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Exploring neighbourhood-level mobility inequity in Chicago using dynamic transportation mode choice profiles

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ABSTRACT

This paper develops a method to dynamically model urban passenger mode trade-offs at fine-grained spatial and temporal scales using data from OpenTripPlanner (OTP) and the City of Chicago's Transportation Network Providers (TNP) dataset. This approach can be used to calculate dynamic modal cost-distance trade-offs for specific times, routes, and geographic areas of interest, providing a framework for creating aggregate mode choice profiles for individual cities and neighbourhoods that can be used to assess structural differences in transportation investment and mobility, as well as to test various assumptions about travel behaviour, observe temporal changes in modal trade-offs, and model the system-wide implications of changes to the transportation system to modal trade-offs. Using this dynamic mode choice framework, this paper explores the features underlying observed structural heterogeneity in the ratio of cost to distance (i.e., speed or potential mobility) for observed flows across the city for each mode. It finds that Census tracts with larger proportions of Black and Hispanic population tend to have significantly larger cost-distance ratios (i.e., slower speeds/lower potential mobility) for non-auto modes, while Census tracts with higher proportions of "creative class" employment and features of walkable built environments have significantly lower cost-distance ratios (i.e., faster speeds/higher potential mobility).

Introduction

Despite decades of research on the role of transportation investment in promoting neighbourhood prosperity and upward mobility, significant structural disparities in transportation investment persist in the US (Kain, 1968; Vojnovic & Darden, 2013; Blumenberg, 2017). In many urban areas, a combination of deindustrialization, poor transit service, and limited residential housing choice continues to drive disparities in economic outcomes, particularly in Black and Hispanic neighbourhoods. These disparities in access and outcomes vary by location, socio-demographic characteristics, and service type (Mobley et al., 2006), but have far-reaching implications, because upward mobility relies on access to both the *right kinds* of job opportunities and a wide range of assets (Chetty et al., 2018), including, e.g., *primary healthcare*, which lowers health system costs and improves a variety of health outcomes, especially for deprived population groups (Shi et al., 2005; Starfield et al., 2005); *grocery stores*, which increases healthy food consumption in low income groups (Wrigley et al., 2002); *jobs*, which improves economic outcomes (Clampet-Lundquist and Massey, 2008; Andersson et al., 2018); and *child care*, which increases mothers' employment (van Ham & Mulder, 2005).

Disparities in the transportation system result from a combination of land planning ("spatial mismatch") - suburbanization, exclusionary zoning, redlining, segregation, affordable housing - and transportation investment decisions ("modal mismatch") often made (implicitly and explicitly) along racial and class lines (Vojnovic & Darden, 2013). And while a substantial body of research has studied this problem from the perspective of *accessibility* in terms of spatially-mismatched jobs and housing locations (Andersson et al., 2018; Gobillon et al., 2007; Kain, 1992; Mouw, 2000) or access to individual assets (D'Angelo et al., 2011; Guagliardo, 2004; Nicholls, 2001), structural inequities in mobility have thus far received somewhat less attention in the research record (Fuller et al., 2013; Guidry et al. 1997; Lee et al., 2018). While some researchers have explicitly taken up the issue of modal mismatch (Grengs, 2010; Kawabata, 2003; Raphael & Stoll, 2001; Yi, 2006), they tend to narrowly construe the problem as a structured lack of access to automobiles rather

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than a broader, interconnected problem of "mobility inequity" across the full range of transportation modes. Even when multiple modes are considered, gaps remain in our understanding of fine-grained temporal and spatial patterns in mobility inequity by mode.

Mobility inequity, conceptualized broadly, is particularly important because non-auto modes have a variety of complimentary social, economic, environmental, and health benefits. Increased transit mobility provides economic benefits, including increased probability of employment, especially for welfare recipients (Kawabata, 2003; Ong & Houston, 2002; Yi, 2006). Transit, walking, and biking have been shown to be associated with a range of health benefits, including lower rates of obesity (Lindström, 2008) and lower BMIs (Frank et al., 2006). Non-auto modes (and the denser urban environments that foster their use) also provide a number of environmental benefits, particularly in terms of greenhouse gas (GHG) emissions reductions (Lee & Lee, 2014; Ercan, Onat, & Tatari, 2016) and fewer deaths from air pollution (Rojas-Rueda et al., 2012).

To better understand the fine-grained spatial (and temporal) patterns in mobility inequity (by mode) – and their determinants – this paper asks three specific research questions: first, to what extent do we see neighbourhood-level heterogeneity in the ratio of cost to distance (i.e., potential mobility) for observed flows (by mode)? Then, given observed heterogeneity, what features (i.e., race/ethnicity, socioeconomic status, class) are related to greater or lesser potential mobility? And finally, do these relationships change by time of day or week?

We study these questions by creating a dynamic mode choice profile for the city of Chicago by systematically querying Census tract-to-tract travel times from the open-source routing service OpenTripPlanner (OTP) for non-auto modes for four chosen times, converting those times into generalized measures of travel cost to consumers, and combining that information with corresponding data from the Transportation Network Providers (TNP) dataset that includes every Uber/Lyft/Via ride in the city since November 2018 (City of Chicago, 2020). This mode choice profile - which can be dynamically adjusted for different times or spatial subsets of the city - is created by plotting paired cost and distance data for each urban transportation mode, and can be used to study heterogeneity in the relationship between cost and distance –i.e., potential mobility –across individual tract-to-tract flows in the city. More generally, dynamic mode choice profiles can also be used to investigate a variety of transportation-related questions, including changes in modal trade-offs for various scenarios –including different times of day, seasons, spatial subsets of origins and destinations, economic cost assumptions (including taking cost as a percentage of income), and changes in service –to better design transportation policy interventions or perform cost-benefit analysis on specific infrastructure improvements. Theoretically, this method could be down-scaled as much as necessary (even to every possible building-to-building trip[1]) and does not rely on empirical data on observed mode share propensities, which can be more difficult to obtain on a fine-grained spatial–temporal scale than travel times.

Analysis of the dynamic mode choice profile developed for Chicago suggests that there is significant heterogeneity in potential mobility (i.e., the cost-distance ratio or travel speed for a given flow) across the city by mode. Interestingly, this heterogeneity is significantly structured by race/ethnicity, class, and the physical form of the built environment: Census tracts with larger proportions of Black and Hispanic population tend to have significantly larger cost-distance ratios for non-auto modes, while, conversely, tracts with higher proportions of "creative class" (Florida, 2012; Mellander and Florida, 2007) employment and features of walkable built environments (Ewing & Cervero, 2010; Jacobs, 1961) have significantly lower cost-distance ratios for generally all modes at all times of day. This lends some support to the hypothesis that walkable built environments decrease the cost of walking, biking, and transit (Ewing & Cervero, 2010; Jacobs, 1961; Newman & Kenworthy, 2006; Ton et al., 2019) and also exposes systematic structural inequalities in infrastructure provision across the city that favour whiter, higher density, and more walkable neighbourhoods.

Literature review

Economist John Kain first identified the "spatial mismatch" between job opportunities and housing in 1968, observing that housing market segregation limited the residential choices of Black households forcing them to reside in inner-city neighbourhoods distant from job opportunities. With postwar suburbanization having decentralized jobs out of the city and into the suburbs, Kain proposed that Black workers suffered adverse employment outcomes as a result of their limited spatial access to these outlying job opportunities (Kain 1968). Following Kain's 1968 paper, other scholars continued to expand the spatial mismatch hypothesis. Empirical studies have tested the causal relationship between spatial mismatch and adverse employment outcomes and extended the findings to other minority populations. Theoretical models for the spatial mismatch hypothesis have also detailed the mechanisms that may limit employment access for populations who are spatially disconnected from jobs (Gobillon et al., 2007).

More recently, spatial accessibility work has expanded to consider inequities in accessibility to other individual types of assets. Health experts have developed spatial methodologies for measuring inequities in healthcare accessibility and availability (Guagliardo, 2004; Mao & Nekorchuk, 2013). In nutrition, a vast array of studies centre around the relationship between neighbourhood food environment and health and socioeconomic outcomes, finding that disparities in proximity and access to supermarkets are associated with differences in health outcomes (Fuller et al., 2013; Leete et al., 2011; Morland et al., 2006; Rose & Richards, 2004). Spatial accessibility methodologies have also been applied to model access and distributional equity of other public amenities such as parks (Nicholls, 2001; Zhang et al., 2011) and libraries (Hong et al., 2020; Park 2012).

While much of the existing work on this topic has focused on unequal *access* as a characteristic of residential location, many transportation scholars have challenged this formulation and instead framed the topic in terms of unequal *mobility* for individuals. Since spatial mismatch does not take into account the substantial differences between travel modes, transportation experts have argued that access to reliable transportation is a much stronger determinant for access to assets (Cervero et al., 2002; Grengs, 2010; Taylor and Ong, 1995). Many studies have been devoted to examining the effects of transportation access on employment outcomes, finding repeatedly that car ownership is significantly correlated with positive job outcomes while reliance on public transit significantly reduces one's access to job opportunities, especially for minority populations (Blumenberg, 2016; Brabo et al., 2003; Kawabata, 2003; Ong & Houston, 2002; Raphael & Rice, 2002; Yi, 2006). Transportation mobility has also been highlighted as one of the largest non-financial barriers to healthcare, with the patients most likely to miss healthcare appointments and forgo crucial health services being those without access to a car (Guidry et al., 1997; Yang et al., 2006).

