

**Methods for Analyzing Transit Accessibility and Equity:
Case Studies from Tennessee**

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Degree
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**Jing Guo
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DEDICATION

This dissertation is dedicated to my fiancé Yuetan Ma, my parents, Zhibing Guo, Fengjiao Gong, my lovely sister Xiyao Guo, and my family for all their endless love and support.

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ABSTRACT

Providing transit service to access job opportunities and essential services is critical for participating in the economy, promoting health, and enhancing the overall quality of life, particularly for populations residing in low income communities and those lacking personal vehicles. Therefore, the main objective of this dissertation is to evaluate transit equity by analyzing transit supply to access job opportunities and essential services for different segments of the population that may rely on transit. This dissertation considers both fixed route transit in urban and suburban areas, as well as demand-response transit (DRT) in rural regions.

This dissertation contains three studies, all employing case studies in the state of Tennessee (TN). The first study aims to evaluate the equity of transit accessibility for people living in affordable housing units in Nashville, Memphis, and Chattanooga, TN. The results show that the transit equity of affordable housing units can vary across different housing programs as well as across different cities within a state. The second study aims to evaluate the equity of transit accessibility to different essential services for three transit-dependent groups (i.e., those in poverty, minorities, and car-limited populations) in Nashville, TN. The results show that transit accessibility to healthcare has the greatest level of inequity. The spatial analysis identifies areas of concern with limited transit accessibility to essential services, which are named *essential service deserts*. The third study aims to evaluate DRT trip patterns and the relationship between DRT trip demand and DRT accessibility to essential destinations using real-world DRT trip data from the rural city of Morristown, TN. The results reveal that women take more DRT trips than men, and the elderly tend to take more healthcare-related DRT trips and make shorter DRT trips. The spatial analysis identifies areas of concern with higher DRT trip demand and limited DRT accessibility, which are referred to as *essential destination deserts*.

The proposed methods are applicable to transit systems in other U.S. cities with comparable contexts and data. Moreover, the results have important implications for transit planners and policymakers, providing insights that can assist in resource allocation and decision-making in transportation planning.

Key words: Transit accessibility, transit equity, transit demand, affordable housing, transit deserts, demand response transit

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CHAPTER 1.
INTRODUCTION

1.1 Problem statement

There is a growing body of research investigating transit accessibility, which refers to the capacity of individuals to reach various destinations using public transportation (El-Geneidy et al., 2016b; Owen & Murphy, 2020a; Stewart, 2017; Welch, 2013; Yan et al., 2022). Providing transit services to access job opportunities and essential services is critical for participating in the economy, promoting health, and enhancing overall quality of life, particularly for populations residing in low income communities and those lacking personal vehicles (Brondeel et al., 2014; Jin et al., 2022; Mao & Nekorchuk, 2013; Martens et al., 2019; National Academies of Sciences Engineering and Medicine, 2022b; Taylor & Morris, 2014; USDA, 2023; Walker et al., 2010; Wood & Horner, 2016; Zhang & Mao, 2019; Zhang et al., 2022). The assessment of transit equity, which examines the geographical distribution of transit services and the provision of transit services to populations with the highest transit needs, has recently gained attention in the transit literature (Aman & Smith-Colin, 2020) and has emerged as an important aspect of the discourse on Environmental Justice for low-income and minority populations (FTA, 2012). Despite the growing body of research on transit accessibility and transit equity, there are still significant gaps that need additional attention and further investigation.

