by applying average adult walking speed (84 m per minute) based upon literature (Browning, Baker, Herron, & Kram, 2006; Levine & Norenzayan, 1999; Mohler, Thompson, Creem-Regehr, Pick, & Warren, 2007) of preferred walking speed. The travel time calculation algorithm does not restrict the number of transfers and people's walking time but optimizes the total travel time from an origin to a destination via the shortest route at a specific departure time (e.g., 9 a.m.). Therefore, a travel time of 20 min could be 20 min of walking, 20 min of walking and transit travel, or other types of travel combining waiting, transferring, riding, and walking that amounts to 20 min (Farber et al., 2014).

5.2. Delineating accessible areas using space-time prisms

We adopt a time geographic accessibility measure based on the *space-time prism*. A space-time prism is the set of feasible paths (or locations) in space and time that an individual can reach assuming a

Note: Lines in isochrone polygons are PMNAs indicating all possible routes that can be traveled in given time budgets. The labels on the vertical sides refer to: Former = the former transit network, TSR = TSR transit network, CMAX = the network of TSR with CMAX, Faster CMAX = the network of TSR with 20% faster CMAX.

Fig. 4. Space-time accessibility maps for weekend times.

speed limit and travel anchored by a departure and/or origin location and a *time budget* or the maximum amount of time available for travel and activity participation. Projecting the space-time prism onto two-dimensional geographical space is individual's potential path area (PPA). The PPA is a well-established accessibility measure that captures both space and time constraints (Hägerstrand, 1970; Miller, 2017).

Researchers have also developed methods for calculating space-time prisms constrained by transport networks; this is referred to as a *network-time prism* (Kuijpers & Othman, 2009; Miller, 1991). Network-time prisms are usually based on a single transportation mode (e.g., automobiles). However, this cannot capture multimodal travel such as the heterogeneous use of transport modes and walking or biking to access and egress public transit. Thus, in this study, we develop and use a multimodal network prism concept for measuring accessibility, the *potential multimodal network area* (PMNA). We generate PMNAs based on 30 min (local accessibility) and 60 min (regional accessibility) time budgets assuming walking to access and egress the public transit system. According to the U.S. Census's 2016 American Community Survey (ACS) data (U.S. Census Bureau, 2016), the average commute time is 26.6 min. We utilize 30 min, therefore, as a representative

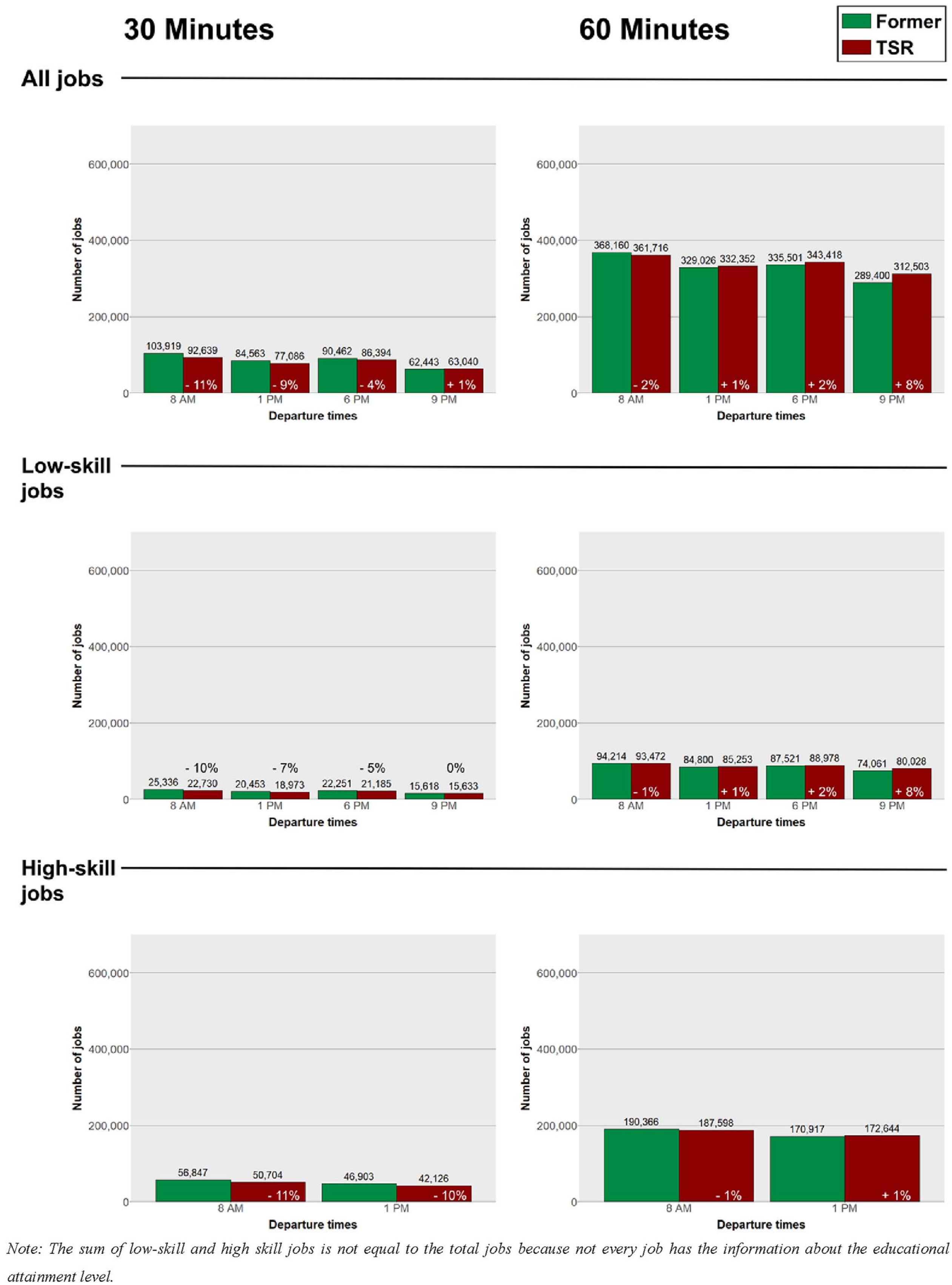
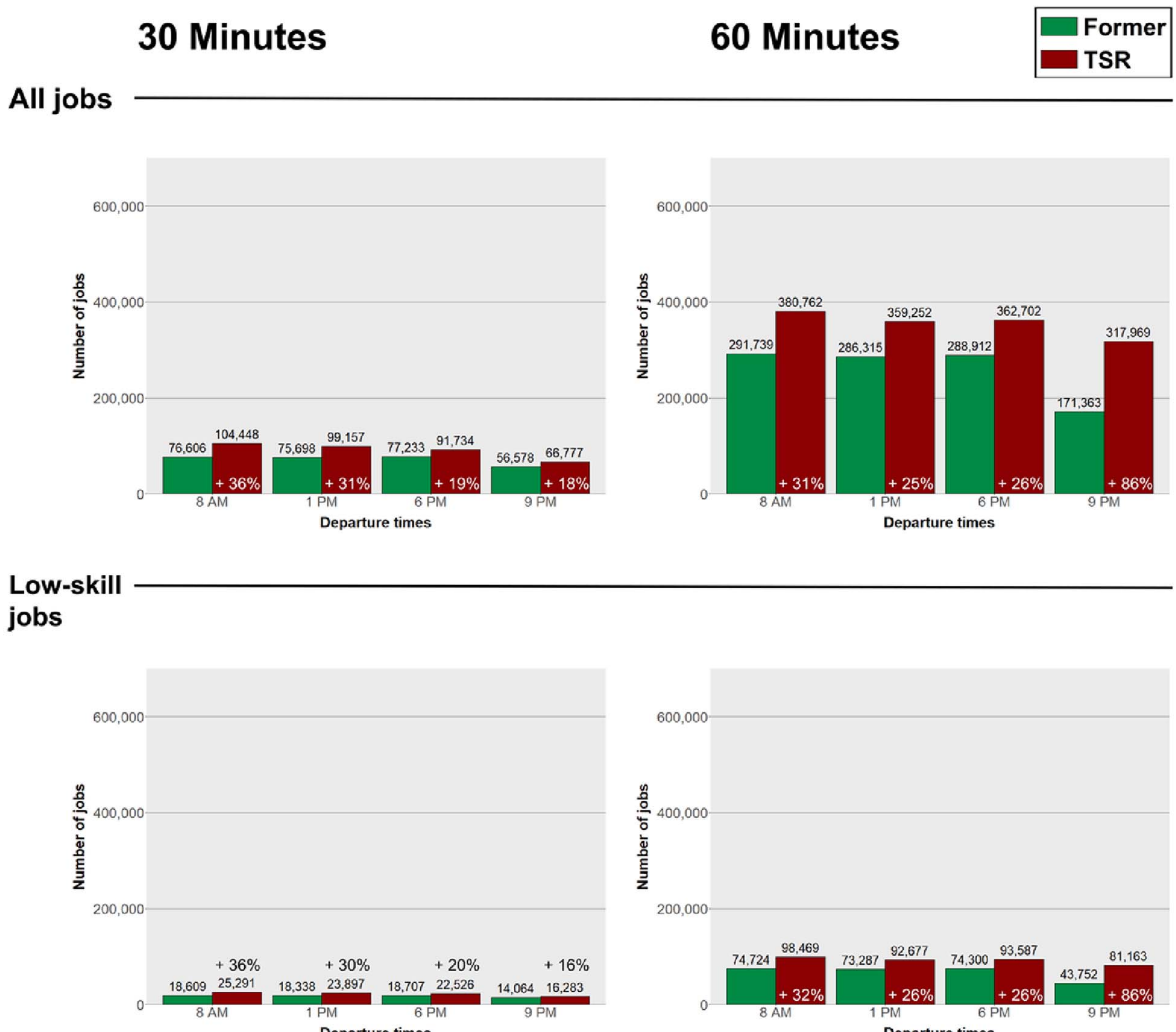


