Transportation Research Interdisciplinary Perspectives 21 (2023) 100870

Contents lists available at ScienceDirect

Transportation Research Interdisciplinary Perspectives

journal homepage: www.sciencedirect.com/journal/transportation-research-interdisciplinary-perspectives

Social equity and public transit in the inland empire: Introducing a transit equity analysis model

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ARTICLE INFO

Keywords:
Transit service
Race
Disadvantaged people
Social equity
Inland empire
COVID-19

ABSTRACT

Public transit is a critical part of transportation infrastructure and social equity. The COVID-19 pandemic had a significant impact on transit systems throughout the nation. The study area for this paper, the Inland Empire (I.E.) in Southern California, has a significant minority and disadvantaged population, highlighting the importance of creating opportunities and new means of transportation. The transportation system has been built to support automobile travel, but public transit is an important mobility factor for many people. This paper aims to study the performance of public transit services and their impact on underserved communities. Pre-pandemic, during and post-COVID-19 vaccination rollout time periods, were selected to analyze the impact on transit equity. A transit equity analysis model was built using multiple linear regression analysis (MLR) on demographic and transit-related data from 645 census tracts. This model creates a transit equity index (TEI), which includes a transit service index (TSI), a socially disadvantaged index (DAI), and a race index (R.I.). The transit equity index shows a strong relationship between TSI and R.I. on DAI, reflecting the region's lack of efficient transit services in racially marginalized census tracts. As a result, new policies are needed to promote public transportation, create adequate infrastructure, and envision urban planning to decrease public transit social inequities within the I.E.

Introduction

Public transit is a critical part of transportation infrastructure and social equity. Planning agencies tend to assess transit services, accessibility, mobility, and effectiveness before implementing any development project. Traditionally, social equality in transportation is reflected by investment distributions across the nation and among states, counties, metropolitan areas, and regions (Sider et al., 2015). Since the ratification of Title VI of the Civil Rights Act of 1964, transportation planning agencies have shifted from equality to equity as a substantial element in the planning process (Martens and Golub, 2021). Equity definitions are shifting as more research is conducted. The definition now includes socio-demographic, accessibility, and environmental factors. Government agencies have led several initiatives to obtain a more equitable system. These include mobility as a Service (MaaS) and the Biden Administration's Executive Order setting Justice 40 as a policy goal (Shalanda Young et al., 2021), which is an excellent example showing the stance of the U.S. governance towards transit equity. Finally, the COVID-19 pandemic has had a critical impact on the transit systems within the nation, as precautions were set to limit ridership and avoid crowding. It is from this context that the work for this paper was based.

This study introduces a robust method that better reflects the state of transit equity within a region so that transit agencies and local and state governments can make more informed decisions that directly benefit their communities. The transit equity matrix is analyzed by modeling

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https://doi.org/10.1016/j.trip.2023.100870
Received 7 March 2023; Received in revised form 13 June 2023; Accepted 19 June 2023
Available online 26 June 2023

transit supply and demand in underserved communities within the I.E., which includes the counties of Riverside and San Bernardino in Southern California. The output will create important insight into areas of potential transit service changes to improve mobility and accessibility in communities across the I.E. The model developed for this paper explores the relationship between disadvantaged communities, transit service supply and demand, and race. The second goal of this paper is to demonstrate how transit equity has changed throughout the COVID-19 pandemic and identify the impacts of the transit schedule changes that occurred with declined ridership.

During the pandemic, many “essential workers” were part of the underserved and disadvantaged populations that relied heavily upon transit. Therefore, the social equity question holds greater importance during this difficult time. When transit equity is prioritized in decision-making, it empowers underserved populations by providing better access to jobs, health, automobile services, and food, to name a few. The results of this research will enhance the interpretation of the transit systems in the I.E., providing the transit agencies and policymakers with an understanding of the service in the region. The change in this service and its impact on underserved communities, along with the race factor that was interpreted as a factor influencing disadvantaged people in a new approach to researching equity.

Literature review

The pandemic

On January 6, 2020, the first case of COVID-19 was confirmed in the U.S. (Centers for Disease Control and Prevention, 2022). By mid-March, to slow down the spread of the virus, states across the U.S. began implementing various policies, including a series of ever-changing statewide executive stay-at-home orders, mask mandates, social distancing, school closures, and business closures that put people in constant uncertainty. This uncertainty has had a substantial impact on the transit sector (Brown and Williams, 2021).

By March 31, 2020, about three months after the first recorded case of COVID-19, transit ridership had dropped by 90% across North America as governments applied quarantine policies (DeWeese et al., 2020). In response, transit agencies cut their service even though many essential and low-income workers relied on it with few alternatives (Brown and Williams, 2021). In Southern California, bus ridership across all agencies from 2019 to April 2020 decreased by 62.9%, where the highest decrease was 89.7%, and the average was 71% (Southern California Association of Governments, 2020).

The public transit sector has struggled to bounce back since the stay-at-home orders were lifted and businesses have reopened. Two and a half years after the first cases were diagnosed, regulations set by local and state governments were still in place to make sure that the shared spaces in transit were safe for the riders and drivers. These regulations have increased hostilities by riders toward transit employees as they try to enforce vaccination requirements, mask mandates, and social distancing (McClain, 2022). Safety concerns around the pandemic are another paradox in governance, as a lack of COVID-19 regulations in the transit system will create an unsafe environment for drivers and riders, and the regulations are creating a backlash and insecurity in the system (Tirachini and Cats, 2020). This continued uncertainty for riders has led to new challenges for transit agencies as they had to develop new security protocols and communication plans for people to feel comfortable returning as riders (Ashraf Javid et al., 2021).

The decrease in public transit services affected various socio-economic groups differently. For example, managerial and tech jobs could better transition to working from home while many essential workers were required to be in person. Therefore, most people who still used public transit were not choice riders and relied on transit services for jobs or access to health services (Liu et al., 2022) – leading to new concerns about social equity.