First, limited research has considered the transit accessibility of affordable housing units. In the U.S., some supply-side affordable housing programs are administered by the federal government, such as Low Income Housing Tax Credits (LIHTC), subsidized Multifamily Housing properties, and public housing. The overall purpose of such housing programs is to make rent more affordable for low income households. However, affordable housing units are sometimes planned without considering transit accessibility as an evaluation criterion, which is partly due to the absence of federal requirements for planning affordable housing as well as the lack of coordination of housing authorities with transit agencies (National Academies of Sciences Engineering and Medicine, 2022b). Furthermore, a recent study from the Transit Cooperative Research Program (TCRP) concluded that many transit agencies often do not specifically prioritize serving neighborhoods with high levels of affordable housing in their transit planning process (Chapple & Loukaitou-Sideris, 2019; National Academies of Sciences Engineering and Medicine, 2022b). Prior studies suggest that there is a need to develop systematic practical guidance and effective approaches that can be implemented by transit agencies and housing authorities to promote the coordination of transit services with affordable housing (Chapple & Loukaitou-Sideris, 2019;

National Academies of Sciences Engineering and Medicine, 2022b). However, housing construction, especially large apartment complexes, and fixed rail transit (such as subway and light rail) are durable and permanent infrastructure investments; bus routes are considerably more adaptable and can be (relatively) easily modified to improve transit accessibility. Therefore, modifications to local bus routes that can be implemented in the short term (e.g., within a few weeks or a few months) provide an important first step to potentially increase transit accessibility for existing affordable housing residents in underserved areas. Accordingly, systematic methods need to be developed to compare the transit equity of existing affordable housing units and to evaluate potential short-term bus service modifications that could increase transit access levels.

Second, prior research on transit accessibility has primarily focused on job access (Hess, 2005; Karner, 2018; Kawabata & Shen, 2006; Yan et al., 2022). The prior literature has paid limited attention to the accessibility of essential services, which also play a critical role in improving the quality of life in local communities. Some travelers use transit to get to essential services such as food stores, healthcare facilities, schools, childcare services, and green spaces. Ensuring equitable access to these essential services should be a consideration for transit planners and stakeholders. Therefore, systematic methods are needed to evaluate transit equity of accessibility to essential services and identify “essential service deserts” characterized by high transit demand and limited transit accessibility.

Last, Demand Response Transit (DRT) services play a crucial part in supporting rural transportation, especially for individuals without private vehicle access. However, prior research has primarily concentrated on assessing the accessibility of fixed-route transit within densely populated urban areas. The limited exploration of DRT in the prior literature can be partly attributed to the unavailability of standard data comparable to the General Transit Feed Specification (GTFS) for fixed-route transit (Transit, 2023). However, the lack of a widely used data standard for DRT, along with other differences, has resulted in a gap in the literature evaluating the accessibility of DRT services. Therefore, methods are needed to evaluate DRT usage and DRT accessibility using other possible datasets, particularly actual DRT trip data, which directly reflects trip demand and is commonly available in a similar format across the DRT system in U.S. rural areas.

1.2 Research objectives and contributions

The main goal of this dissertation is to evaluate transit equity based on the relationship between transit demand and transit supply to access job opportunities and essential services. The specific objectives are to develop methods that:

- Evaluate transit accessibility and equity to jobs from affordable housing units and propose practical short-term transit service modifications for underserved locations.
- Analyze transit accessibility and equity to essential services for transit-dependent populations, including those in poverty, minorities, and car-limited populations, and identify “essential service deserts”.
- Assess rural transit accessibility using DRT trip distance, analyze age and gender differences in DRT travel patterns, and identify potential “essential destination deserts”.

1.3 Methodological framework

Figure 1 shows the framework of this dissertation. The left side of the figure shows the transit demand groups and data sources considered in the three studies, which each uses distinct data sources to quantify potential transit needs. In prior research, the evaluation of transit demand commonly involved two perspectives: potential demand, which identifies individuals who are likely to use public transit as primary transportation mode, and actual demand, derived from historical transit ridership data (Deepa et al., 2022; Yao, 2007). This dissertation considers both potential transit demand groups and actual demand. In the first study, affordable housing size and location data are used to represent the potential transit needs of low income residents. In the second study, Census data is used to identify those living in poverty, minority populations, and car-limited populations, offering insights into the potential transit demand within the region. The third study estimates transit demand directly from the real-world trip data taken by DRT users in the study area, as these trips inherently reflect the DRT needs of the population.