Clearly, both the accessibility and mobility components of our urban systems contribute to disparate outcomes as the built environment influences modal availability and vice-versa. Neighbourhoods that are spatially distant from assets and amenities are also those that are most poorly connected via public transportation and tend to house lower-income, minority populations (Lee et al., 2018). In fact, these components are often planned together to explicitly disadvantage minoritized populations (Vojnovic & Darden, 2013). Suburbanization drew the wealthy out of the city, reducing the tax-base in cities and leading to

[1] As discussed in further detail below, default OTP travel times do not take into account congestion on the network, so in order to accurately downscale these results, an estimate of congestion-adjusted travel times would need to be used, or another dataset that contains observed travel times used (as is done in this paper with the TNP dataset), such as OSRM or pgRouting.

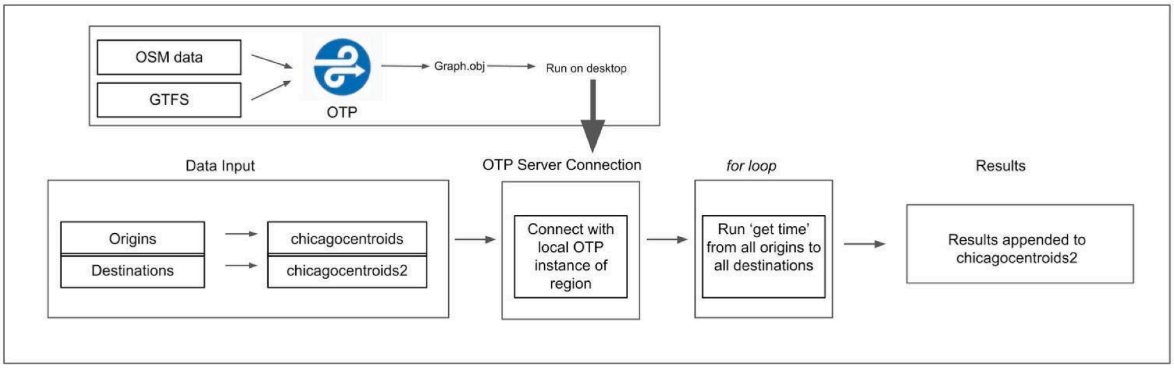

Fig. 1. Architecture of travel time data collection.

chronic underinvestment in inner-city neighbourhoods. Minority households, however, were initially restricted from moving into the suburbs through racial restrictive covenants that prevented white suburban homeowners from selling their properties to non-white buyers. When these covenants were declared unenforceable, housing discrimination continued in the form of redlining and minimum lot size requirements, which excluded lower-income groups from moving in. Unsurprisingly, both accessibility and mobility literature have found large disparities in access and mobility across race. For instance, studies have found that impoverished Black neighbourhoods were on average a mile further from the nearest supermarket than impoverished White neighbourhoods (Zenk et al., 2005). The positive effects of car ownership on employment are greatest for Black workers in more segregated neighbourhoods, who are the least likely to own cars and most spatially disconnected from job opportunities (Raphael & Stoll, 2001). Patients who forgo crucial health services due to transportation issues are most often minorities, who are less likely to have access to reliable transit (Guidry et al., 1997; Yang et al., 2006).

However, while this literature has addressed a range of very important questions related to inequities in the structure of the transportation system, specific gaps in our knowledge remain. The focus on "modal mismatch" tends to focus primarily on the disparities in access resulting from differences in car-ownership and policy recommendations tend to circle around helping people gain access to automobiles. Even when modal mismatch literature considers modes of transportation other than driving, it tends only to look at public transit and diminishes the importance of non-auto modes - particularly walking and biking - which is disappointing given the range of additional health (Booth et al., 2005; Saelens et al., 2003; Lindström, 2008), economic (Kwan et al., 2017), and environmental benefits (Ercan et al., 2016; Rojas-Rueda et al., 2012) that these modes provide.

This paper addresses that gap by taking a broader perspective of "mobility inequity" and analysing disparities in potential mobility across all modes, which include walking, biking, public transit, driving, and even rideshare. Additionally, this paper provides a comprehensive framework (generally missing in existing work) for analysing the structural characteristics of mobility across all neighbourhoods at sufficiently fine-grained spatial and temporal scales. With the ability to subset to different spatial subsets and times, this method can be leveraged to study the heterogeneity in the relationship between cost and distance across different neighbourhoods in the city.

Methods

Dynamic mode choice profiles

The primary data used in this paper are travel times by mode to and from all 2010 Census tract centroids in the city of Chicago, obtained from OpenTripPlanner (OTP). As the OTP project's front-page documentation clearly explains, it is an open-source Java-based routing service that uses the General Transit Feed Specification (GTFS) data for various public transit agencies - which provides routing, headway, and arrival information[2] - as well as open source OpenStreetMap (OSM) data on the street, bicycle, pedestrian, and transit networks themselves - to calculate travel times for transit, pedestrian, bicycle, and auto modes (OSM, 2021; OTP, 2021). As shown in Fig. 1, to obtain the travel times, we first built an "OTP instance" for the Chicago region by creating an OTP graph in Java using GTFS and OSM data for Chicago[3] (Young, 2021). Then we created a loop using the R package 'otpr' to execute the 'get time' command to query travel times by mode using each of the city's Census tract centroids as both origins and destinations at four specific times (in 2020): 1) weekday morning = June 29 at 8:00AM; 2) weekday afternoon = June 26 at 5:00PM; 3) weekend midday = June 27 at 12:00PM; and 4) weekend late night = 28 at 12:00AM. The raw data outputted from this operation includes: 1) the total travel duration to all destinations; 2) the total travel time broken down by minutes spent walking, on transit, and waiting; and 3) the number of transfers a user has to make throughout his itinerary. Results for each combination of mode of transportation and date were listed and later stored in a unique CSV file. These files were used to plot the empirical travel time cost-curves.

By default, OTP computes travel times for the auto, walking, and bicycling modes based on the characteristics of the OSM network itself, without taking into account traffic congestion or other dynamic temporal conditions. While this makes sense for the walking and cycling modes - whose travel speeds are not significantly impacted by congestion - it is a less defensible choice for auto trips, particularly since one of the goals of the analysis is to look at changes in the trade-offs between modes at various times of day. Thus, to calculate the travel time-distance trade-offs for the auto mode, this paper makes use of a unique open-source dataset provided by the City of Chicago, the Transportation Network Providers (TNP) dataset, which contains all individual trips made by rideshare companies (including Uber, Lyft, and Via) operating in the city from November 2018, due to a city ordinance requiring routine reporting from these companies (2020). While the point-to-point pickup and drop-off locations are aggregated to the nearest Census tract centroid (and in some cases suppressed), the dataset contains the actual

[2] From gtfs.org (2021): "The General Transit Feed Specification (GTFS) is a data specification that allows public transit agencies to publish their transit data in a format that can be consumed by a wide variety of software applications. Today, the GTFS data format is used by thousands of public transport providers. GTFS is split into a static component that contains schedule, fare, and geographic transit information and a real-time component that contains arrival predictions, vehicle positions and service advisories."

[3] See Appendix 1 for a supplement containing the full code for creating the OTP instance and obtaining tract-to-tract travel times. R code for calculating trade-off curves using these travel times available from authors at request.

distance and travel time (rounded to the nearest 15 min) for each trip, which provides us with a highly accurate window into the travel time-distance relationship - and, in fact, the overall activity pattern of transportation in the city - at any time of day. The dataset also contains the fare paid for each trip (rounded to the nearest $2.50), which provides a useful empirical basis for computing travel costs for a "rideshare" mode separate from baseline assumptions for the costs of automobile ownership, maintenance, and use.

To match the times of day selected for analysis, the full TNP database was filtered for the following times (in 2020): 1) weekday morning = all trips between June 29 and July 3 with pickup times from 7:00AM to 9:00AM; 2) weekday afternoon = all trips between June 22 and June 26 with pickup times from 4:00PM to 6:00PM; 3) weekend midday = all trips on June 13–14, June 20–21, and June 27–28 with pickup times from 11:00AM to 1:00PM; and 4) weekend late night = all trips on June 12–14, June 20–21, and June 26–28 with pickup times from 11:00PM to 1:00AM. A slightly larger bracket of times and dates was chosen in the case of the TNP data (compared to a single point in time queried from OTP for other modes) in order to capture a more representative pattern of travel activity at each chosen time of day without moving too far outside of the month of June (to avoid issues with holiday and seasonal effects, etc.). These observed trips (aggregated to their Census tract origins and destinations) - which constitute a smaller subset of all possible tract-to-tract trips in the city[4] - are used in each case to subset the travel times obtained by OTP for the walking, bicycling, and transit modes, providing a more useful picture of "realistic" (i.e., observed) travel behaviour for these modes at each given time[5].

With travel times and distances for all observed TNP automobile trips at each of the selected times of day obtained, as well as tract-to-tract travel times and distances for walking, bicycling, and transit gathered from OTP (for flows observed for a given time of day in the TNP dataset), modal trade-off curves are found by plotting the least-squares line between travel time in minutes (*T*) (y-axis) and distance in meters (*d*) (x-axis) for a given mode m_1, shown in Equation 1[6]:

$$T_1 m_1 = \beta_1 d + \varepsilon_1 \tag{1}$$

Since more detailed information on observed travel distance between origins and destinations is not available for the transit, walking, and bicycling modes - and the overarching concept of building theoretical trade-off curves is to compare modal performance over a stable, consistent measure of distance - Euclidean distance between tract centroids is used as the absolute distance measure for comparing these modes. For TNP trips, the actual distance travelled for each individual trip is available, and thus used, as it provides much more interesting (and useful) variation in the travel time-distance relationship than aggregating these trips to Census tract centroids.