Disadvantaged population

There is no standardized definition of a socially disadvantaged person. Generally, it includes people affected by prejudice or cultural bias that results in an unfair lack of opportunities (United States Depratment of transportation, 2013). In transit, there are choice riders with access to an automobile but still, use the public system and those who are transit-dependent and do not have access to an automobile. Research indicates that the transit-dependent population is likelier to be lower-income persons of color (Karner, 2018). A lack of accessibility results in more difficulties accessing economic opportunities, education, health facilities, and everyday needs (Guzman et al., 2017).

Previously, the transit agencies focused on service and routes for choice riders which helped to reduce congestion and vehicle miles traveled (VMT). This ultimately limited the funds going to the transit-dependent riders (Karner, 2018). However, now empowering the disadvantaged population is at the forefront of current policies. For example, the Biden Administration enacted the Justice 40 Initiative, where 40% of Federal funding will improve the environment and access to clean energy innovations in disadvantaged communities (Shalanda Young et al., 2021).

It can be challenging for agencies to implement policies based on social equity goals as there needs to be a shared understanding of which variables will be used to define and determine disadvantaged populations. Several indices account for the disadvantaged characteristics of a population. Lyons and Choi (2021) use income and race only (Lyons and Choi, 2021). Several other scholars (Lyons and Choi, 2021; Guo et al., 2020b; Sider et al., 2015; Foth et al., 2013; Goodman et al., 2011) defined the social disadvantage index by the unemployment rate, immigration rate, housing accessibility, and income as variables. These were the variables used in this research.

Transit equity

A common confusion is that social equity means equality. However, two ways to look at equity are – horizontally and vertically. Horizontal equity is considered the fairness of cost and benefits allocated among individuals and groups comparable in wealth and ability. Vertical equity ensures that those who need more assistance have proportionate access accordingly (Foth et al., 2013).

Equity in transportation examines the barriers to access to transportation, such as socioeconomic status or physical limitations (Carter, 2021). The U.S. government has enacted policies to ensure that transportation industries account for equity in their decision-making. If it negatively impacts a disadvantaged area, then it is considered not to be equitable. Sometimes, making inequitable changes can limit a state or local agency’s access to federal funding (Lyons and Choi, 2021).

Transit equity is the accessibility and mobility of socially disadvantaged people to the public transit system. However, there is no standard transit equity definition, making it difficult to quantify and apply (Foth et al., 2013). For example, if automobile mobility is predominant in a region because of past population density and planning decisions, those with access to an automobile are in the majority and support more policies and spending to support the use of private vehicles. In this case, those without access to an automobile rely upon the transit system, which might not have the same systemic efficiencies found in infrastructure developed for private vehicles. In other communities with more density, financial support for transit might be more viable and supported by the local community. The equity considerations are, therefore, different, and one solution does not apply to all situations. Each agency must closely evaluate its service areas to find the most equitable solution.

Another way to consider equity in transit is by calculating the difference between regional supply and demand. Many agencies use ridership numbers to determine the service and frequency in an area. Equity adds to this by including population demographics in service adjustments. In this case, horizontal equity is the balance between population density and transportation service, and vertical equity is the balance between social needs and transit supply to each area (Manrique et al., 2020).

Transit equity and the pandemic

The pandemic helped recognize people and communities most in need of public transit (Palm et al., 2021). The pre-, during, and post-vaccination time of the pandemic provides an interesting space to further understand the implications of equity in the transit sector. As of the writing of this article, there is a lack of scholarly research to investigate the equity considerations for the decrease in transit services during the pandemic (Kar et al., 2022).

Pre-COVID-19, the percentage of disadvantaged people was high transit riders, which increased more during the early months of the pandemic (Paul and Taylor, 2022). Marginalized and disadvantaged people were affected the most by the services drop of transit agencies (Kar et al., 2022). Moreover, the decrease in transit use was the least amongst marginalized people during the pandemic due to inaccessibility to private transportation means and less adaptation to working from home (Kar et al., 2022). Nevertheless, while some of the impacts between marginalized neighborhoods' socioeconomic and race/ethnicity variables and transit use deteriorated as the pandemic advanced, many continued to be significant (Paul and Taylor, 2022). These changes are most likely to reflect the restrictions riders in disadvantaged communities face in adjusting to the new normal in transit services relative to those who are less disadvantaged (Paul and Taylor, 2022).

These changes in public transit services due to the pandemic significantly impacted disadvantaged communities in the short run and after the rollout of the vaccination (Abdoli and Hosseinzadeh, 2021).

Methods

Study area, data source, and time periods

The primary study area in this paper is the I.E., also called the "Inland Southern California" geographically. This area is one of the largest regions in the U.S., with two counties and 49 cities, covering more than 27,000 square miles. Three transit agencies were selected to analyze the public transportation services based on their service frequency, service area, and importance. Moreover, this research utilized two primary data sources: the U.S. Census Bureau data and the General Transit Feed Specification (GTFS) data (OpenMobilityData, 2022). The areas were divided by census tract GEOIDs, and a final total of 645 census tracts were included in the study.

Furthermore, the data selection was based on three main time periods, evaluating the availability of the three transit agencies' GTFS updated data feeds and matching periods. The below dates and labels were used for the model:

Period 1: Pre-COVID-19 – September 2019 to April 2020.

Period 2: During COVID-19 pre-vaccination – May 2020 to January 2021.

Period 3: Post-COVID-19 vaccination rollout – February 2021 to December 2021.

The reason for choosing these three different periods helps analyze the change in transit services through the pandemic. It will also elucidate the effect on the disadvantaged communities within the study area.

Transit service index

After identifying the dates, the area, and the data source, the first step in developing a transit equity index (TEI) was to calculate the transit service index (TSI). The TSI is a complex set of calculations that reflect the difference between the transit supply and the population needing these services. To perform this calculation, GTFS data and census data were utilized. Both datasets were imported to ArcGIS Pro, and the study was done at the census tract level. To calculate the TSI, the following **Eq. (1)** was used:

$$TSI_j = TS_k^{'} - TD_k^{'} \tag{1}$$

where TSI_j is the transit service index, $TS_k^{'}$ is the transit supply and $TD_k^{'}$ is the transit demand (O'Sullivan and Morrall, 1996; Jiang et al., 2012; Daniels and Mulley, 2013; Zhao and Deng, 2013; El-Geneidy et al., 2014; Li and "David" Fan, 2021).