The right side of **Figure 1** shows the transit supply measures, objectives, and data sources. Two accessibility approaches are included in this dissertation: potential accessibility and actual accessibility. Calculating potential accessibility requires making assumptions about travel behavior, such as travel thresholds or preferences for destinations. This approach is often used in situations where there is no reference to actual travel behavior (Niedzielski & Boschmann, 2014). Actual accessibility, on the other hand, is measured by the actual travel distance or travel time

directly (Niedzielski & Boschmann, 2014). In the fixed-route transit context, this dissertation quantifies two aspects of potential accessibility: (1) the number of job opportunities reachable under specific thresholds (e.g., within an hour), and (2) the travel time to access the closest service facility, with the assumption that individuals prioritize proximity. For DRT, actual accessibility is quantified without presuming specific travel behavior and instead relying on recorded travel distances to reach actual trip destinations.

The middle of **Figure 1** shows the methods used to evaluate transit equity. Various statistical and spatial methods are used to quantify the differences between transit demand and transit supply to access job opportunities and essential services. In Chapter 2, the Lorenz curve and Gini coefficient are used to evaluate transit equity of affordable housing programs at the city level. Within each city, a simple inequity index is proposed to identify specific affordable housing locations with inequitable transit services to access job opportunities. The study presented in Chapter 3 employs the Theil index to estimate the spatial inequity associated with transit supply to access essential services and LISA clustering to identify essential service deserts characterized by low transit supply and high potential transit-dependent demand. In Chapter 4, the Chi-Square test and logit regression analysis are used to statistically analyze gender and age differences in the travel patterns of DRT, and a quadrant classification is employed to spatially analyze the relationship between DRT trip demand and DRT accessibility to identify potential essential destination deserts in a rural setting.

1.4 Dissertation structure

This dissertation is structured in a multi-chapter format. This work is divided into five chapters, as follows:

- Chapter 1 defines the problem, research objectives and contributions, methodological framework, and outline of this dissertation.
- Chapter 2 describes the method for analyzing transit access to jobs from affordable housing units and evaluating short-term transit modifications.
- Chapter 3 analyzes the spatiotemporal transit access to multiple essential services for transit-dependent populations and identifies “essential service deserts”.
- Chapter 4 explores gender and age differences in DRT travel patterns, assesses DRT accessibility, and identifies potential “essential destination deserts”.

- Chapter 5 concludes the findings and limitations of this work and provides recommendations for future research.