Fig. 5. Job accessibility analysis for Scenario 1 (Former versus TSR) during weekdays. Note: The sum of low-skill and high skill jobs is not equal to the total jobs because not every job has the information about the educational attainment level.



Note: The sum of low-skill and high skill jobs is not equal to the total jobs because not every job has the information about the educational attainment level.

Fig. 6. Job accessibility analysis for Scenario 1 (Former versus TSR) during weekends.

threshold for job accessibility. In case of healthcare access, 30 min travel time has been considered as a standard/desired threshold for access to healthcare (Bosanac, Parkinson, & Hall, 1976). We use 60 min time budget to capture people who are willing to take long commute trips. Approximately 9.1% of Americans' commute times are 60 or more minutes (U.S. Census Bureau, 2016). For healthcare accessibility, 60 min threshold is often used as a time standard for measuring regional-level accessibility (Elikan, 2012; Skinner, 2010).

We use the 33 CMAX stops in the proposed service map (Central Ohio Transit Authority, 2017b) as the trip origins for all accessibility analysis in this study. Since there are no fixed destinations, we only use forward cones of space-time prisms: this measures accessibility based on a specified origin only with no specified destination. To automatically create PMNAs for each CMAX stop based on different transport networks, we utilize the programming language Python and the ArcPy module (the site package provided with ESRI ArcGIS software). We write and execute the Python scripts in PythonWin, a Python development environment in Windows operating system.