Transit supply

The service area and available transit capacity were considered to determine the actual transit supply in a census tract k. The model was developed by several scholars O'Sullivan and Morrell, 1996; Jiang et al., 2012; Daniels and Mulley, 2013; Li and "David" Fan, 2021.

The calculation matrix consists of three **Eqs. (2),3,4** that are shown below:

$$TSC_k = \frac{RUC_k}{RUT_k} \tag{2}$$

$$D_k = \frac{\sum_i \frac{\sum_l F_l \times C_l \times RUC_{lik}}{RUC_k}}{P_k} \tag{3}$$

$$TS_k = TSC_k \times D_k \tag{4}$$

In **Eq. (2)**, TSC_k is the ratio covered by transit; RUC_k is the amount of housing units (not overlapping) accessible within 0.5 miles of all bus stops; and RUT_k is the amount of housing units. To calculate the TSC_k, the service area analysis tool was used in ArcGIS Pro. This tool was set on 0.5 mile – 86 m/s, equivalent to 10 min walking distance. **Eq. (3)** looks at the number of riders, the frequency of the routes, and the number of passengers' capacity compared to the population. Where for each route, D_k is maximum seats available per capita; F_l is the bus frequency; C_l is the average capacity per bus; RUC_{lik} is the number of housing units that can be reached within 0.5 miles of a route; RUC_k*is* the total housing units reached within 0.5 mi of each bus stop and P_k is the population. To calculate D_k, each of the variables was calculated individually and then used in the equation. The frequency was calculated for each route, and the bus capacity was set at 35 passengers, the average bus capacity according to the participating transit agencies. In **Eq. (4)**, TS_k is the transit supply was calculated by multiplying TSC_k and D_k.

Transit demand

For transit demand, the transit-dependent score is calculated by determining the amount of the population per census tract in the service area that would rely on public transit compared to the total population. The model below was adopted from several previous studies like Capital Area Transit Authority in Lansing, Michigan and Yang et al. (CATA (Capital Area Transit Authority), 2011; Li and "David" Fan, 2021). It considers the people eligible to rely on public transit compared to the number of vehicles available as a portion of the population. To calculate transit demand, a two-step **Eq. (5)** and **Eq. (6)** matrix was used, based on the below equations:

$$Driving-age\ population = (population\ age\ 15\ and\ over) - (people\ living\ in\ group\ quarters).$$

$$Transit-dependent\ household\ population = (driving\ age\ population) - (vehicles\ available).$$

$$TDP_k = (Transit - dependent\ household\ population) + (population\ age\ 10 - 14) + (noninstitutionalized\ population\ living\ in\ group\ quarters) \quad (5)$$

To calculate the transit demand within a census tract k, the following equation was used:

$$TD_k = \frac{TDP_k}{TTP_k} \quad (6)$$

where, TD_k is transit demand, TDP_k is transit-dependent population score and TTP_k is the total population within a census tract.

Socially disadvantaged index

A socially disadvantaged index (DAI) was developed to quantify the degree of disadvantage compared to advantage in terms of equity for a service area. This index used census tract-level data from the American Community Survey 2020 (ACS) developed by the U.S. Census Bureau. The ACS is a rolling five-year estimate of a nationwide survey of socio-economic data done yearly. This set of data was used as the decennial census had not been published at the time this research was done. For the DAI calculation, the following variables were obtained from the ACS 2020 (2016–2020):

- Median household income
- Unemployment rate
- Percentage of population that had immigrated within the last five years
- Percentage of households that spend over 30% of their income on rent

The DAI uses a balance of social and material indicators to account for both factors equally. The social indicators are unemployment and immigration, and the material indicators are income and housing affordability. The Z-score of the unemployment rate, immigration rate, and 30% income on rent are added together. For each indicator, the higher the number, the more disadvantaged. Then the Z-score of median income is subtracted because the lower the income, the more disadvantaged using the following **Eq. (7)**:

$$DAI = Z_{unemploymentrate} + Z_{immigrationrate} + Z_{30\%ofincomeonrent} - Z_{medianincome} \quad (7)$$

Once the calculation was complete for each census tract, the data was cleaned by removing any zones with insufficient data or with a population below 1.

Race index

The race index is based on individual census tracts and population distribution. The U.S. literature and the census data have standard race and ethnicity categories used in every demographic analysis. For this research, the race index is a simple calculation represented in the **Eq. (8)** below:

$$RI = \frac{PW}{TP} \quad (8)$$

where RI is the race index, PW is white/Caucasian, and TP is the total population within a census tract. The following index was mentioned in several U.S. studies to analyze disadvantaged populations within a census tract or a census block or any area (Lyons and Choi, 2021; Guo et al., 2020a).

Data normalization and outliers

The data normalization method was utilized to normalize transit supply and demand before calculating the transit service index. In addition, the disadvantaged index and the race index were also normalized using the following **Eq. (9)**:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (9)$$

where X' is the new index value, X is the old index value, X_{max} is the maximum value within the dataset of the variable, and X_{min} is the minimum value. This calculation will enable the regression analysis, representing the data on the same scale (Abebe et al., 2022; Li and "David" Fan, 2021).

The next step was detecting and eliminating outliers within the datasets. All missing values were excluded. Their existence was caused by missing census data for a particular census tract. Additionally, a Skewness and Kurtosis calculation was done for each variable in all periods to detect skewed data. Finally, Mahalanobis distance (Jasińska and Preweda, 2021) was used to detect outliers based on the **Eq. (10)** below:

$$MD^2 = \left(x - \underline{x}\right)^T . (x) . \left(x - \underline{x}\right) \quad (10)$$

Where MD^2 is the square of Mahalanobis Distance, x is the observation vector, $\underline{x}$ is the arithmetic mean values of I.V.s, and Cov^{-1} is the inverse covariance matrix of IV.

As a result, the original dataset was composed of 873 census tracts covered by the three transit agencies selected for the study; the final sample out of the 873 census tracts was 645. These calculations were run on RStudio version 4.1.3 (Murphy and Murphy, 2020).