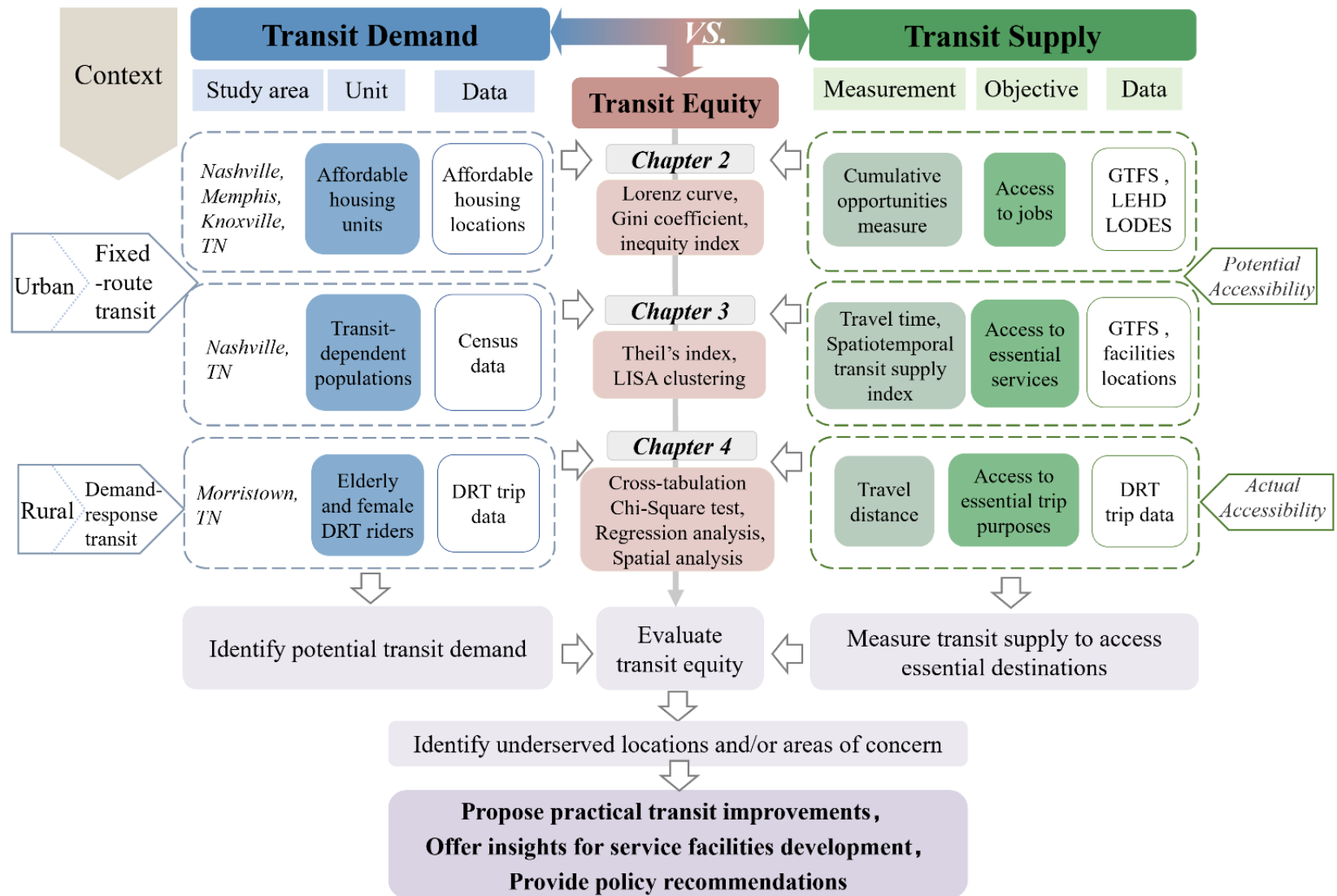


Figure 1 Framework of the dissertation

CHAPTER 2.
EVALUATING TRANSIT ACCESSIBILITY AND EQUITY FOR
AFFORDABLE HOUSING UNITS

A version of this chapter was originally published by Jing Guo, Candace Brakewood, Ashley Hightower, and Christopher Cherry: "Evaluating Equity: A Method for Analyzing the Transit Accessibility of Affordable Housing Units." *Transportation Research Record* (2023). The paper was presented at the Transportation Research Board 102nd Annual Meeting 2023 in Washington, D.C. This research paper also received first place in the 2023 Annual Technical Paper Competition, Southern District Institute of Transportation Engineers, and second place in the 2023 Annual Student Paper Competition, Tennessee Section Institute of Transportation Engineers.

Abstract

Improving transit access for people in low income communities is an important consideration for transit providers. However, limited research has considered the transit accessibility of affordable housing units. This paper aims to develop a method to evaluate transit equity of existing affordable housing units and propose easy-to-implement modifications to local bus service to increase transit accessibility levels (assuming housing locations do not change in the short term). The proposed method has three steps, and it is applied to three Tennessee cities with primarily bus-based transit systems. The first step measures transit accessibility of specific affordable housing locations and citywide transit accessibility levels using a web-based platform built on open-source software. The second step evaluates the transit equity of affordable housing programs at the city level using Lorenz curves and Gini coefficients and evaluates the transit equity of specific affordable housing locations by proposing a simple inequity index. The results reveal that the level of transit equity for affordable housing units differs across housing programs and cities. In the third step, an example of a bus service modification is evaluated for one affordable housing location with a high inequity index to demonstrate the applicability of the method. The substantial increase in accessible jobs after modification, from 135 to 6,400, highlights the potential effectiveness of implementing short-term transit service changes to improve the accessibility of existing affordable housing locations. This three-step method primarily relies on open datasets that are also available for other regions of the United States.