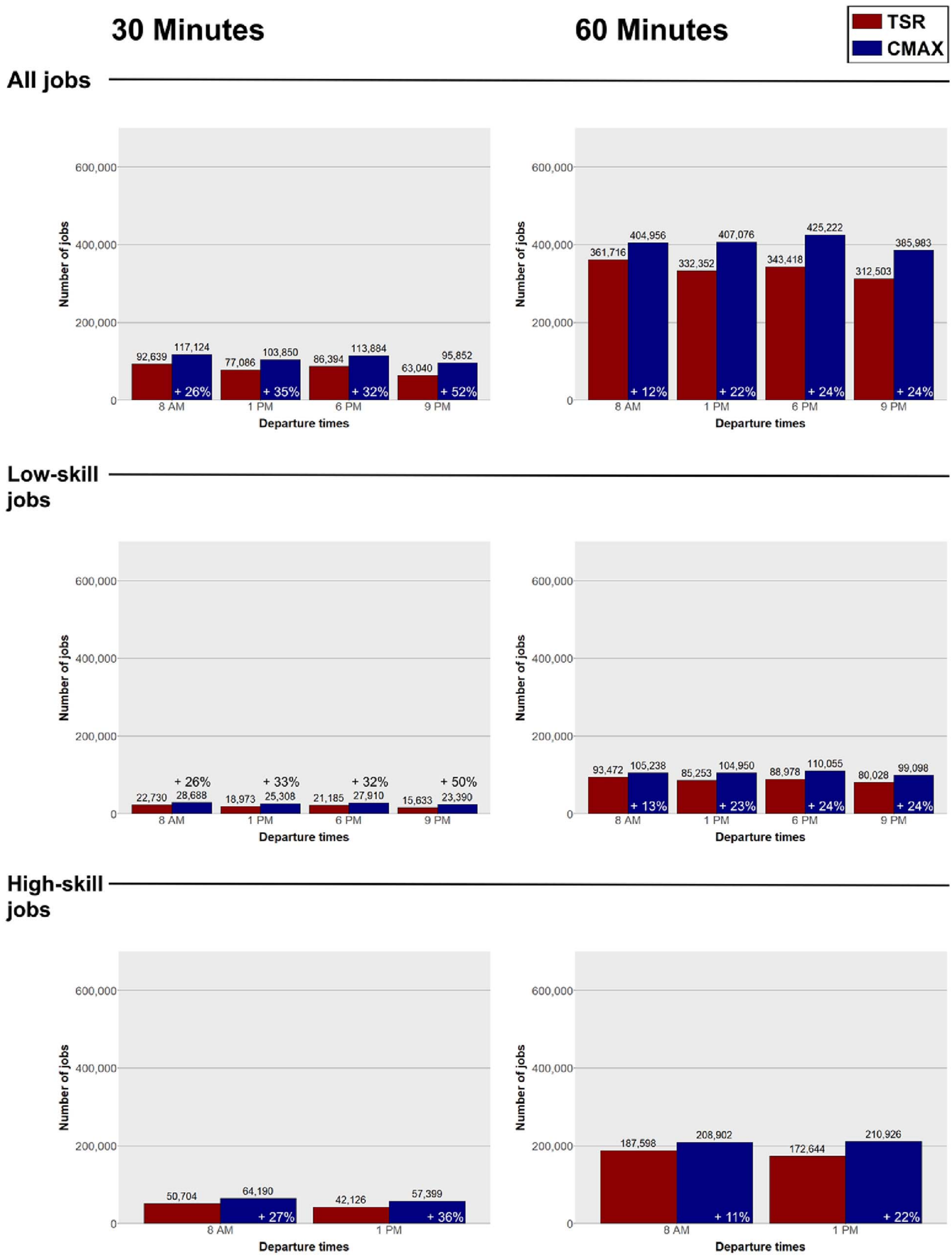
5.3. Calculating space-time accessibility

Using the space-time prism as a basis, we calculate space-time constrained cumulative opportunity measure to count the number of jobs and healthcare services can be reached based on travel from designated origins given a time budget via walking and public transit (El-Geneidy & Levinson, 2006; Horner, Duncan, Wood, Valdez-Torres, & Stansbury, 2015; O'Sullivan et al., 2000):

$$A_s(t) = \sum_{i \in N_s(t)} O_i \tag{1}$$

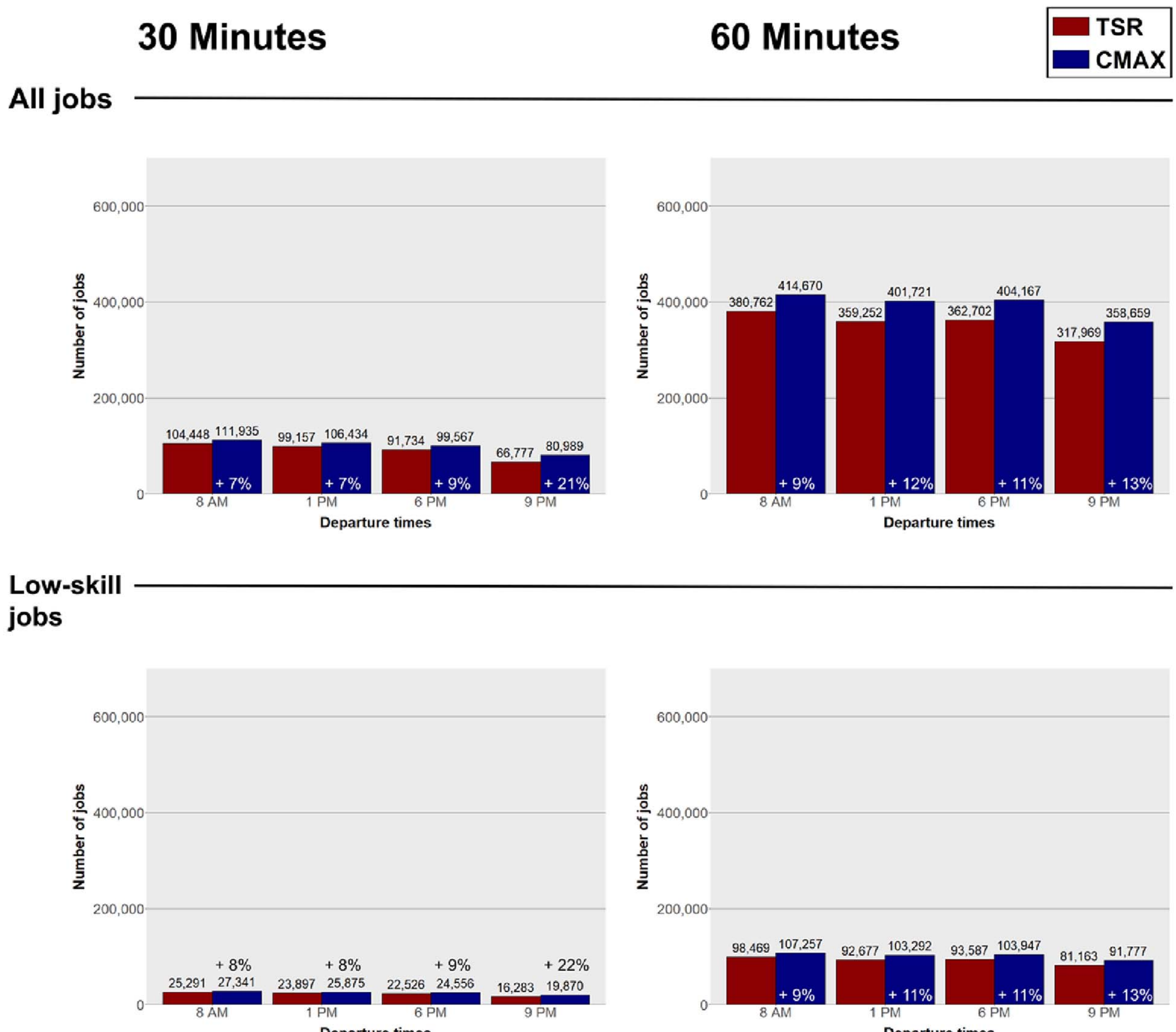
where $A_s(t)$ is the number of accessible jobs (or healthcare services) based on travel from public transit stop s with a time budget t (in this study, $t = 30,\ 60$ minutes), O_i is the number of jobs or healthcare services in a census tract i, $N_s(t)$ is the subset of census tracts that can be reached from a stop s with time budget t.