Performance matrix

Several studies are available in today's literature discussing transit services and equity. Few academic papers discuss transit services and disadvantaged people, meaning the present and future status. Moreover, a study published in 2018 discussed transit equity from a financial perspective utilizing equity index and regression modeling to assess governmental budgeting for transit services (Hudspeth and Wellman, 2018). However, no academic research has previously related the transit service index to the disadvantaged one. Hence, this research used an inductive method to hypothesize transit equity.

Multiple Linear Regression (MLR) is a statistical matrix with a simple build of variables that analyzes factors and their performance within a unique set. MLR is utilized to define and analyze the relationship between two or more independent variables. In this case, the disadvantaged index acts as the dependent variable, whereas the transit service index and race index act as the independent variables. In general, the MLR variable relationships are represented in the below **Eq. (11)**:

$$y = b_0 + b_1.x_1 + b_2.x_2 + e \quad (11)$$

where y is the dependent variable, x_1 and x_2 are the independent variables, b_0 is the intercept, or the constant coefficient, and e is the residual.

To analyze the performance of the regression model, several indicators were calculated: collinearity, R-square, F and T statistics, Accuracy, root mean squared error (RMSE) and mean absolute error (MAE).

Results

Indices

An integral part of computing the TEI was calculating the TSI, DAI, and R.I. for the three time periods mentioned in the methods P1, P2, and P3. The figures below reflect a snapshot of these calculations:

In Fig. 1, the TSI measures the difference between supply and demand for transit services in each census tract. A negative value indicates

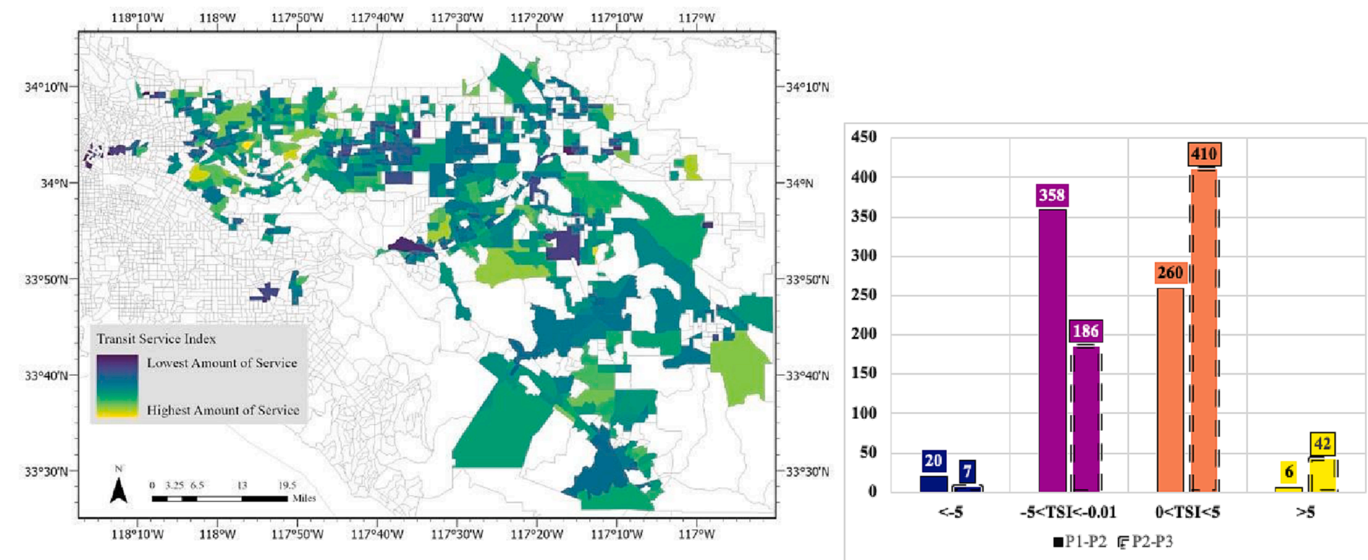

Fig. 1. The map shows the percentage change P1-P2 for TSI; the histogram shows the percentage change of the three time-periods.

that the demand exceeds the supply, whereas a positive value indicates that the supply exceeds the demand. The histogram above shows the difference in service for the entire service area of the Inland Empire by census tract. In addition, the data showed that the most significant percentage change was between P2 and P3, where the positive values were 410.

While in Fig. 2, the DAI illustrates the advantaged level of populations across the Inland Empire by census tract, census tracts toward the edge of the transit service area tend to be more advantaged, while census tracts closer to the central areas of the transit service area tend to be less advantaged. The most significant percentage change is between P2 and P3, where the positive values of the percentage change were 482.

The map of R.I. (**Fig. 3**) shows the difference in race by census tract across the transit service area of the Inland Empire. The more central areas of the Inland Empire have a lower ratio of white people, as seen by the darker purple color, compared to the outskirts of the transit service area, as seen in yellow.

Transit equity

In this study, DAI served as the dependent variable (DV), and TSI and R.I. served as the independent variables (IV). These variables were calculated based on three time periods mentioned in the methodology section. Below are the preliminary results of the relationship between the DV and I.V.s:

Table 1 shows that the data studied is quantitative continuous, where the values of the variable DAI belong to the interval [-1,0], TSI and R.I. values belong to the interval [0,1], with a standard deviation of 0.15 ± 0.046. The above table also shows the descriptive statistics of the three variables used in the model related to the three-time periods, where there is a strong negative correlation between DAI and TSI and between DAI and R.I., whereas the positive correlation between TSI and R.I. is weak.