With the least-squares travel time-distance curves plotted for each mode at each of four times of day, we are primarily interested in finding the point of intersection along the x-axis between the curves of competing modes in order to see at what distance one mode outperforms the other (and thus, in this theoretical framework, should be chosen). Formally, the intersection, *I*, between the linear curve for modes m_1 and m_2 can be calculated according to the algebraic formula given in Eq. (2) (based on inputs from Eq. (1)):

$$I_{m_1-m_2} = \frac{\varepsilon_1 - \varepsilon_2}{\beta_2 - \beta_1} \tag{2}$$

Calculating travel costs

With travel times and distances for all observed TNP automobile trips at each of the selected times of day obtained, as well as tract-to-tract travel times and distances for walking, bicycling, and transit gathered from OTP (for flows observed for a given time of day in the TNP dataset), the full economic cost to the consumer (*C*) for each trip from origin *i* to destination *j* for the rideshare (*share*), auto (*auto*), bicycling (*bike*), walking (*walk*), and transit (*trans*) modes were calculated according to Eqs. (3a)–(3e), respectively:

$$C_{share_{ij}} = \left(T_{share_{ij}} N_{avg_t} d_{share_{ij}}{}^{-0.044}\right) + l_{ij} \tag{3a}$$

$$C_{auto_{ij}} = \left(T_{auto_{ij}} N_{avg_t}\right) + \left(\frac{M_{auto} + O_{auto}}{1.60934} d_{auto_{ij}}\right) \tag{3b}$$

$$C_{bike_{ij}} = \left(T_{bike_{ij}} N_{avg_t}\right) + \left(\frac{M_{bike} + O_{bike}}{1.60934} d_{bike_{ij}}\right) \tag{3c}$$

$$C_{walk_{ij}} = \left(T_{walk_{ij}} N_{avg_t} T_{walk_{ij}}{}^{0.098} e^{0.158}\right) + \left(\frac{M_{walk}}{1.60934} d_{walk_{ij}}\right) \tag{3d}$$

$$C_{trans_{ij}} = \left(T_{trans_{ij}} N_{avg_t} d_{trans_{ij}}{}^{-0.044} e^{-0.4}\right) + F + q_{ij} \tag{3e}$$

where N_{avg} is the average opportunity cost per minute of travel for a Chicago resident for time *t* – peak (weekday times) or off-peak (weekend times). Opportunity cost estimates were taken from a comprehensive *meta*-analysis of travel time value studies (Abrantes & Wardman, 2011), which found that, empirically, peak travel was valued at 1.4 times off-peak travel. Thus, $N_{avg_{offpeak}}$ was simply calculated based on the per capita income for the city from the 2013–2017 American Community Survey ($32,560 per capita yearly income/525,600 min in a year) (Manson et al., 2020), while $N_{avg_{peak}}$ was valued at 1.4 times that figure. In addition to differences based on time of day, users of different modes have also been shown to value time differently – helpfully, Abrantes and Wardman (2011, p. 16) also provide an equation for calculating the value of travel time for bus users relative to auto users. Here we employ an inverse distance decay factor for the transit and rideshare modes (the assumption being that users of modes that are involved in actively piloting – bicycling and auto – tend to value their time at higher rates as trip distance increases) and a positive distance decay for walking[7].

Further, *M* are the per-mile maintenance costs by mode and *O* are the per-mile ownership costs by mode. These, of course, vary significantly

[4] With 795 Census tracts in the city of Chicago, there are 635,225 possible tract-to-tract trips. However, only a small subset of unique tract-to-tract flows are observed in the TNP dataset for each time period: weekday morning = 9,748 (1.5%), weekday afternoon = 18,403 (2.95), weekend midday = 15,159 (2.4%), and weekend late night = 18,280 (2.9%).

[5] If, for example, no trips are observed in the TNP leaving tract *i* and arriving at tract *j* in the bracket of weekend late night times, it does not make sense to include this flow as a data point for calculating the theoretical cost-distance curve for the transit, walking, and cycling modes, i.e., we consider these flows as "theoretically impossible" for the purposes of creating different modal trade-off curves at different times of day.

[6] In previous analyses of modal competition using the cost-distance framework (Min, 1991; Hayuth, 1987; Beresford and Dubey, 1990; Kwak and Seo, 2016; Taafe et al., 1996; Rodrigue, 2020), trade-offs are typically examined for one specific origin and destination combination; thus, terminal and line-haul costs are derived and plotted manually. Since the scope of the dynamic mode choice profiles is much larger – encompassing the aggregate relationship between cost and distance across all origins and destinations in the city – a least squares line is used to determine the empirical average intercept (terminal) and slope (line-haul) for each mode. However, it is possible to manually change the intercept values of these aggregate curves to test different scenarios (e.g., decreasing transit headways by a specified amount).

[7] While a somewhat imperfect comparison, we use the estimate for walking based on bus customers' valuations from Abrantes and Wardman (2011, p. 16), which derives walking time value as a function that increases with travel time (relative to auto users' valuations). Our estimates for rideshare inverse distance decay function come simply from the base elasticity reported by auto users of increasing value of time with trip distance (0.044) (Abrantes and Wardman, 2011, p. 9)

by mode - for M_{auto} , the Internal Revenue Service (IRS) standard per-mile maintenance and fuel costs for 2020 are used ($0.575), while O_{auto} was estimated by taking the average cost of a new car in 2019 ($36,718) (Edmunds, 2019) and applying an average interest rate for a 60 month loan of 5.27% (Wamala, 2021) in a standard loan calculator to obtain an actual total payment figure of $41,847.86 (TruChoice, 2021), which was then divided by 200,000 miles (the average lifespan for a contemporary new automobile (Budd, 2018) to obtain a "per-mile" estimate of ownership costs[8].

Since empirical data on M_{bike} and O_{bike} are less readily available, an assumption was made for a new bicycle cost of $1,000 and yearly (per 6,000 miles) maintenance costs of $100 (Bicycle Habitat, 2020); these are added together and divided by an estimate of a 50,000-mile lifespan for a new bicycle (Bike Forums, 2009) to provide a per-mile figure for bicycle ownership and maintenance costs. M_{walk} is assumed to be simply the cost of a new pair of good walking shoes ($150) divided by the (low-end) recommended mileage for shoe replacement, 300 miles (Livingston, 2021). Finally, l is the "trip total" cost paid for a rideshare trip from the TNP dataset (City of Chicago, 2020), F is the standard Chicago Transit Authority (CTA) fare for a single bus trip ($2.25) and q is the number of transfers required for a trip (provided by OTP) times the standard CTA transfer fare, $0.25 (CTA, 2018).

These total costs by mode (C) can be inserted into Eq. (1) in place of T to create *cost*-distance modal trade-off curves. Additional adjustments can be made for, e.g., a set parking rate (auto terminal cost) and/or different estimates for N that vary by mode and a calculation of costs as *a percentage* of a given modal user's income (rather than a flat cost) in order to account for the fact that higher transportation costs for higher income people will not be felt as heavily - or impact transportation decision-making - in the same way that higher costs are felt by people with lower incomes[9].

Heterogeneity in potential mobility

In order to better understand heterogeneity - and possible inequity - in accessibility by transportation mode across the city, we calculate a cost-distance ratio (R) for a given mode m for each individual trip between origin i and destination , as shown in Eq. (4):

$$R_{m_{ij}} = \frac{C_{m_{ij}}}{d_{ij}} \tag{4}$$

where C is the total cost and d_{ij} is distance in meters.[10] $R_{m_{ij}}$, then, provides a measure of modal (cost-based) speed, which we can compare across trips based on the characteristics of those trips' origins and destinations. While the naive null hypothesis might be that the cost-distance ratio for a given mode would not change depending on the location of the origin or destination across the city (i.e., modes travel at the same speed no matter where the trip starts or ends), we can test whether or not there is heterogeneity due to (primarily) the specific location of various infrastructure investments that make some tract-to-tract flows relatively less costly than others by assessing the heteroskedasticity in the linear relationship between distance and cost for each mode using a studentized Breusch-Pagan test (Breusch & Pagan, 1979). Statistically-significant heteroskedasticity would suggest that some flows have significantly lower cost-distance ratios (i.e., higher speed or potential mobility) than others.

Given evidence of heterogeneity, the second research question is to better understand the role that racial/ethnic, class, and built environment features play in driving structural disparities in potential mobility. To do this, a series of 20 "gravity" spatial interaction models are run for each mode m at each of the four times of day, according to the standard specification laid out in Eq. (5) (Fotheringham & O'Kelly, 1989; Rodrigue, 2020):

$$lnR_{m_{ij}} = k + \mu lnV_i + \alpha lnW_j - \beta lnd_{m_{ij}} \tag{5}$$

where V_i indicates a vector of origin-based characteristics (i.e., "push" factors) and W_j indicates a vector of destination-based characteristics (i.e., "pull" factors); the natural log of each term is taken based on the standard transformation of the gravity model equation to a linear function (Fotheringham & O'Kelly, 1989; Rodrigue, 2020). Standard transportation gravity models generally include the number of employees (or jobs) in a given destination (j), the number of residents in a given origin (i), and the distance between i and j.