Calculating equation (1) involves four steps. First, we generate the PMNAs using the tools and procedures described above. Then, we create isochrone polygons covering the PMNAs using the service area algorithm in the ArcGIS software. Next, the isochrone polygons are overlaid with census tracts that were spatially joined with job and healthcare data. Census tracts intersected with the boundaries of the isochrone polygons are included although the census tracts are not totally inside the isochrone polygons. Lastly, we analyze the number of jobs and healthcare businesses. After cumulative accessibility is



Note: The sum of low-skill and high skill jobs is not equal to the total jobs because not every job has the information about the educational attainment level.

Fig. 7. Job accessibility analysis for Scenario 2 (TSR versus CMAX) during weekdays.



Note: The sum of low-skill and high skill jobs is not equal to the total jobs because not every job has the information about the educational attainment level.

Fig. 8. Job accessibility analysis for Scenario 2 (TSR versus CMAX) during weekends.

measured for each CMAX stop, and then we compute the average of the results from all stops as the final product.

6. Study design

6.1. Dynamic accessibility analysis

We compute space-time accessibility using four different departure times (8 a.m., 1 p.m., 6 p.m., and 9 p.m.) for two representative days (Thursday and Sunday) based on the operating schedules of the local transit authority. These times and days capture the major public transit schedule variations in the study area. To explore accessibility variations between weekdays and weekends, we calculate accessibility to job and healthcare in weekends as well. We implement the dynamic accessibility analysis using a Python script for incrementing departure times (in both Thursday and Sunday).

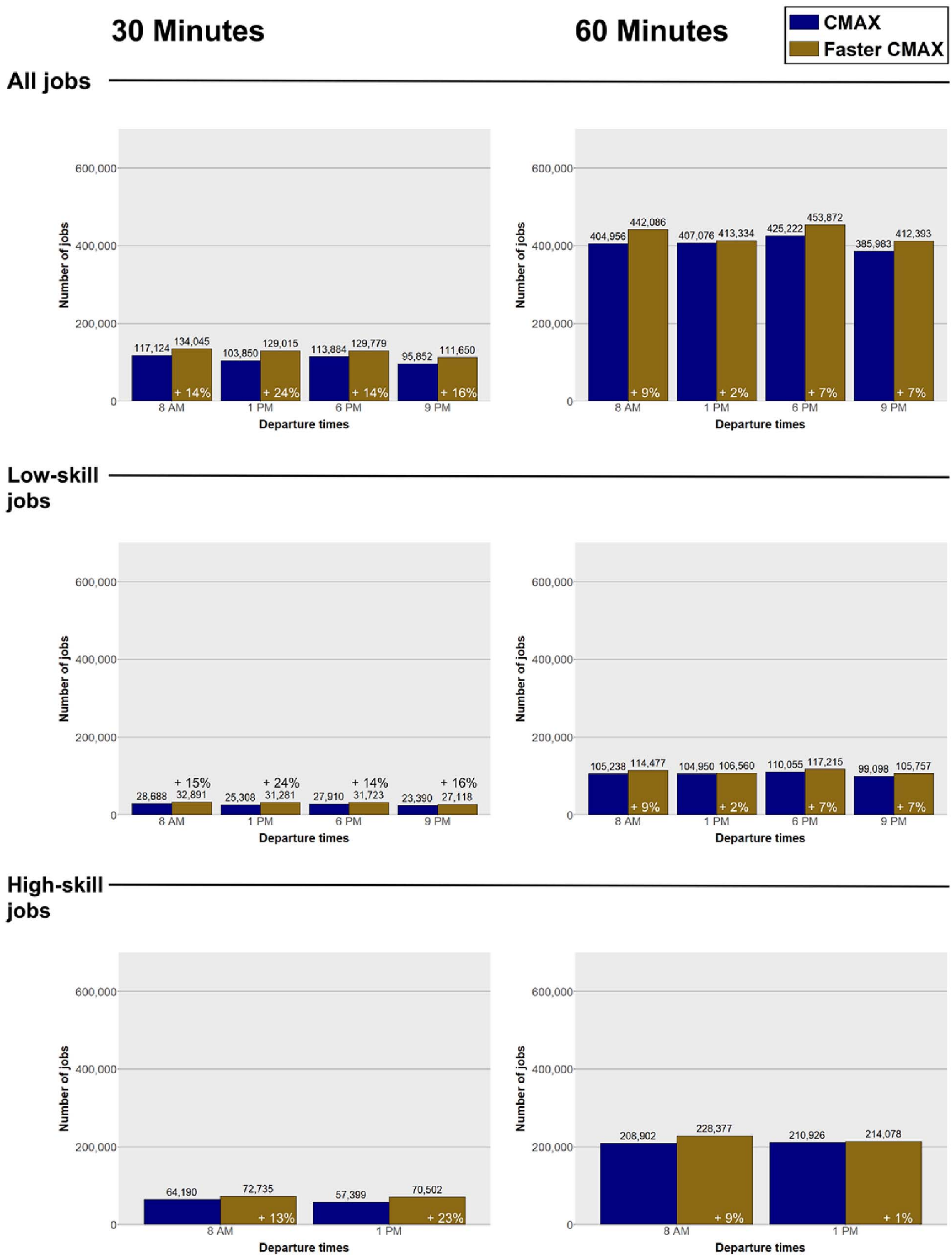
Besides transit schedule changes, variations in working hours (job) and operating hours (healthcare) also affect people's accessibility. According to the report on working hours (Acs & Loprest, 2008), high-skill employees with bachelor's degree or more tend to work in the regular daytime schedule, 9 a.m.-to-5 p.m. on weekdays. In contrast, jobs that do not require a college education are more likely to involve working hours outside of the 9 a.m.-to-5 p.m. range such as night time or weekends. Given this information, we apply all four departure times in both weekdays and weekends to the accessibility analysis for low-skill jobs. 8 a.m. and 1 p.m. on weekdays are used as high-skill workers' departure times to workplaces. For the healthcare accessibility, we utilize the 8 a.m. and 1 p.m. departure times on weekdays, reflecting typical operating hours of healthcare services.