The VFI for the variables TSI and R.I. is close to 1, implying that there is no multicollinearity between the independent variables of this model. In addition, the tolerance for both variables is greater than 0.70, which illustrates the previous result. The mean absolute deviation (MAD) is

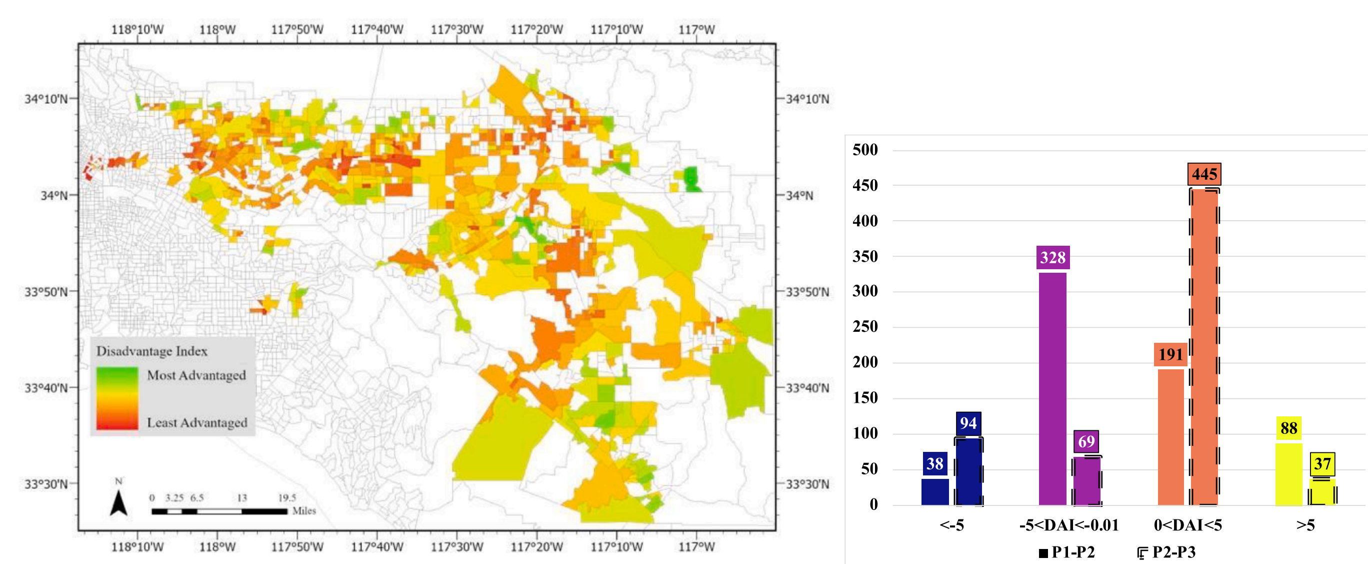

Fig. 2. The map shows the percentage change P1-P2 for DAI; the histogram shows the percentage change of the three time-periods.

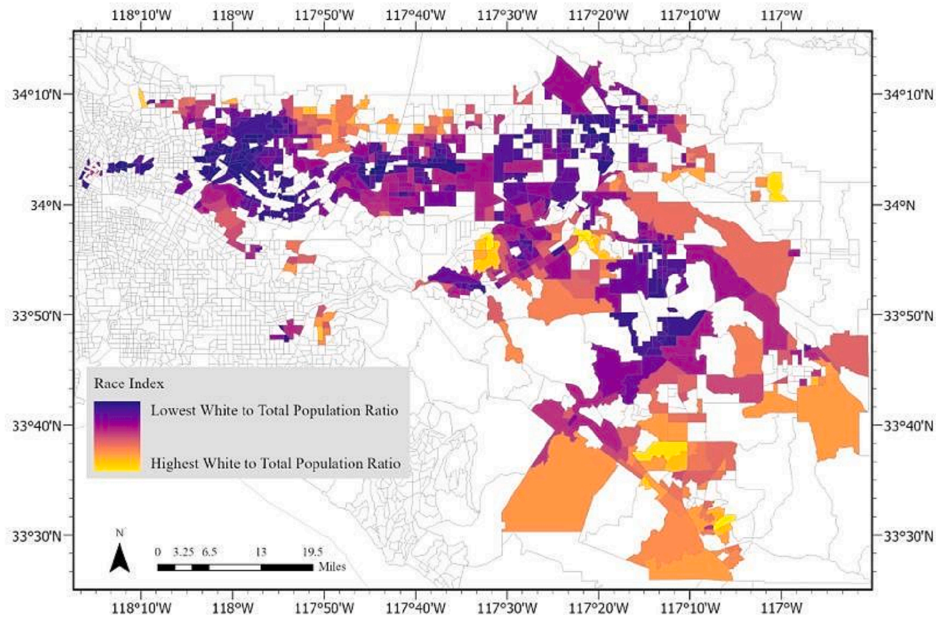

Fig. 3. A map snapshot for R.I.

low for the three variables showing the absence of spread of the data. The root mean squared error of the dependent variable DAI compared with TEI (the predicted variable) is almost equal to zero, illustrating the strong relation of the predictor variables.

The next step was to run the model fit. This step is essential to understand the effect of IV, meaning TSI and R.I., on the DAI. The table below shows the model fit for the three different periods:

Table 2 points out how well the regression model can fit the dataset. First, the coefficient of determination R^2 is greater than 0.7 for the three periods mentioned above, which indicates that the predictor variables can explain the proportion of the variance in DAI. For instance, the year P1, TSI, and the Race Index can define 73.3% of the variance in the DAI index. Second, the fisher statistic results that show the dispersal of the data points around the mean are much greater than the critical value, implying that the regression model is well-fitted with a significance level of almost zero. Finally, the standard error, the average distance that the observed values fall from the regression line, is small enough.

After verifying the coefficient of determination R^2 and the model fit of the data, MLR analysis was run on R-square to get the coefficients for the I.V.s and the p-values. The table below shows the MLR analysis results:

In Table 3, the coefficient estimates of the two independent variables, TSI and R.I., are negative, expressing the inverse relation between them and DAI. However, the estimates for P1 are greater than those of P3, which are greater than that of P2. Thus, the relation between DAI on the one hand and TSI and R.I. on the other was the strongest for P1. Furthermore, the standardized standard error that measures the uncertainty around these estimated coefficients is 0.02, which is small enough to conclude that the coefficients are significant. The table also represents the 95% confidence interval for each of the estimated coefficients, where the margin of error for all these intervals does not exceed ± 0.05. Lastly, performing a two-tailed test on the coefficient estimates, where H_0 is defined as the coefficient is equal to zero, and the alternative hypothesis is that the coefficient is not equal to zero. For instance, considering the coefficient of TSI, the absolute value of the hypothesis test statistic is 18.35, which is greater than 3.3, the critical value extracted from the T-statistic table with a degree of freedom of 645. Hence, the null hypothesis is rejected, implying that all the estimates are not equal to zero, with a significance level of 99.999%. These results are plotted below:

The graphs in Fig. 4 are extracted from a 3D plot, where the three variables of the model are represented. All three charts look similar, where the variables TSI and R.I. affect DAI in the opposite direction. Thus, the data distribution illustrates the inverse relationship between DAI and the two predictor variables, TSI and R.I. Hence, as the values of TSI and R.I. increase from -0.8 to -0.2 and from 0 to 0.8, the DAI values decrease from 0.8 to 0. This implies that as effect of these variables on the DAI can and racial disparities are reduced, the overall social disadvantage (DAI) may decrease.