Hypotheses

In addition to these standard predictors, this paper includes several features from the transportation and urban planning literature in V_i and W_j to explicitly test two primary hypotheses:

$H_1 =$ **Racial, ethnic, income, and class-based disparity hypothesis:** Black and Hispanic neighbourhoods will display significantly lower potential mobility by mode, while "creative class" neighbourhoods will display significantly higher potential mobility by mode.

$H_2 =$ **Walkable neighbourhood hypothesis:** Neighbourhoods with more-walkable built environments will display significantly lower potential mobility for auto modes and higher potential mobility for transit, bicycling, and walking.

Based on historic race-based inequality in urban planning and transportation investment in the US (as described in the literature review above), the racial, ethnic, and income features of residents are included in the analysis to evaluate systematic differences in potential mobility by socioeconomic and demographic group (H_1). In addition to these traditional sociodemographic indicators, we have also included an indicator of class: the percentage of people working in "creative" occupations - designated as "Management, business, science, and arts occupations" in the American Community Survey (ACS). Recent theories on the "creative class" posit that people employed in creative professions constitute a unique contemporary social class that highly values urban amenities and thus may tend to be better served by pedestrian, bicycling, and transit infrastructure than those employed in other professions (Florida, 2012; Mellander and Florida, 2007). While the segregated nature of American cities - and associated historic and ongoing patterns of racial exclusion, investment, and (re-)development - means that areas with high concentrations of creative class employment may also tend to be areas with larger proportions of white population, it is important to note that this does not mean that we can assume anything about the race of individual members of the creative class (the ecological fallacy), or

[8] Here we are conceptualizing ownership costs as the per-mile break-even "rent" for the utilization of a given vehicle, the idea being that access to the vehicle itself is a cost that should not be ignored when considering the total cost of using a mode. However, since ownership costs are (in reality) one-time costs, it might also be appropriate to consider them separately.

[9] To estimate the average income of a "representative" user of each mode, data from the 2013–2017 ACS on the number of workers commuting by each mode within a set range of income bands can be used.

[10] Since more detailed information on observed travel distance between origins and destinations is not available for the transit, walking, and bicycling modes - and the overarching concept of building theoretical trade-off curves is to compare modal performance over a stable, consistent measure of distance - Euclidean distance between tract centroids is used as the absolute distance measure for comparing these modes. For TNP trips, the actual distance traveled for each individual trip is available, and thus used, as it provides much more interesting (and useful) variation in the travel time-distance relationship than aggregating these trips to Census tract centroids.

that members of the creative class are more likely to be individually-creative in some kind of innate sense[11].

In addition to these indicators, a large body of work, beginning with Jane Jacobs' seminal *The Death and Life of Great American Cities* (1961), has identified a number of land use characteristics – generally involving the letter "D" – that influence urban vitality, activity, and walkability. In general, areas with higher densities, a larger diversity of building ages, shorter blocks, higher land use diversity, and lower distance to transit would be expected to encourage walking, biking, and transit use (H_2)[12] (Ewing & Cervero, 2010). A complete list of the variables of interest (and more details on their source and construction) can be found in Table 1. To assess the degree of change in the influence of specific predictors on $R_{m_{ij}}$ across the four date/times studied in this paper, the standard deviations of the regression coefficients for each covariate are calculated and compared.

Results and discussion

Dynamic mode choice profile for Chicago

Before discussing the results of the potential mobility analysis, it is useful to first take a look at the dynamic mode choice profile used to generate these travel cost-distance relationships for Chicago. Fig. 2 shows the individual cost-distance pairs for all tract-to-tract flows within the city for the weekday morning time by mode, with each point representing a unique tract-to-tract flow.

While it is apparent from Fig. 2 that each mode has a relatively distinct cost-distance profile, fitting the least-squares line from Eq. (1) to each mode allows us to examine specific trade-offs in the theoretical "equilibrium" mode choice for trips of a given distance (i.e., the theoretical rational choice for a given commuter would be to take the lowest-cost mode for a trip of a given distance, following the lowest of the cost-distance curves). Eq. (2) can then be used to find the exact distance at which one mode trades off for another. Given the flexible format of this approach, it is possible to produce temporally- and spatially-dynamic profiles to assess how these modal trade-offs (i.e., $I_{m_1-m_2}$) change for different temporal and spatial subsets of the data. Fig. 3a-d shows the linear cost-distance curves for each mode at each of the four times of interest, and Fig. 4a-d shows the linear cost-distance curves for each mode for four spatial "quadrants[13]" of the city for the weekday morning time. To illustrate the changes in trade-offs for each of these subsets more clearly, Table 2 shows the total cost for each mode on a trip of 15 km (roughly the average commute distance in Chicago).

These results indicate that, in general, when considering the full economic cost to the consumer, the bicycle and transit modes are quite competitive compared to the other modes. In particular, the transit mode, with a low fare that does not increase much with distance travelled (only through the number of transfers) is not *so much slower* than the auto as to lose out on this significant cost advantage over longer distances. Bicycling is similarly advantaged here, as the mode's maintenance/ownership costs are nowhere near as high as the auto, despite relatively slower speeds. We can also see that rideshare users pay a significant premium compared to auto users for the various advantages that mode confers (e.g., ease of not having to drive/park oneself, on-demand travel, ability to drink alcohol, etc.)[14].

In terms of temporal changes (perhaps unsurprisingly, given that we explicitly valued the opportunity cost of travel ($N_{avg_{peak}}$) at 1.4 times off peak travel), the weekday rush times - and, in particular, the weekday afternoon rush - are the most costly (i.e., have the least potential mobility) for a set distance across all modes. More interesting is that spatial subsets of the city display relatively stark divides on potential

Table 1
Variables of interest in assessing heterogeneity in cost-distance ratio by mode.

Variable	Source	Location
Cost-distance ratio by mode ($/km)	2020 OTP and 2020 TNP	*ij*
Total employed residents	2015 LODES	*i*
Total employees	2015 LODES	*j*
Distance (km)	Euclidean and 2020 TNP	*ij*
Percent Black population	2013–2017 ACS	*i, j*
Percent Hispanic population	2013–2017 ACS	*i, j*
Percent working in "creative" occupations[1]	2013–2017 ACS	*i, j*
Per capita income	2013–2017 ACS	*i, j*
Jacobs Index[2]		*i, j*
Street network **d**esign (average block length[3])	2010 Census	
Density (housing units per square meter)	2013–2017 ACS	
Building age **d**iversity[4]	2013–2017 ACS	
Distance to transit (transit station density[5])	Chicago Open Data	
Land use **d**iversity (employment diversity[6])	2015 LODES	

[1] Designated as "Management, business, science, and arts occupations" in the ACS.
[2] Calculated by finding z-score of each of the five subsidiary variables and combining them into an index by subtracting block length and adding the others together.
[3] Calculated by averaging the perimeter (in m) of Census blocks within containing Census tracts.
[4] Calculated using a Herfindahl Index (1-the sum of squared shares) by decade; larger values (to 1) represent more equal allocations of building age across decades.
[5] Calculated by combining CTA station, CTA bus stop, PACE bus stop, and Metra station shapefiles and creating a Kernel Density Estimation (KDE) surface using a radius of 1000 m (a realistic threshold for walking to transit) and a pixel size of 65.98 m. Average density values by pixel centroid were joined to tract boundaries.
[6] Calculated using a Herfindahl Index (1-the sum of squared shares) by industry employment categories; larger values (to 1) represent more equal allocations of employment types by industry.

[11] Following Florida's (2012) conceptualization, the creative class is a *social class* based on occupations that tend to deal with creative job functions, new knowledge creation, etc. The fact that these occupations are often less open to people from minoritized communities is a reflection of the historic and ongoing social and racial divisions in American society and inequality in access to educational opportunities. In fact, the final chapter of Florida's seminal work (2012) is titled "Every Single Human Being is Creative," centering the idea that more resources need to be deployed to open avenues for creative education and employment for people of all races and backgrounds to capitalize on their inherent human creativity.

[12] Since the five built environment variables of interest are correlated, violating one of the primary assumptions of linear regression, we create an index that is a composite of these individual variables that captures the "Jacobian" built environment concepts in one measure by calculating the z-score of each variable. This converts each raw data value into units of that variable's standard deviation, allowing them to be added to form a composite index. In the Jacobs Index used in this paper, we add together the z-scored variables that we think positively contribute to built environment diversity, i.e., density, age diversity, land use diversity, and transit density – and subtract the variables that negatively contribute to built environment diversity (i.e., block length, because shorter blocks are seen as encouraging more activity). Thus, in the resulting composite variable, high values then correspond to high values of each of these constituent variables (and shorter blocks), and thus we can assume are more fine-grained, walkable, diverse built environments.

[13] To illustrate the concept of spatial subsets, a simple k-means clustering algorithm was used in GeoDa v.1.18 on the coordinates of the tract centroids with k=4 clusters. Smaller spatial subsets could also be used.

[14] We could also think of the difference between these two curves as the profits obtained by the rideshare driver.