6.2. Scenario analysis

We design three scenarios to measure impacts of new public transportation services and technologies on space-time accessibility:

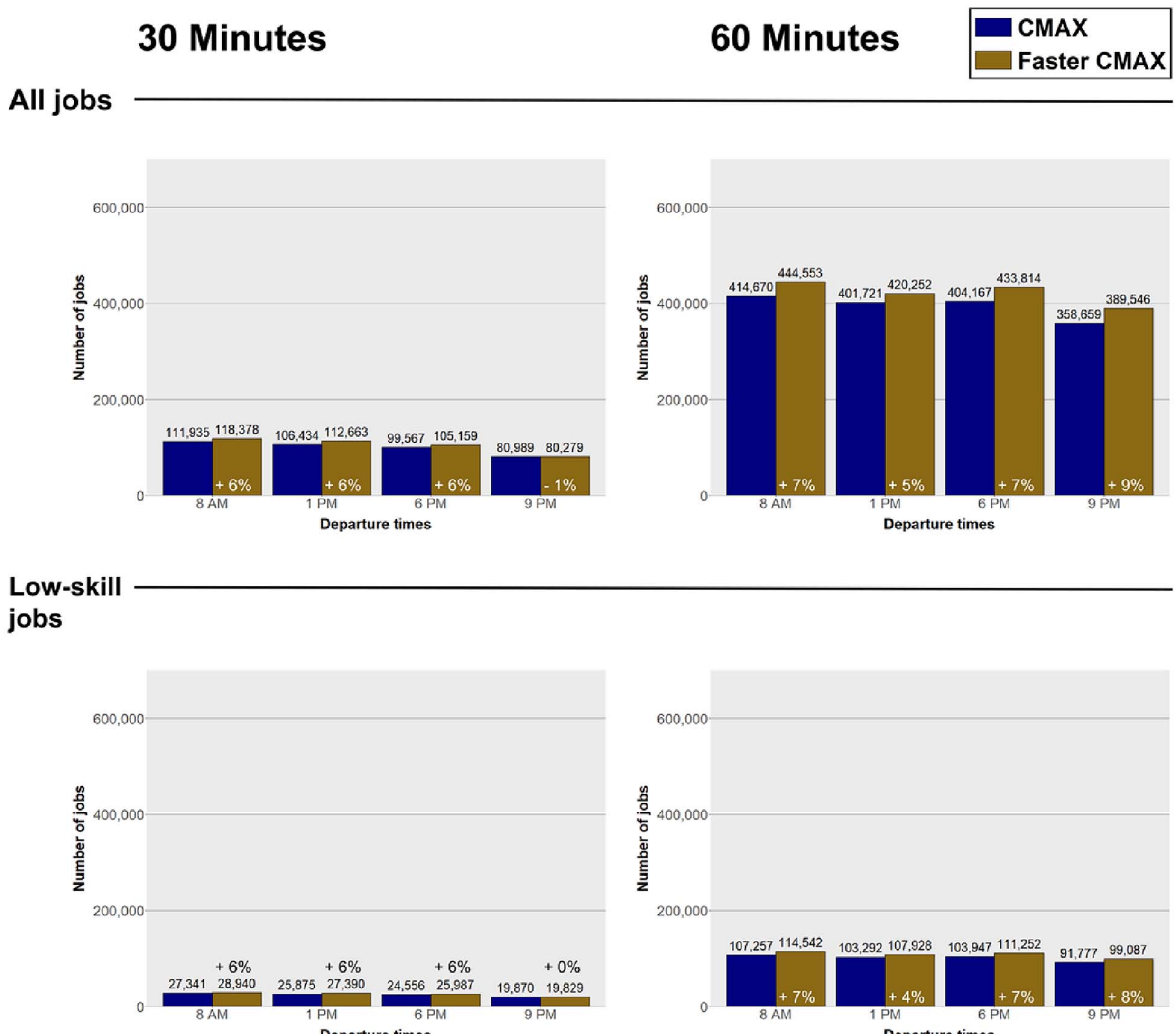
- **Scenario 1**: the change from Former (pre-TSR) to TSR transit network
- **Scenario 2**: the change from TSR to TSR + CMAX
- **Scenario 3**: the change from TSR + CMAX to TSR + faster CMAX.

We use faster CMAX speed as a proxy for time savings from CMAX upgrades for reducing delays. When a transit agency implements technical and operational upgrades for removing delays, vehicles usually run faster (Walker, 2012). Several researchers (Diab & El-



Note: The sum of low-skill and high skill jobs is not equal to the total jobs because not every job has the information about the educational attainment level.

Fig. 9. Job accessibility analysis for Scenario 3 (CMAX versus Faster CMAX) during weekdays.



Note: The sum of low-skill and high skill jobs is not equal to the total jobs because not every job has the information about the educational attainment level.

Fig. 10. Job accessibility analysis for Scenario 3 (CMAX versus Faster CMAX) during weekends.

Geneidy, 2013; Song, Zlatkovic, & Porter, 2016; Surprenant-Legault & El-Geneidy, 2011; Turnquist, 1981) have confirmed that strategies for minimizing delays such as Transit Signal Priority (TSP), dedicated lane, and off-board, contactless card or mobile phone-based fare payment lead to faster average transit speeds. Since a TSP system is already included in CMAX operation plan, we focus on the dedicated lane and off-board fare payment can potentially change accessibility.

Based on the literature, we assume that the dedicated lane and off-board/contactless/mobile fare payment could improve the average operating speed by 20%. The city of New York has implemented a pre-payment system for bus routes included in Select Bus Service program. New York City's Metropolitan Transportation Authority (MTA) found that the off-board fare collection system alone decreased bus travel times from 10 to 15% (Meyer, 2016). Research examining the impacts of reserved bus lanes on transit running times suggest that dedicated transit lanes reduce bus travel times by approximately 2% (Diab & El-Geneidy, 2013; Surprenant-Legault & El-Geneidy, 2011). For example, Diab and El-Geneidy (2013) suggest that the use of exclusive bus lanes during peak hours in Montreal, Canada yielded average 2.7% running time savings. To simulate the faster CMAX, we modify the pseudo-GTFS for CMAX created above based on 20% enhanced bus speed.

7. Results

7.1. Space-time accessibility maps

This section presents a qualitative analysis based on space-time accessibility maps for the four networks: former, TSR, TSR with CMAX, and TSR with 20% faster CMAX. Maps comprising the full set of accessibility maps for all trip starting locations (CMAX stops) cannot be displayed here due to space limitations. Instead, we select two representative locations representing stops from the high-frequency and low-frequency segments of the CMAX route: Linden Transit Center and Community Park, respectively. To visually illustrate the impacts of temporal differences in services during a day, we employ two departure times: 1 p.m. (midday off-peak) and 6 p.m. (afternoon peak).