Finally, The transit equity index was formed to comprehend the relationship between transit services, race, and disadvantaged populations. It is a new method that can help analyze the regional stance on transit equity. This index shows the relationship between a disadvantaged index, transit service index, and a race index. This approach allows for a more comprehensive analysis of public transportation equity at the regional level. Prior to COVID-19 these variables had a negative effect on disadvantaged populations; this effect decreased during the pandemic and increased again after the distribution of vaccines. The results are reflected in the maps below:

The two maps in Fig. 5 illustrate the percentage of change in the transit equity index between the periods indicated. A negative percent change indicates a decrease in equity between two time periods, and a positive percent change indicates an increase in transit equity. P1 to P2 had a general increase in equity across the entire Inland Empire region, whereas P2 to P3 decreased in most regions. The transit equity index percent change determines a significant positive equity impact moving from P1 to P2., especially in the northeast and southeast parts of the Inland Empire. However, moving from P2 to P3, transit equity changes reflected in blue and dark purple showing a decrease in equity with the “return to normal”.

Discussion

Equity implications of shifts in transit services during the pandemic

During the pandemic, shifts and cutoffs in transit services had a substantial influence on local communities and equity implications in many U.S. metropolitan areas (Kar et al., 2022). Essential workers who needed to be onsite came predominantly from lower-income, racial, and ethnic minority groups. These individuals are disproportionately employed in industries such as healthcare, transportation, and food

Table 1
Correlation Analysis Between Three Indices, Descriptive Statistics, Collinearity, and Error Estimates.

P	Est.	Correlation			Descriptive Statistics						Collinearity		Error	
		DAI	TSI	RI	n	Min.	Max.	Mean	Median	S.D.	Tolerance	VIF	RMSE	MAD
1	DAI	1			645	0.0746	0.8339	0.4949	0.4981	0.1296	n/a	n/a	0.0669	0.132
	TSI	−0.6179	1			−0.8963	−0.1709	−0.5204	−0.5096	0.1262	0.879	1.136	n/a	0.117
	RI	−0.7701	0.3467	1		0.0000	0.8156	0.2694	0.2217	0.1961	0.879	1.136	n/a	0.200
2	DAI	1			645	0.1005	0.8073	0.4946	0.4987	0.1209	n/a	n/a	0.0656	0.120
	TSI	−0.6130	1			−0.8978	−0.1287	−0.5170	−0.5079	0.1267	0.886	1.128	n/a	0.119
	RI	−0.7475	0.3375	1		0.0000	0.8156	0.2694	0.2217	0.1961	0.886	1.128	n/a	0.200
3	DAI	1			645	0.0598	0.8101	0.4902	0.4975	0.1280	n/a	n/a	0.0673	0.128
	TSI	−0.6124	1			−0.9126	−0.1539	−0.5219	−0.5111	0.1267	0.888	1.126	n/a	0.121
	RI	−0.7612	0.3345	1		0.0000	0.8156	0.2694	0.2217	0.1961	0.888	1.126	n/a	0.200

service, which require physical presence and, thus, the continued use of public transit (Mack et al., 2021).

In the Inland Empire, the results of the study show that these modifications were more in favor of the disadvantaged population during the pandemic. Communities with higher unemployment rates, lower median income, a high number of immigrants, and high rent-to-income ratios were better served by transit agencies in the region. These results indicated that transit agencies serving the Inland Empire were proactive in their decisions and their shifts in services made due to the pandemic. However, after the rollout of vaccinations and return to normal operations, they readopted the original routes with little to no change leading to a decrease in transit equity. This return to normal is alarming, as its persistence may put the significance of transit systems at risk.

In relation to racial equity, the pandemic further highlighted the societal fissures along racial and socioeconomic lines. The Inland Empire has a racially diverse population. People of color, mainly Black and Hispanic populations, are less likely to have jobs that allow them to work from home. These demographic groups continued to rely heavily on public transit systems, which have often been under-resourced in serving these communities, even before the pandemic (Paul & Taylor, 2022).For many white-collar professionals and those in roles that can be easily done remotely, the pandemic brought an abrupt but manageable shift to digital workers. Technology provided the means to continue performing tasks from home, limiting exposure to the virus and maintaining income stability. This sudden shift immediately reduced transit demand and caused a parallel revenue fall.

The racial disparities in transportation access, with minority and disadvantaged communities disproportionately reliant on public transit (bus and rail) and less likely to have access to personal vehicles. Therefore, when health risks associated with public transit rose during the pandemic, these communities were left particularly vulnerable.

Policy implications

The study presented in this paper has important implications for equity issues and the recovery of public transit, which has been a social stabilizer traditionally. Post COVID-19 vaccinations rollout, the return to normal for transit services led to a decrease in service for those living in marginalized areas, leading to continued negative consequences on disadvantaged communities. Hence, policies adopted during COVID-19 could be strengthened and applied more widely to promote transit equity. More government funding and priority is needed for transit agencies. Additionally, updates to planning policies to improve the built environment in affected communities, thereby reducing urban sprawl and improving local mobility.

This study shows the benefits of additional funds from the US federal government as service improved with funding for transit agencies' operation costs through COVID-19 relief packages, federal aid focusing on infrastructure and maintenance costs (Rothengatter et al., 2021). Short-term funding efforts should be expanded in the long run to enable the restoration, enhancement, and operational efficiency of transit services. Additionally, transit agencies should prioritize people with critical mobility disadvantages while restoring transit service post-lockdown.