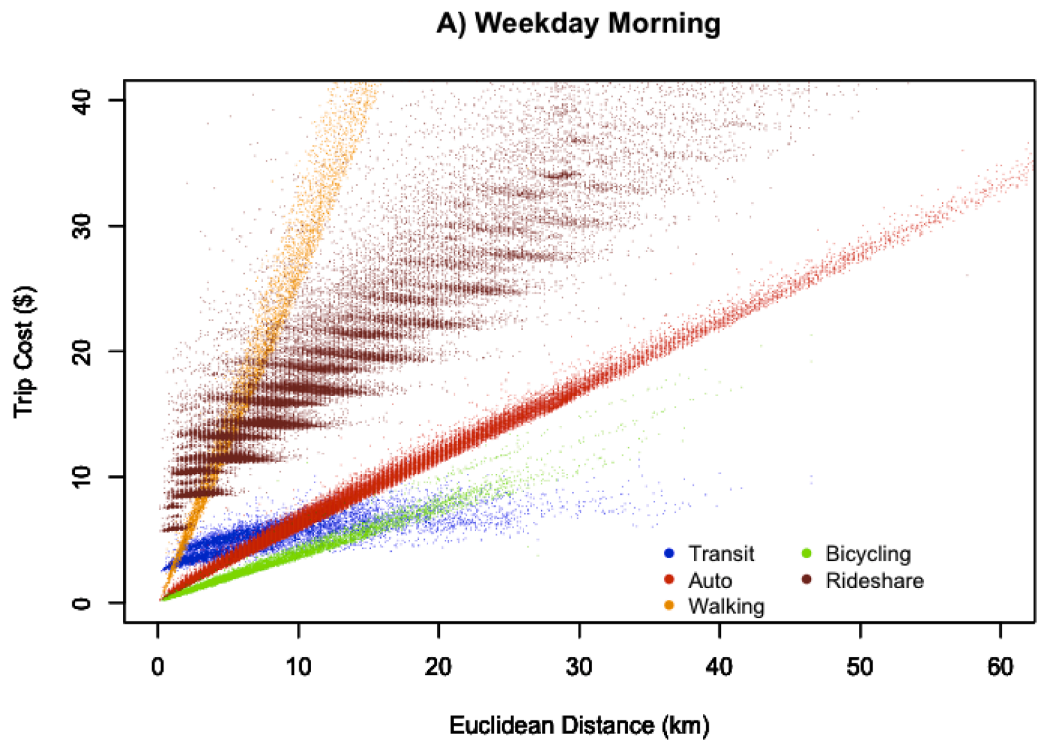

Fig. 2. Weekday morning cost-distance pairs by mode.

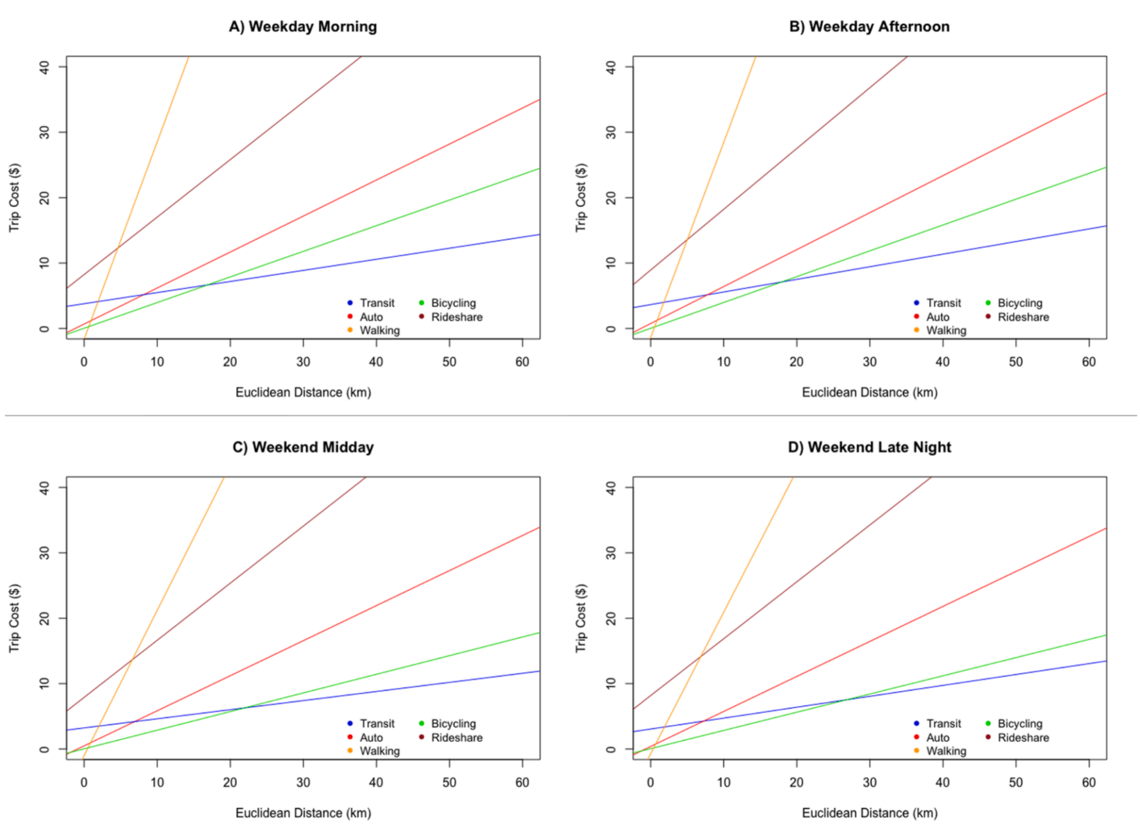

Fig. 3. a-b Modal cost-distance trade-off curves for different times of day.

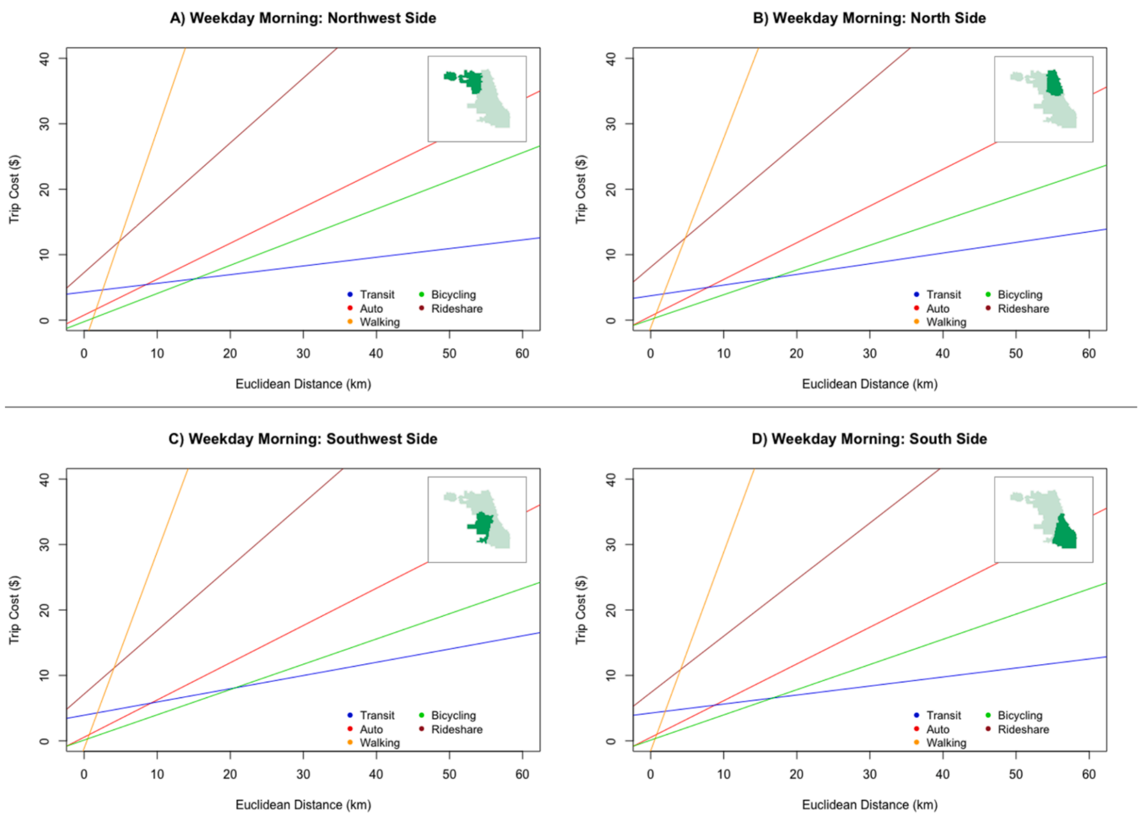

Fig. 4. a-d. Modal cost-distance trade-off curves for different city quadrants.

Table 2
Total economic cost to go 15 km by mode.

Mode	Weekday Morning	Weekday Afternoon	Weekend Midday	Weekend Late Night	North Side	South Side	Northwest Side	Southwest Side
Rideshare	$21.42	$22.87	$20.99	$21.22	$22.23	$20.33	$22.13	$21.74
Auto	$8.93	$9.23	$8.53	$8.43	$9.02	$8.95	$9.00	$9.09
Transit	$6.33	$6.54	$5.32	$5.56	$6.27	$6.79	$6.83	$6.47
Bicycling	$5.92	$5.95	$4.31	$4.24	$5.77	$5.89	$6.22	$5.91
Walking	$43.61	$43.39	$32.30	$31.77	$42.30	$44.04	$45.33	$43.91

mobility, particularly in terms of the non-auto modes. The north side displays substantially lower costs (i.e., higher potential mobility) for transit, bicycling, and walking - as well as the highest concentration of white population in the city - than the other three quadrants, in particular the more suburban and less-connected northwest side. Given the spatial layout of Chicago, and the relative (built environment and sociodemographic) meaningfulness of these rough quadrant subsets, these results provide a strong initial indication as to the direction of heterogeneity in potential mobility throughout the city, explored in more detail below.