2.1 Introduction

Prior research suggests that low income people who cannot afford a personal vehicle rely on public transit for their transportation needs (Martens et al., 2019; National Academies of Sciences Engineering and Medicine, 2022b; Taylor & Morris, 2014). Many American cities are automobile-oriented, which presents significant mobility challenges to those who cannot drive or do not want to drive. Transit authorities in the United States play a critical role providing essential mobility services to these often disadvantaged populations.

Along with transportation, housing expenses contribute to a significant financial burden on households, particularly those with low incomes. According to the consumer expenditures from the U.S. Bureau of Labor Statistics, housing and transportation are the two primary expense categories for U.S. households (U.S. Bureau of Labor Statistics, 2021). However, some studies suggest that transit services tend to be more frequent and widespread in dense, downtown areas (Kawabata & Shen, 2006) where housing prices are normally higher (Cervero, 2004; Immergluck, 2009). Some low income households who cannot afford high housing prices and private cars are often compelled to make trade-offs between housing and transportation costs. Therefore, the concept of affordable-accessible housing, which is inexpensive housing in walkable urban neighborhoods, has been proposed to try to improve transit equity among low income households (Litman, 2022).

In the U.S., some supply-side affordable housing programs are administered by the federal government, such as Low Income Housing Tax Credits (LIHTC), subsidized Multifamily Housing properties, and public housing. The overall purpose of such housing programs is to make rent more affordable for low income households. However, affordable housing units are sometimes planned without consideration of transit accessibility as an evaluation criterion, which is partly due to the absence of federal requirements for planning affordable housing as well as the lack of coordination of housing authorities with transit agencies (National Academies of Sciences Engineering and Medicine, 2022b). Furthermore, a recent study from the Transit Cooperative Research Program (TCRP) concluded that many transit agencies often do not specifically prioritize serving neighborhoods with high levels of affordable housing in their transit planning process (Chapple & Loukaitou-Sideris, 2019; National Academies of Sciences Engineering and Medicine, 2022b).

Prior studies suggest that there is a need to develop systematic practical guidance and effective approaches that can be implemented by transit agencies and housing authorities to

promote the coordination of transit services with affordable housing (Chapple & Loukaitou-Sideris, 2019; National Academies of Sciences Engineering and Medicine, 2022b). However, housing construction, especially large apartment complexes and fixed rail transit (such as subway and light rail) are durable and permanent infrastructure investments; bus routes are considerably more adaptable and can be (relatively) easily modified to improve transit accessibility. Therefore, modifications to local bus routes that can be implemented in the short-term (e.g., within a few weeks or within a few months) provide an important first step to potentially increase transit accessibility for existing affordable housing residents in underserved areas.

By quantifying transit accessibility among existing affordable housing units, this research contributes to the literature in two important ways. First, this paper proposes a three-step method to systematically compare the transit equity of existing affordable housing units and to evaluate potential short-term bus service modifications that could increase transit access levels. Second, this three-step method primarily relies on open datasets, specifically General Transit Feed Specification (GTFS) data and affordable housing locations from the U.S. Department of Housing and Urban Development (HUD), which makes this method widely applicable to other regions of the U.S. with fixed route transit service.

2.2 Literature review

The following sections briefly review relevant literature pertaining to transit accessibility and transit equity.

2.2.1 Transit accessibility

Transit accessibility refers to one's ability to reach opportunities via transit (Manout et al., 2018). A growing number of studies published in the last decade have focused specifically on transit accessibility (El-Geneidy et al., 2016b; Owen & Murphy, 2020b; Stewart, 2017; Welch, 2013). The following section reviews previous research on transit accessibility from the perspective of measurement methods and factors that contribute to calculation accuracy.