Our results showed that during the pandemic, most disadvantaged areas had improved level of service. As these communities are more transit dependent, the results were improved social equity. Moreover, the race factor enhanced the model and showed the real impact of racial distribution vs. disadvantaged index within the region and its impact on the transit service index, highlighting a more equitable transit service during COVID-19.

Restructuring the transportation system should be done alongside reconfiguring land use patterns. In I.E., cities should use the opportunity presented by the COVID-19 disruption to rethink and redesign urban areas in more resilient ways, which may include updating zoning ordinances to allow mixed land use, removing minimum parking

Table 2
Model Fit.

	Model Fit				
P1 Regression	R^2	Adjusted R^2	F-Statistic	p-value	Residual Standard Error
value	0.733	0.7322	881.4	$2.2{*}e^{-16} \sim 0$	0.067
df			2 and 642		642
P2 Regression					
value	0.7056	0.7047	769.4	$2.2{*}e^{-16} \sim 0$	0.065
df			2 and 642		642
P3 Regression					
value	0.7235	0.7227	840	$2.2{*}e^{-16} \sim 0$	0.067
df			2 and 642		642

Table 3
Multiple Linear Regression Results Summary of Transit Equity.

	DAI P1							
Predictors	Estimates	std. Error	std. Beta	standardized std. Error	CI	standardized CI	T-Statistic	p-value
(Intercept)	0.394	0.014	0	0.02	0.37 – 0.42	−0.04 – 0.04	28.74	<0.001
TSI P1	−0.409	0.022	−0.40	0.02	−0.45 – -0.37	−0.44 – -0.36	−18.35	<0.001
RI P1	−0.417	0.014	−0.63	0.02	−0.45 – -0.39	−0.67 – -0.59	−29.06	<0.001
	DAI P2							
Predictors	Estimates	std. Error	std. Beta	standardized std. Error	CI	standardized CI	T-Statistic	p-value
(Intercept)	0.395	0.013	0	0.02	0.37 – 0.42	−0.04 – 0.04	29.82	<0.001
TSI P2	−0.388	0.022	−0.41	0.02	−0.43 – -0.35	−0.45 – -0.36	−17.90	<0.001
RI P2	−0.376	0.014	−0.61	0.02	−0.40 – -0.35	−0.65 – -0.57	−26.82	<0.001
	DAI P3							
Predictors	Estimates	std. Error	std. Beta	standardized std. Error	CI	standardized CI	T-Statistic	p-value
(Intercept)	0.389	0.014	0	0.02	0.36 – 0.42	−0.04 – 0.04	28.73	<0.001
TSI P3	−0.403	0.022	−0.40	0.02	−0.45 – -0.36	−0.45 – -0.36	−18.30	<0.001
RI P3	−0.409	0.014	−0.63	0.02	−0.44 – -0.38	−0.67 – -0.58	−28.45	<0.001

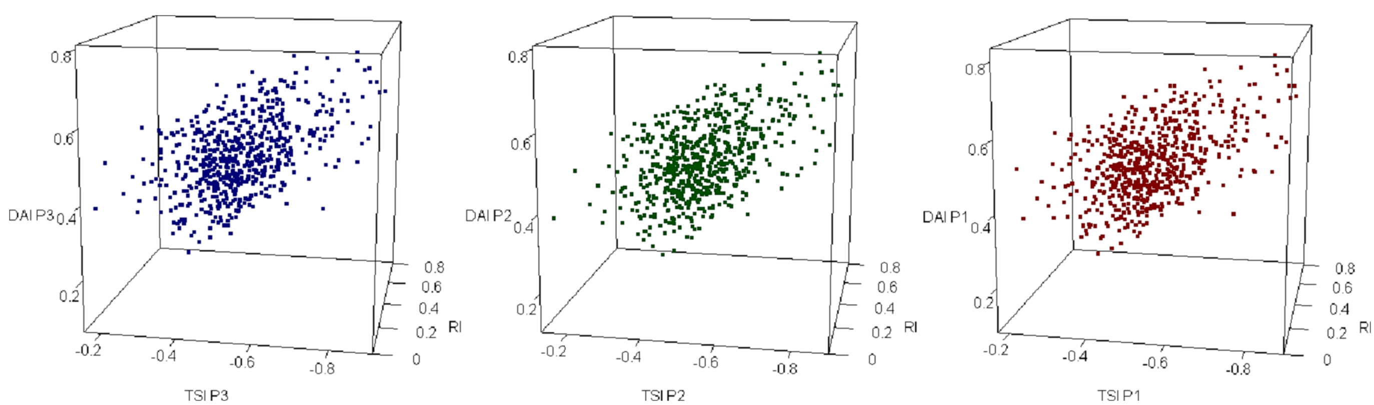

Fig. 4. MLR summary for three time periods: P1, P2, and P3 respectively.

requirements, and supporting public transportation infrastructure.

To improve mobility and access in the Inland Empire, transit agencies must revise their planning policies to best fit the needs of the disadvantaged communities. Transit-oriented development and urban densification should also be promoted, although policies need to be in place to reduce the impacts of gentrification. In addition, alternative modes like biking and walking has been brought into sharper focus. However, the existing infrastructure supporting these modalities often needs to improve in the communities that need them the most. This presents an urgent call for policy interventions, from enhancing pedestrian and cycling infrastructure to providing secure bike storage facilities in these communities (Suraci, 2022).

Conclusions

During the pandemic and before the vaccination rollout, transit equity was at its peak, meaning that transit agencies had adjusted their services and directed attention toward the underserved. Most of these people were essential workers that served residents and worked hard to bypass the hardship of COVID-19. This adjustment is a critical piece of information proving that "there is always room for improvement."

The change in service equity in transit during the COVID-19 pandemic is related to the use of public resources. The level of riders in many of the non-disadvantaged communities decreased with the lockdowns during the early part of the pandemic. Those who were part of the nonessential workforce stopped traveling for work. The allocated resources for these riders were transferred to the disadvantaged sectors, as most of the bus riders in these zones were part of the essential workforce that still needed to travel to work. After vaccinations against the virus were released, bus routes almost returned to the pre-pandemic system. Thus, we see a return to inequities in the service level based on the definition of equity providing more services to those in need and not equality through the system, with all areas receiving the same amount of service.