Characterizing heterogeneity in potential mobility

The primary goal of this paper is to better characterize the trips by mode at different times of day in order to understand heterogeneity in travel costs (i.e., potential mobility) across the city. The first step, of course, is to determine whether there is significant heterogeneity in the first place. To do this, studentized Breusch-Pagan tests are run for each mode on Eq. (1) (using the calculated total economic costs) to determine whether or not there is statistically-significant heteroskedasticity in the relationship between distance and cost. In each case, the tests (available in Appendix B) are highly significant (p-value $< 2.2e-16$), providing empirical confirmation that the relationship between cost and distance is not constant across flows.

Given this evidence of heterogeneity, cost-distance ratios for each trip are calculated according to Eq. (4) for each mode and date/time, providing 20 sets of dependent variables that are inserted into 20 spatial interaction models (based on the specification described in Eq. (5)). Table 3 presents a summary of the results of each of the 20 individual models run; full regression results appear in Appendix C. Table 3 is color-coded according to the primary hypotheses tested - green-coloured boxes indicate results that support the hypothesis (H_1) that there is racial, ethnic, income, or class-based inequality in travel cost to/from Census tracts with particular features, while the yellow-coloured boxes indicate mixed results that do not support H_1 . Blue-colored boxes show results that match the hypothesis (H_2) that more walkable, dense built environments support lower cost (i.e., faster) travel by transit, bicycling, and walking.

In general, the results indicate that all modes are less costly to and from tracts with larger proportions of creative-class employment, while transit, walking, and bicycling are significantly more costly to and from tracts with larger proportions of Black and Hispanic residents. These results hold (essentially) across all four time periods, even when controlling for the distance of each trip and the per capita income and built environment characteristics of origin and destination tracts, suggesting that there is indeed some structural inequality in the deployment of infrastructure investments (particularly for transit, bicycling, and walking) in the city that favours creative class neighbourhoods, or

Table 3
Summary of regression results on cost-distance ratio for individual trips by mode, categorized based on primary hypotheses (full results in Appendix C).

Auto	Rideshare	Transit	Bicycling	Walking
Generally faster to + from Black n'hoods		Slower to + from Black and Hispanic n'hoods		
Generally slower to + from Hispanic n'hoods	Sometimes faster to + from Hispanic n'hoods			
Faster to + from creative n'hoods				
Generally slower to + from Jacobs n'hoods		Faster to + from Jacobs n'hoods		
Generally slower to + from higher income n'hoods	Generally faster to + from higher income n'hoods	Slower to + from higher income n'hoods	Faster to + from higher income n'hoods	Generally slower to + from higher income n'hoods

Supports H1: Racial, ethnic, income, or class-based inequity observed
Contradicts H1: Mixed results that do not indicate strong inequity
Supports H2: Supports walkable neighborhoods hypothesis

Supports H1: Racial, ethnic, income, or class-based inequity observed.
Contradicts H1: Mixed results that do not indicate strong inequity.
Supports H2: Supports walkable neighborhoods hypothesis.

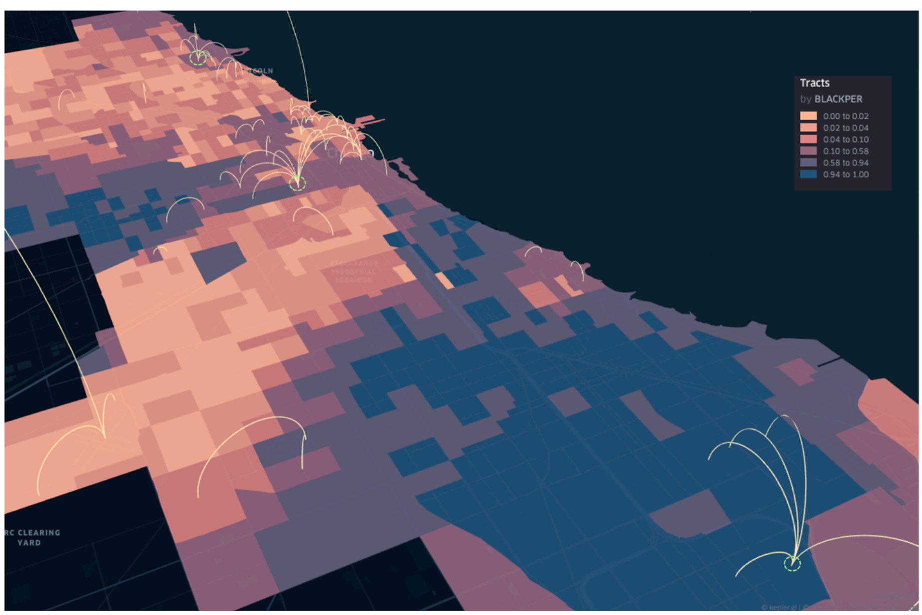

Fig. 5. Map showing relatively "slowest" weekday morning bicycling trips (those with largest 1% cost-distance ratios (0.580–1.138)) in yellow, overlaid on Black population percent values by Census tract. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

perhaps that creative class members have moved into neighbourhoods with high levels of existing accessibility (residential self-selection). In addition, rideshare trips are generally less costly to and from tracts with higher per capita incomes.

At the same time, the results indicate that some modes do not disadvantage non-white, low-income neighbourhoods - in particular, the auto and rideshare modes are less costly to and from tracts with larger proportions of Black population. However, this could be due to the fact that major highway investments in the city, e.g., I-90 and I-94, were built explicitly through historically Black communities on the city's south side. In addition, major employment and activity centres (and associated auto congestion) in the city tend to be concentrated in the white-majority north side neighbourhoods, which could mean that lower auto and rideshare costs to and from Black neighbourhoods are simply a reflection that these neighbourhoods have been systematically excluded from large scale economic investment in the city. Lower rates of auto ownership in these neighbourhoods could also contribute to relatively lower congestion to and from these neighbourhoods. The auto, transit, and walking modes are significantly more costly to and from tracts with higher per capita incomes, which could also be a result of activity-related congestion.

As for the walkable neighbourhoods hypothesis, these results suggest that travel to and from tracts with larger Jacobs Index values (i.e., more walkable tracts) is significantly more costly by auto and rideshare and

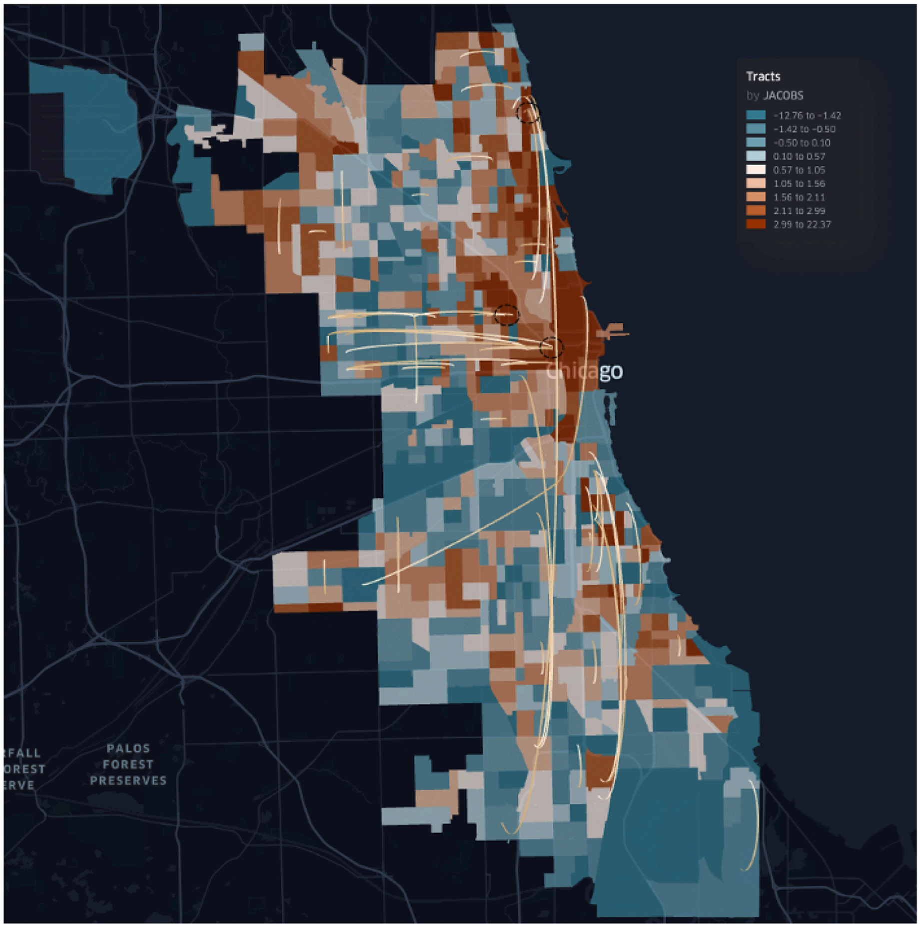

Fig. 6. Map showing relatively "fastest" weekday morning bicycling trips (those with lowest 1% cost-distance ratios (0.139–0.342)) in yellow, overlaid on Jacobs Index values by Census tract. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4
Standard deviation of regression coefficients across each time period.