Fig. 3 shows the space-time accessibility maps for weekdays (Thursday). Compared to accessibility maps based on the former bus network (Fig. 3a), the TSR maps (Fig. 3b) do not correspond to larger accessible regions. In the case of the low-frequency stop, Fig. 3b indicates a relatively smaller accessible regions. A considerable reduction of bus routes after TSR innovation could have contributed to the decrease in accessibility in the low-frequency segment. However, when

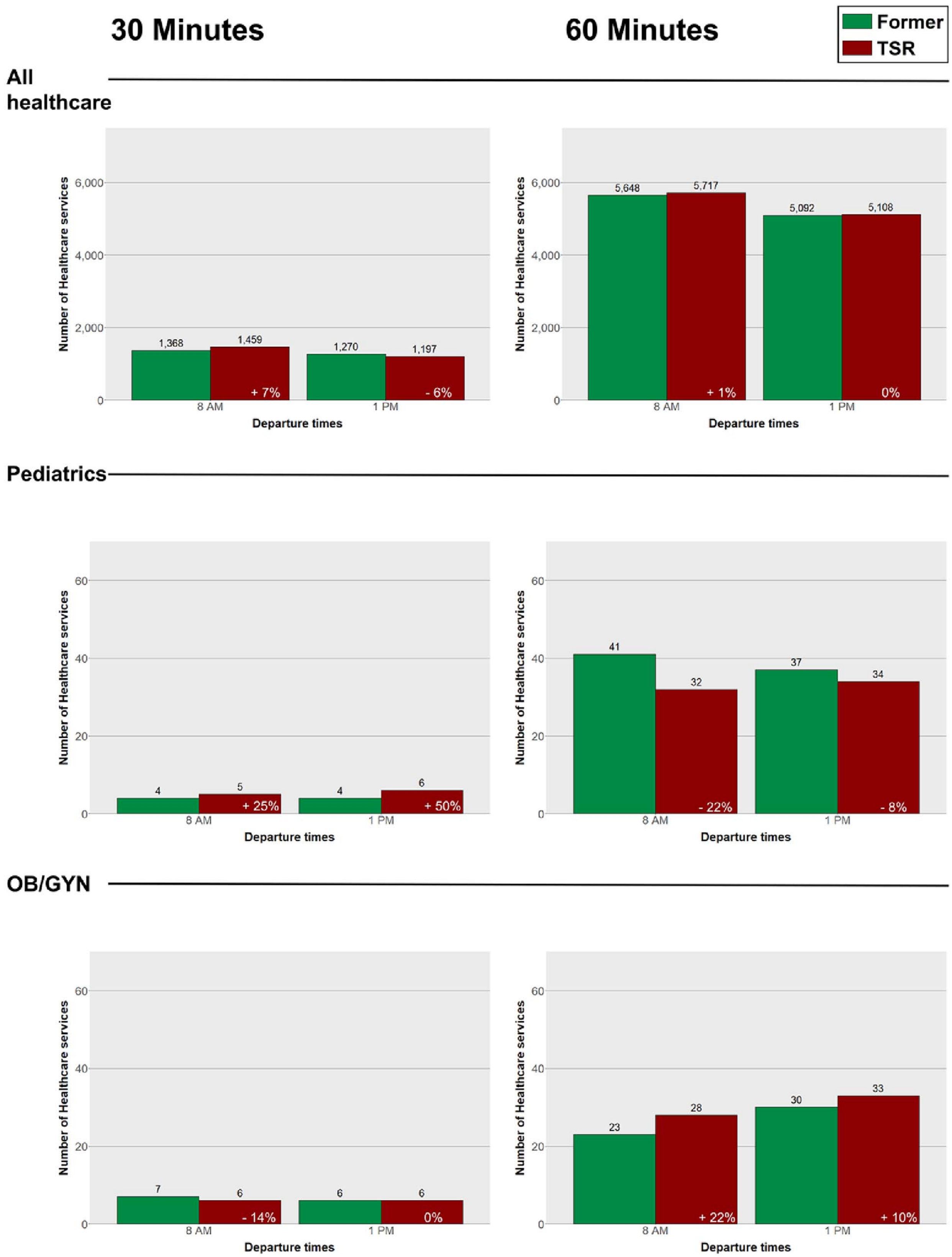


Fig. 11. Healthcare accessibility analysis for Scenario 1 (Former versus TSR).

CMAX is added to the TSR network, Fig. 3c indicates that the accessibility regions become larger than the corresponding regions based upon TSR system alone. In particular, major improvements in accessibility towards the north and south can be observed along the CMAX corridor. Improving CMAX speeds by 20% further expands the accessible areas (see Fig. 3d). In particular, the accessible regions in 30-min time budget expand to the west and east side.

Fig. 4 presents the space-time accessibility maps for weekends (Sunday). In the case of the high-frequency stop, the TSR accessibility regions (Fig. 4b) are relatively larger than the pre-TSR accessibility