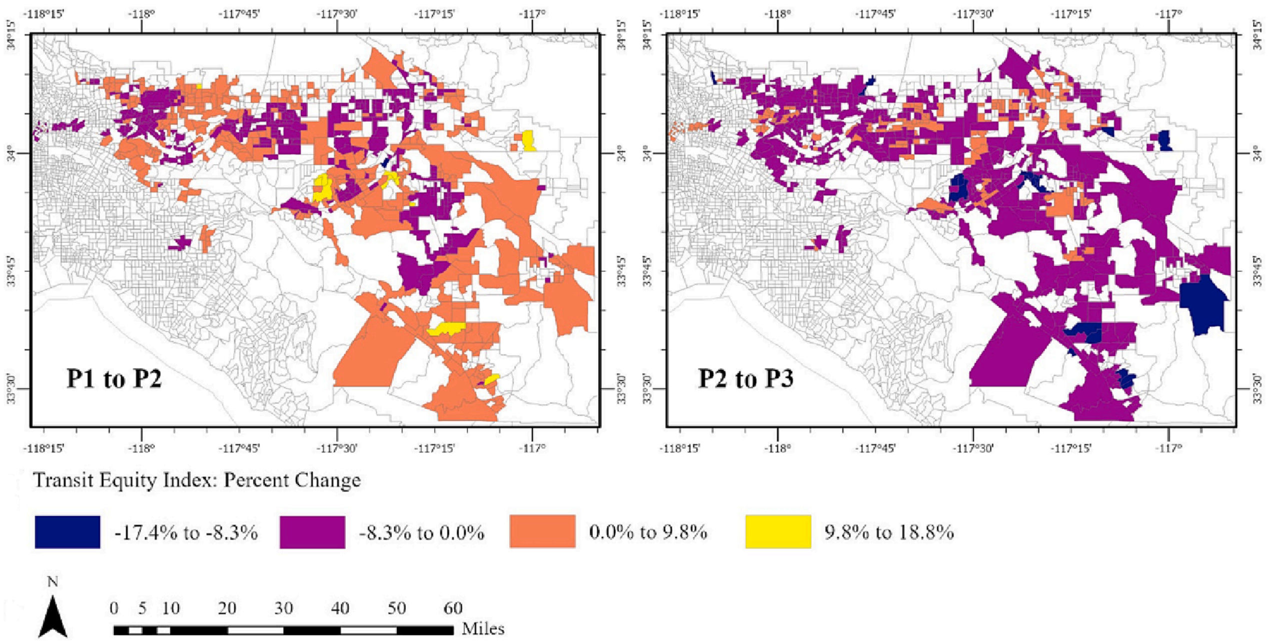

Fig. 5. Transit equity percent change between the three time periods: P1-P2-P3.

This data-driven approach allows for a nuanced understanding of how improved transit services and the reduction of racial disparities can influence the level of social disadvantage, paving the way for the formation of more equitable and sustainable suburban and rural environments.

Long-term policy amendments and equity considerations are required. The focus of these adaptations should be the continuity of enhanced transit equity, which saw an ephemeral rise during the pandemic. Recommendations include sustained public transit investment, which is crucial in the post-pandemic era to improve the quality and reach of services for marginalized communities. Governments should allocate more funding to transit agencies, particularly for underserved areas. Additionally, transit routes should be reformulated for equitable resource distribution, informed by insights from the pandemic.

Emphasis should also be placed on transit-oriented development to foster equitable access to opportunities and tackle issues such as urban sprawl. Active transportation infrastructure warrants enhancement, underscored by the increased usage of walking and biking during the pandemic. While these strategies may induce gentrification, measures such as affordable housing mandates and community benefits agreements should counteract potential negative impacts.

Additional recommendations include integrating transportation and land-use policies and investment in workforce development for transit agencies. These measures can ensure high-quality public transit in high-density areas and maintain a skilled workforce respectively.

These could include, but are not limited to, the enhancement of pedestrian walkways, the creation of safe cycling networks, the establishment of efficient micro-transit services, and the formation of partnerships with ride-hailing platforms. By addressing these facets, rural and suburban areas can be redesigned to be more resilient, adaptable, and equitable, ultimately fostering a more inclusive urban environment.

Moving forward, community leaders, local, state, and federal government agencies must work together to improve the quality of life for those living in the I.E. The model helps understand why the prioritization of transit services in the region is vital to improving quality of life. Transit is and will always be crucial to boost the economy, help people access work, and improve their quality of life. Therefore, the resilience of the transit system needs to be methodically and administratively reinforced by reallocation of resources, updates on policies and procedures, workforce development, coordination on all governmental levels, and planning a sustainable transit system for the future.

Some limitations exist in the research: the sample size, and the number of variables that reflect social equity. However, this is considered an opportunity for future research. Other variables might be included in analyzing transit equity, including land use, population density, and a more detailed calculation of transit demand capturing potential riders. In addition, a smaller geographical level might be utilized, i.e., census block group or census block, to run the same analysis and find out how this model might change.

For the future, the effect of TSI and RI on the DAI can inform strategies to tackle first-and-last-mile problems, and the TSI improvements might involve introducing micro-transit solutions or partnering with ride-hailing services to address areas with limited access. In addition, incorporating these indices into urban planning and engineering can facilitate the development of infrastructures that are more responsive to the needs of socially disadvantaged populations, thus promoting social resilience.

Credit authorship contribution statement

Kimberly Collins: Conceptualization, Funding acquisition, Formal analysis, Project administration. **Raffi Der Wartanian:** Conceptualization, Data curation, Formal analysis, Methodology, Review & editing. **Preston Reed:** Data curation, Visualization. **Holly Chea:** Data curation, Visualization. **Yunfei Hou:** Investigation, Supervision, Validation. **Yongping Zhang:** Investigation, Supervision, Validation, Review & editing.

Funding

We express our heartfelt gratitude to the William and Barbara Leonard Family for their generous support and contribution, which has been indispensable to the completion of this research.

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.

Data availability

Data will be made available upon request.

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