	Auto	Rideshare	Transit	Bicycling	Walking
(Intercept)	0.06	0.60	0.06	0.22	0.19
Employees (orig)	0.00	0.02	0.00	0.00	0.00
Employees (dest)	0.00	0.01	0.00	0.00	0.00
Distance	0.02	0.01	0.03	0.00	0.00
Black % (orig)	0.00	0.00	0.00	0.00	0.00
Black % (dest)	0.00	0.00	0.00	0.00	0.00
Hispanic % (orig)	0.00	0.00	0.00	0.00	0.00
Hispanic % (dest)	0.00	0.00	0.00	0.00	0.00
Creative Occupations % (orig)	0.00	0.01	0.00	0.00	0.00
Creative Occupations % (dest)	0.01	0.02	0.00	0.00	0.00
Jacobs Index (orig)	0.01	0.05	0.02	0.01	0.00
Jacobs Index (dest)	0.00	0.06	0.03	0.02	0.01
Per Capita Income (orig)	0.00	0.00	0.00	0.00	0.00
Per Capita Income (dest)	0.00	0.01	0.00	0.00	0.00

less costly by transit, bicycling, and walking. These results, which hold across all time periods and while controlling for trip distance and tract-level racial/ethnic characteristics, per capita income, and even occupational structure, provide strong support for Jacobs' (1961) assertion that neighbourhoods with smaller blocks, higher densities, and a diverse mix of land uses and building ages do in fact foster more efficient non-auto travel.

A set of maps, created in kepler.gl, helps to illustrate these relationships more concretely for the bicycling mode in the context of weekday morning trips cantered on the city's north/northwest side. Fig. 5 shows the "slowest" 1% of bicycle trips for this time period overlaid on Black percent. We can see that, even though the city is generally segregated overall, many of the highest-cost bicycle trips start or end in tracts with *relatively* larger proportions of Black population, such as the UIC area, Buena Park, and Pullman. It is important to note here again that these values do not reflect the *number* of travellers by a given mode, but only their relative cost per a given distance; with that in mind, we can clearly see from Fig. 5 (and the full spatial interaction model results) that bicycle pathways to and from areas of larger Black population in the city often tend to be more costly - and likely less invested in, etc. - than pathways to and from white neighbourhoods. On the other hand, Fig. 6 shows the relatively "fastest" bicycle trips between tracts (i.e., those with the lowest 1% of cost-distance ratios) overlaid on Jacobs Index values. We can see that many of these lowest-cost trips occur between tracts with high walkability values (marked in darker blue) in neighbourhoods such as Wicker Park, Edgewater, and the Near West Side.

The final research question concerns variability in these results across the four time periods, which is assessed by calculating the standard deviation of each covariate's regression coefficients across each date/time. As Table 4 indicates, there is not much observed variability across time periods; in general, the rideshare mode demonstrates the largest variability across different time periods, which may be due to the fact that rideshare cost values are much more noisy than the other modes in general, perhaps due to the inclusion of tipping into the total cost value or inefficient behaviour from rideshare drivers. While the Jacobs Index coefficients for rideshare show the largest variability across time periods, they are consistently positively related to cost-distance ratio for rideshare (with a smaller or insignificant relationship on the weekend as compared to the weekday time periods).

Conclusions

Of course, there are several limitations to this analysis that should be noted - the selection of travel times during the COVID-19 pandemic could not be avoided, as data from the OTP API is not archived; however, future analysis to see whether the modal trade-offs and heterogeneities in potential mobility observed here remain stable in the post-pandemic environment will be illuminating[15]. The choice of the Census tract scale (specifically, using tract centroids as origins and destinations), while providing useful links to additional secondary Census data, is also not a perfect representation of travel behaviour, and future work employing smaller standardized grid cells or hexagons would be interesting to compare to these results. The use of information on observed travel behavior and trip purpose, if available, would also significantly enhance the analysis here. While observed trips in the TNP data were used to subset all possible origin–destination combinations for the bicycling, walking, and transit modes, information on the propensity of travel by mode between specific origins and destinations could be used to weight the results more realistically. Data on trip purpose would also allow us to make more concrete interpretations of the model results, since the paper currently (essentially) assumes that the neighbourhood characteristics of origin and destination locations equally affect potential mobility no matter the purpose of the trip, which is of course not the case in reality.

Additionally, the choice of a single time for querying the transit network (rather than an average of larger time ranges), while significantly lowering the total computation time employed for making OTP queries, certainly interjects some randomness to the obtained transit times (based on the specific time selected). However, the aggregation of all possible tract-to-tract trips in the creation of the modal trade-off curves helps to mitigate these effects. While averages of longer time periods might be more realistic, this increases computational demands significantly. Finally, it is important to note that while the cost framework used here is entirely consumer-oriented, there are of course additional (consumer-centric) benefits fostered by each mode, and a wide range of additional positive and negative externalities born by society at large for each mode. While it is beyond the scope of this paper to calculate these full costs and benefits, perhaps this framework can provide a starting point for future, society-wide analyses of transportation costs and benefits by mode.

Despite these limitations, we feel that this paper's development of an approach to calculate dynamic mode choice profiles using open source data based on the full cost (to the consumer) of traveling a given distance by each urban passenger mode, has the potential to further urban transportation analysis in a number of important ways. The citywide mode choice profile suggests that bicycling and transit (as well as walking, over short distances) modes are underutilized compared to what the theoretical-economic analysis presented here suggests. While there are a variety of reasonable explanations for this - including the disutility of physical exertion and lack of ease and comfort some feel in active transportation modes - if lack of complete information on the full cost of a trip by each mode is one, the framework developed in this paper could be usefully applied to provide that information to travellers to help them make more cost-effective decisions. Given the additional positive externalities associated with bicycling, walking, and transit travel (including physical health, lower congestion and emissions, etc.), this kind of information intervention could even be used by local governments to help encourage residents to take these modes, which, as this paper shows, would be justified economically (on average) as well.

In addition, this paper's primary analysis suggests that there is substantial, spatially-structured disparity in potential mobility across the city. A formal examination of cost-distance ratios for trips by mode using spatial interaction models sheds important empirical light on inequalities stemming from the design of the municipal transportation system. In Chicago, communities that have been traditionally marginalized in terms of access to urban investment and infrastructure – particularly Black and Hispanic neighbourhoods – are faced with systematically *higher* travel costs (and thus lower potential mobility) by the transit, bicycling, and walking modes, while those in creative class occupations tend to be privileged with *lower* travel costs by *all* modes. Given the additional social and economic barriers that members of these non-white racial and ethnic groups often face – including reduced spatial access to economic opportunities and services – as well as the important role that active transportation behaviour plays in public health outcomes (Frank et al., 2004, 2006; Lindström, 2008; Wang et al., 2016), the fact that travel by transit, bicycling, and walking tends to be *more expensive* to and from these neighbourhoods is an important finding that provides a clear target for progressive policy intervention.

At the same time, however, the analysis finds that the physical built environment characteristics theorized by Jacobs (1961) and others to promote non-auto transportation do, in fact, significantly relate to *lower* cost travel by the transit, bicycling, and walking modes, and *higher* cost travel by the auto and rideshare modes. While there are a variety of factors (discussed at length above) that complicate the final mode choices that people end up making, this finding suggests that, at the very least, these types of physical environments – neighbourhoods with shorter blocks, higher densities, and a diversity of building ages and land uses – can provide for faster, lower cost travel via non-auto modes, lending support to the idea that land use interventions that support these types of built environments can potentially foster more non-auto travel.

CRediT authorship contribution statement

Kevin Credit: Conceptualization, Formal analysis, Writing-original draft. **Gustavo Dias:** Data curation, Methodology. **Brenda Li:** Writing-original draft, Writing-review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

See Table A1.

Table A1
R Code for Calculating Tract-to-Tract Travel Times from OTP.

```
setwd("C:/Users/gusta/Dropbox/Desktop/OTPR")
chicagocentroids <- read.csv("destinations.csv")
chicagocentroids2 <- read.csv("destinations.csv")

install.packages("otpr")

library(otpr)

otpcon <- otp_connect(hostname = "localhost", router = "current", port = 8080, ssl = FALSE)

total <- nrow(chicagocentroids)
total2 <- nrow(chicagocentroids2)


lista <- list()
k<-0

for (i in 1:total){
  for (j in 1:total2){

    print(i)
    print(j)
    print(k)

    lista[[i]] <-
      otp_get_times(
        otpcon,
        fromPlace = c(chicagocentroids[i, ]$latitude, chicagocentroids[i, ]$longitude),
        toPlace = c(chicagocentroids[j, ]$latitude, chicagocentroids[j, ]$longitude),
        mode = 'TRANSIT',
        detail = TRUE,
        date = "06-28-2020",
        time = "00:00:00",
        maxWalkDistance = 1600,
        walkReluctance = 5,
        minTransferTime = 600
      )


    if (lista[[i]]$errorId == "OK"){
      chicagocentroids2[k+j, "From(x)"] <- chicagocentroids[i, ]$longitude
      chicagocentroids2[k+j, "From(y)"] <- chicagocentroids[i, ]$latitude
      chicagocentroids2[k+j, "To(x)"] <- chicagocentroids[j, ]$longitude
      chicagocentroids2[k+j, "To(y)"] <- chicagocentroids[j, ]$latitude

      chicagocentroids2[k+j, "duration"] <- lista[[i]]$itineraries$duration
      chicagocentroids2[k+j, "walk"] <- lista[[i]]$itineraries$walkTime
      chicagocentroids2[k+j, "transit"] <- lista[[i]]$itineraries$transitTime
      chicagocentroids2[k+j, "waiting"] <- lista[[i]]$itineraries$waitingTime
      chicagocentroids2[k+j, "transfers"] <- lista[[i]]$itineraries$transfers

    } else {
      chicagocentroids2[k+j, "From(x)"] <- lista[[i]]$errorId
      chicagocentroids2[k+j, "From(y)"] <- lista[[i]]$errorId
      chicagocentroids2[k+j, "To(x)"] <- lista[[i]]$errorId
      chicagocentroids2[k+j, "To(y)"] <- lista[[i]]$errorId
    }
  }
  k <- k+j
}

write.csv(chicagocentroids2, "TRANSIT_06-28-2020_00AM.csv")
```

Appendix B

See Table A2.