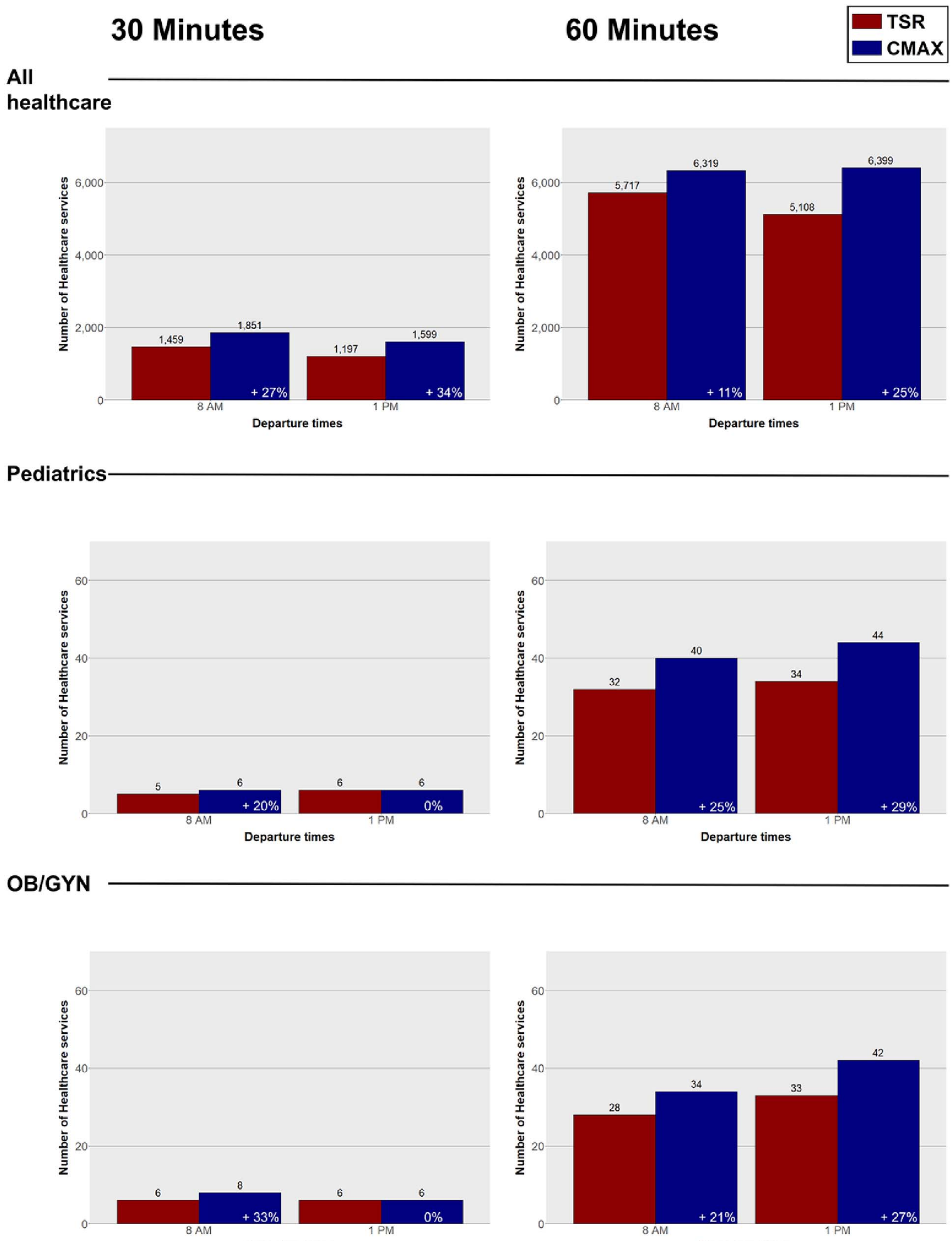


Fig. 12. Healthcare accessibility analysis for Scenario 2 (TSR versus CMAX).

regions (Fig. 4a). With respect to the low-frequency stop case, TSR results in considerable positive increases in the accessibility regions (Fig. 4b). A possible reason for this accessibility improvements is TSR's higher operation frequency in weekends than the former bus system. The CMAX service leads to a spatial expansion of accessibility areas (Fig. 4c). The CMAX's positive accessibility impacts are particularly remarkable for the stop in the high-frequency segment. Similar to the results for weekdays (Fig. 3d), the upgraded CMAX further enlarges the accessibility regions on weekends (see Fig. 4d).

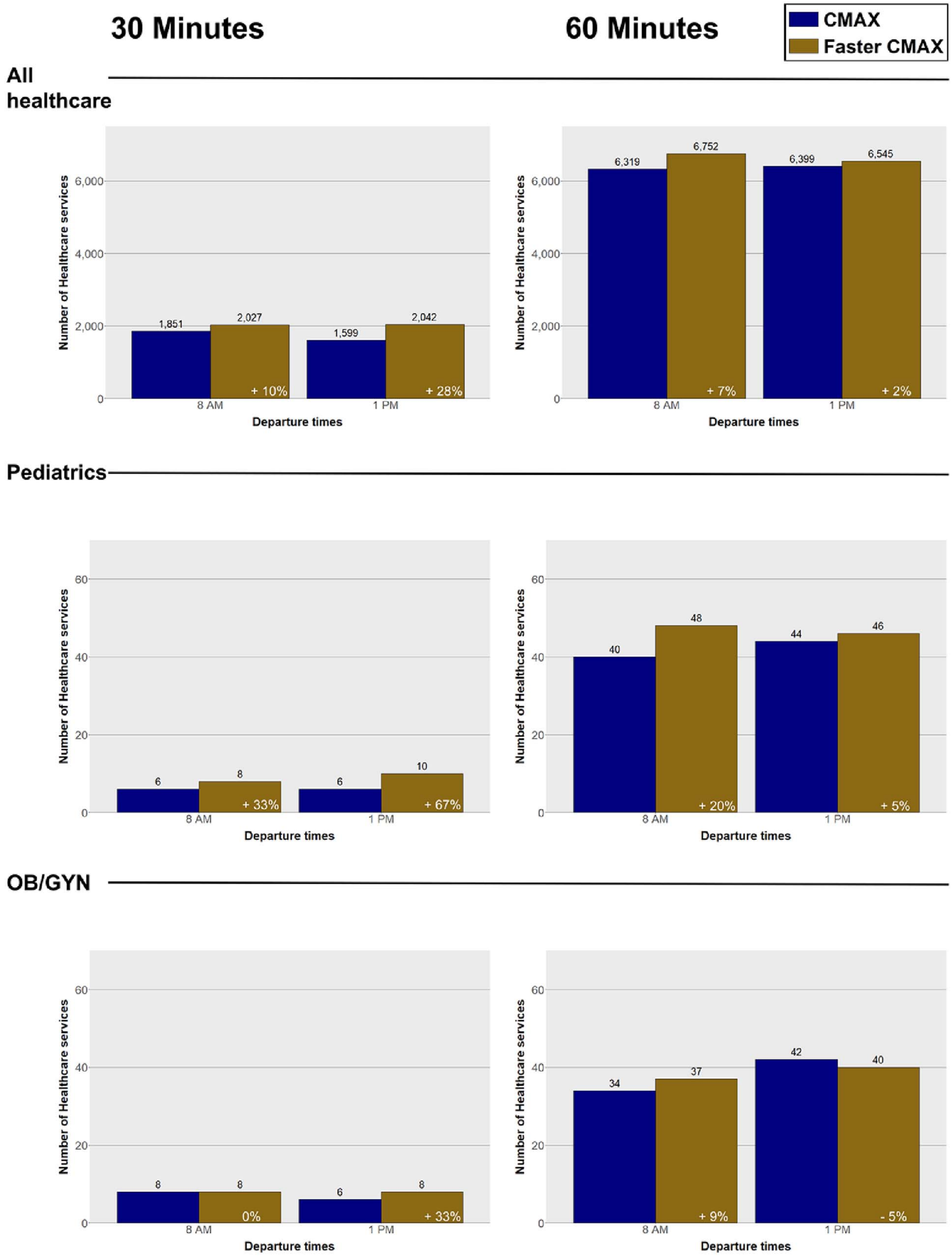


Fig. 13. Healthcare accessibility analysis for Scenario 3 (CMAX versus Faster CMAX).

7.2. Job and healthcare accessibility analysis

Figs. 5 and 6 summarize the results of job accessibility analysis before and after TSR implementation for weekdays (Thursday) and weekends (Sunday), respectively. On average, TSR decreases job accessibility by 2%[2] in weekdays (Fig. 5). In particular, the most significant decreases are observed in the local accessibility (30-min budget) for 8 a.m. and 1 p.m. departures, 11% and 9% declines in access to total jobs, respectively. Considering 8 a.m. and 1 p.m. are the most likely departure times for working trips, the accessibility decrease in those times is an undesirable outcome of TSR. However, we can note an advantage of TSR for job accessibility based on a 9 p.m. departure. The 60-min access to all jobs and the low-skill jobs is enhanced by approximately 8%. This improvement is meaningful for low-skill employees who often work at night. In weekends (Fig. 6), TSR yields a considerable increase in job accessibility by an average of 34%. As mentioned above, TSR operates with a consistent schedule; thereby, providing better access seven days a week. The results presented in Figs. 5 and 6 confirm the visualization results (Figs. 3b and 4b) which suggest TSR's negative accessibility impacts on weekdays and positive impacts on weekends.

Figs. 7 and 8 provides results from the job accessibility before and after the CMAX service for weekdays (Thursday) and weekends (Sunday), respectively. In general, similar to the accessibility mapping results illustrating the spatial accessibility impacts of CMAX (Figs. 3c and 4c), the CMAX service increases job accessibility in both weekdays (an average of 27%) and weekends (an average of 11%). Notably, unlike TSR, CMAX demonstrate positive impacts on job accessibility with the 30-min budget at 8 a.m. and 1 p.m. on weekdays.

Figs. 9 and 10 show the results of job accessibility analysis pre and post CMAX's potential speed enhancement for weekdays (Thursday) and weekends (Sunday), respectively. Both in weekdays and weekends, a faster CMAX service leads to positive impacts on the job accessibility with an average of 12% (weekdays) and 6% (weekends) improvements. These results are in congruence with the maps in Figs. 3d and 4d that show expanded accessible areas after the speed increase. However, we can also see a counterintuitive outcome: a minor decrease in local (30-min budget) job accessibility for all jobs at 9 p.m. during weekends. Speed improvement naturally changes bus stop times; thereby, possibly resulting in an unexpected increase of waiting time. The counter-intuitive outcome may be an artifact of changes in bus stop wait time combined with using a fixed departure time in the analysis.

Figs. 11–13 summarize the results for healthcare accessibility. Fig. 11 presents the results of the Scenario 1. On average, TSR implementation slightly increases healthcare access by around 5%. However, we can also observe some decreases in access to pediatrics and obstetrics/gynecology. This is an opposite effect to what was intended by the city. Thus, the TSR's impacts on the healthcare accessibility are ambiguous. Fig. 12 presents the CMAX's impacts on the healthcare accessibility. In contrast with the TSR's ambiguous influences on the healthcare access, the CMAX service clearly enhances citizens' access to the healthcare services by approximately 21% on average. Fig. 13 presents the impacts of faster CMAX service on the healthcare accessibility. The figure indicates overall positive impacts of faster CMAX on the access to the healthcare services (an average of 17% increase). A small decrease in access to obstetrics and gynecology at 1 p.m. could also be due to the schedule change from the speed improvements combined with the fixed departure time used in the analysis.

8. Discussion and conclusion

This study measures the impacts of new public transportation services, specifically a major Transit System Redesign (TSR) and the addition of bus rapid transit (BRT) on space-time accessibility to job and healthcare in an underserved neighborhood of Columbus, Ohio, USA. Further, we explore the potential of improving operating speeds (via dedicated bus lane or off-board/contactless/mobile payment system) on improving accessibility. Although TSR has intended to increase accessibility by providing frequent as well as consistent service, it was not clear that TSR offers better accessibility than the former bus system in the Linden neighborhood. TSR showed both positive (e.g., job accessibility in weekends) and negative impacts (e.g., employment accessibility in weekdays) on accessibility. However, the combination of TSR and the CMAX BRT service substantially improves accessibility to both job and healthcare accessibility on weekdays and weekends for this neighborhood. Simulating enhanced CMAX service via faster speed, reflecting technologies for minimizing delays, also apparently has positive influences on residents' access to jobs and healthcare.

This study has some limitations that should be considered in future research. This study only measures changes in the physical limits on accessibility; it does not take into account possible behavioral changes due to the new transit services, for example, changes in ridership levels due to the system change. In fact, one potential benefit of the TSR is to make the bus network more legible and reliable, hopefully leading to greater ridership; we do not consider this behavioral change. Similarly, because we focus on physical limits on accessibility, we do not consider limitations associated with attitudes towards waiting time, or risk attitudes regarding missing a bus. Also, while our method captures the time required transfers and walking, we do not place a hard limit on either. Since these factors are heterogeneous across travelers, capturing these effects on accessibility require preference or behavioral data.

To address temporal fluctuations in accessibility due to transit schedule changes, we use four departure times, namely, 8 a.m., 1 p.m., 6 p.m., and 9 p.m. Although these are representative of likely travel times and corresponding transit schedules, the time differences among departure times are relatively coarse and may not enough to reveal full dynamics. Dynamic accessibility analysis using higher temporal resolution such as minute by minute would be useful to uncover temporal dynamics in transit accessibility. Indeed, we notice some temporal boundary effects that may be created by using a sparse number of designated departure times.

Although access to jobs and healthcare from home is a meaningful and common benchmark, our analysis neglects return trips as well as possible multistop/multipurpose travel. This would require activity data. Also, our accessibility analysis tends to overestimate the accessibility because we assume trips start at the CMAX stops and include census tracts intersected with the boundaries of the isochrone polygons for the accessibility calculation although the census tracts are not fully inside the isochrone polygons.

In Scenario 3, due to the absence of comparable local examples, we use the cases of New York City and Montreal to derive the degree of improvement in operating speed from reducing delays. However, the two big cities' examples are not directly comparable to Columbus regarding the city size, urban structure, and traffic environment. Using more comparable examples, if available, could make future studies more accurate with respect to time savings.

Finally, we generate the PMNAs with a limited number of public transportation modes since these are the modes that are relevant to our study area. Future studies in other cities with a wider range of available modes could build and construct more complex multimodal networks comprising various transit options such as bus (regular/BRT/mini-transit), train, subway, and ferry for measuring multimodal accessibility. Similarly, we only consider walking as a mode for achieving last mile access to destinations. Integrating various first-mile/last-mile mobility options (e.g., bike share system, ride sharing), as well as innovative modes associated with the Smart Columbus project, is a worthwhile next step for this investigation.

The implications of this research are as follows. From a methodological perspective, the multimodal network-time prism concept in this study fills the gap between the single mode network-time prisms and the people's use of various transport modes. Also, our research further demonstrates the value of GTFS data for studying accessibility. From an

[2] The overall average change (%) is calculated by simply averaging all the changes from different departure times, different time budgets, and different categories.

empirical perspective, this research provides evidence that new public transit services do not always have intuitive outcomes; indeed, we noted some unintended outcomes for jobs and healthcare access in Linden. Therefore, to avoid unintended outcomes, required are careful scientific investigation and planning. This study's time geographic accessibility analysis is one way to measure the accessibility impacts of new or proposed public transit services and technologies.

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