Table A2
Bruesch-Pagan Test Results for Each Mode/Time Combination.

Mode	Weekday Morning	Weekday Afternoon	Weekend Midday	Weekend Late Night
Rideshare	BP = 4245.8, df = 1, p-value < 2.2e−16	BP = 5233.2, df = 1, p-value < 2.2e−16	BP = 3516.5, df = 1, p-value < 2.2e−16	BP = 2642.4, df = 1, p-value < 2.2e−16
Auto	BP = 1760.9, df = 1, p-value < 2.2e−16	BP = 14581, df = 1, p-value < 2.2e−16	BP = 6562.6, df = 1, p-value < 2.2e−16	BP = 5727.8, df = 1, p-value < 2.2e−16
Transit	BP = 801.19, df = 1, p-value < 2.2e−16	BP = 2188.9, df = 1, p-value < 2.2e−16	BP = 1792.1, df = 1, p-value < 2.2e−16	BP = 236.74, df = 1, p-value < 2.2e−16
Bicycling	BP = 766.94, df = 1, p-value < 2.2e−16	BP = 3285.7, df = 1, p-value < 2.2e−16	BP = 703.27, df = 1, p-value < 2.2e−16	BP = 773.56, df = 1, p-value < 2.2e−16
Walking	BP = 424.55, df = 1, p-value < 2.2e−16	BP = 3570.7, df = 1, p-value < 2.2e−16	BP = 335.13, df = 1, p-value < 2.2e−16	BP = 316.31, df = 1, p-value < 2.2e−16

Appendix C

See Table A3.

Table A3
Full Regression Results on Cost-Distance Ratio for Individual Trips by Mode.

a. Weekday morning.

	Auto		Rideshare		Transit		Bicycling		Walking	
(Intercept)	−0.385	***	1.021	***	1.592	***	−0.438	***	1.387	***
Employees (orig)	0.004	***	0.034	***	0.004		0.012	***	0.0005	
Employees (dest)	0.001	***	0.021	***	−0.006	***	0.001		−0.001	*
Distance	−0.110	***	−0.601	***	−0.719	***	−0.081	***	0.024	***
Black % (orig)	−0.0003		−0.005	***	0.003	***	0.004	***	0.005	***
Black % (dest)	−0.002	***	−0.006	***	0.004	***	0.003	***	0.004	***
Hispanic % (orig)	0.001	***	−0.001		0.003	***	−0.0001		0.0003	
Hispanic % (dest)	−0.00001		−0.003	***	0.004	***	0.002	***	0.002	***
Creative Occupations % (orig)	−0.011	***	−0.013	**	−0.003	**	−0.001		−0.001	.
Creative Occupations % (dest)	−0.002		−0.014	*	−0.001		−0.001	.	−0.002	**
Jacobs Index (orig)	0.006	.	0.106	***	−0.121	***	−0.066	***	−0.067	***
Jacobs Index (dest)	0.011	***	0.095	***	−0.098	***	−0.062	***	−0.086	***
Per Capita Income (orig)	0.006	***	−0.009	***	0.010	***	−0.005	***	0.000	
Per Capita Income (dest)	0.002		−0.002		0.005	***	0.000		0.002	**
Adjusted R2	0.708		0.913		0.948		0.318		0.237	
Degrees of Freedom	13,636		13,636		9034		9100		9101	

b. Weekday afternoon.

	Auto		Rideshare		Transit		Bicycling		Walking	
(Intercept)	−0.438	***	0.687	***	1.645	***	−0.484	***	1.367	***
Employees (orig)	−0.004	***	0.039	***	−0.002		0.011	***	−0.001	
Employees (dest)	0.001	***	0.021	***	−0.002	**	0.003	***	0.002	***
Distance	−0.108	***	−0.590	***	−0.716	***	−0.077	***	0.028	***
Black % (orig)	−0.003	***	−0.008	***	0.002	***	0.003	***	0.004	***
Black % (dest)	−0.001	**	−0.002	***	0.002	***	0.004	***	0.005	***
Hispanic % (orig)	0.002	***	−0.001	*	0.003	***	0.001	*	0.001	***
Hispanic % (dest)	0.001	***	−0.001	.	0.003	***	0.001	**	0.001	***
Creative Occupations % (orig)	−0.019	***	−0.017	***	−0.003	**	−0.002	**	−0.003	***
Creative Occupations % (dest)	−0.020	***	−0.047	***	−0.002	*	−0.002	*	−0.002	**
Jacobs Index (orig)	−0.007	*	0.147	***	−0.135	***	−0.081	***	−0.079	***
Jacobs Index (dest)	0.007	**	0.106	***	−0.123	***	−0.038	***	−0.079	***
Per Capita Income (orig)	0.014	***	−0.009	**	0.012	***	−0.003	***	0.002	***
Per Capita Income (dest)	0.010	***	0.015	***	0.010	***	−0.002	**	0.001	
Adjusted R2	0.565		0.875		0.946		0.294		0.206	
Degrees of Freedom	28,691		28,691		17,267		17,367		17,367	

c. Weekend midday.

	Auto		Rideshare		Transit		Bicycling		Walking	
(Intercept)	−0.404	***	1.851	***	1.535	***	−0.814	***	1.067	***
Employees (orig)	−0.002	**	0.011	***	0.003		0.011	***	−0.001	
Employees (dest)	−0.001	**	0.002	**	−0.005	***	0.003	***	0.001	**
Distance	−0.088	***	−0.601	***	−0.761	***	−0.073	***	0.027	***
Black % (orig)	−0.002	***	−0.007	***	0.003	***	0.004	***	0.004	***

(continued on next page)

Table A3 (*continued*)

Black % (dest)	−0.001	***	−0.004	***	0.002	***	0.004	***	0.005	***
Hispanic % (orig)	0.001	**	0.001		0.003	***	0.0004		0.001	**
Hispanic % (dest)	0.001	***	0.001	*	0.003	***	0.001	***	0.001	***
Creative Occupations % (orig)	−0.011	***	−0.006		−0.002	*	−0.001	*	−0.002	*
Creative Occupations % (dest)	−0.004	.	0.00002		−0.002	*	−0.002	*	−0.002	**
Jacobs Index (orig)	−0.002		0.028	***	−0.129	***	−0.070	***	−0.073	***
Jacobs Index (dest)	0.001		0.003		−0.117	***	−0.042	***	−0.081	***
Per Capita Income (orig)	0.008	***	−0.005		0.009	***	−0.004	***	0.001	.
Per Capita Income (dest)	0.002		−0.010	*	0.009	***	−0.002	*	0.002	**
Adjusted R2	0.576		0.861		0.961		0.266		0.214	
Degrees of Freedom	24,001		24,001		14,247		14,317		14,317	

d. Weekend late night

	Auto		Rideshare		Transit		Bicycling		Walking	
(Intercept)	−0.514	***	1.892	***	1.657	***	−0.869	***	1.044	***
Employees (orig)	−0.001		−0.0003		0.002		0.010	***	0.000	
Employees (dest)	0.002	***	0.004	***	−0.004	***	0.002	***	0.001	
Distance	−0.079	***	−0.586	***	−0.763	***	−0.074	***	0.027	***
Black % (orig)	0.0003	*	−0.003	***	0.002	***	0.004	***	0.004	***
Black % (dest)	0.0004	*	−0.0005		0.001	*	0.004	***	0.004	***
Hispanic % (orig)	−0.0001		0.0005		0.003	***	0.001	**	0.002	***
Hispanic % (dest)	−0.0002		0.003	**	0.004	***	0.0002		0.001	.
Creative Occupations % (orig)	−0.012	***	−0.004		−0.005	***	−0.002	**	−0.002	***
Creative Occupations % (dest)	−0.005	***	0.009		−0.004	***	−0.001		−0.001	*
Jacobs Index (orig)	0.014	***	0.088	***	−0.159	***	−0.052	***	−0.071	***
Jacobs Index (dest)	0.007	***	0.004		−0.160	***	−0.018	***	−0.067	***
Per Capita Income (orig)	0.006	***	−0.010	.	0.013	***	−0.005	***	0.001	
Per Capita Income (dest)	0.001		−0.015	**	0.013	***	−0.004	***	−0.001	
Adjusted R2	0.519		0.748		0.934		0.263		0.185	
Degrees of Freedom	33,651		33,651		17,373		17,432		17,432	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

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