2.2.1.1 Transit accessibility measures

Transit accessibility measures can generally be grouped into two categories: opportunity-based measures (also known as primal measures) and time-or cost-based measures (also known as dual measures) (Cui & Levinson, 2020b). Opportunity-based measures are the most commonly

used method in previous research (Levinson & King, 2020). Opportunity-based measures require a pre-assumed cutoff travel time that has no standard value under different scenarios (Levinson & King, 2020). Hence, previous research employing opportunity-based measures was often conducted in situations where individuals have multiple options, such as job opportunities (Cui & Levinson, 2020b; Zuo et al., 2020). Commonly used opportunity-based measures include the cumulative opportunity measure, the weighted cumulative opportunity measure, and the competitive access measure; each of these measures is briefly described in the following paragraphs.

The cumulative opportunity measure is the most popular of the opportunity-denominated measures in previous research (El-Geneidy & Levinson, 2006; Owen & Murphy, 2020b). A cumulative opportunities metric measures the number of opportunities - such as jobs - that one can reach within a given period of time (e.g., 60 minutes) via transit service. The cumulative opportunity measure has been used in many previous studies due to its minimal data requirements, ease of comprehension, and consistent interpretation across different times and locations, which enables greater comparison, tracking, and benchmarking (Levinson & King, 2020). For example, one recent study of the San Francisco Bay Area, California applied the cumulative opportunity measure in a transit accessibility analysis that calculated the total number of jobs accessible within 40 minutes of transit travel time during AM peak hours (7-10 am) (Blanchard & Waddell, 2017).

The weighted cumulative opportunity measure (also known as the gravity-type measure) is converted from the cumulative opportunity measure by adding weights to all the opportunities by a specific impedance function (e.g., distance decay functions, time decay functions, or cost decay functions), making opportunities with higher impedances from a certain location less attractive (El-Geneidy & Levinson, 2022; Levinson & King, 2020). For example, one relevant study conducted in Detroit calculated transit accessibility to jobs by using an impedance function of travel cost (Grengs, 2010). Although the weighted cumulative opportunity measure can better describe human behavior, it is more challenging to interpret than the cumulative opportunity measure since the impedance formula can vary from time to time and from location to location (Levinson & King, 2020; Palacios & El-geneidy, 2022).

The competitive access measure is another opportunity-based measure that considers the competition among travelers and opportunities (Levinson & King, 2020). As an example of a related study of the Boston area, Shen proposed the competitive access measure model that

included competition at workplace locations to measure the employment accessibility of low-wage workers (Shen, 1998). The competitive access measure has been widely used in research on measuring transit accessibility (Allen & Farber, 2020; Kawabata & Shen, 2007; Merlin & Hu, 2017). However, compared to the cumulative opportunity measure, the competitive access measure requires more computation and may be more difficult to apply and understand in real-world practice (Levinson & King, 2020).

In contrast to the previous approach of calculating the number of opportunities that can be reached within a given time threshold, time- or cost-based measures calculate travel time or cost to achieve a fixed number of opportunities. Depending on the preset number of opportunities, this approach can be further divided into time- or cost-based measures for a single opportunity and time- or cost-based measures for multiple opportunities. For the single-opportunity measure, the number of opportunities is 1, while for the multiple-opportunities measure, that threshold is 2 or more. This measure is often used when the time or cost to access the opportunity is more important than the number of opportunities accessible (Cui & Levinson, 2020b). As an example, Farber et al. (Farber et al., 2014) measured accessibility to food stores in Cincinnati by calculating the travel time from each census block to the nearest one supermarket and the closest three supermarkets. Similar approaches have been successfully applied in measuring the accessibility of other essential services, such as one recent study of healthcare accessibility in Florida (Ghorbanzadeh et al., 2020). Time-or cost-based measures provide a straightforward way to compare transit accessibility levels between different locations and cities. They may also be more easily understandable to the public because measuring access in minutes provides an easy-to-interpret scale (Levinson & King, 2020). However, without a suitable reference point, determining a threshold number of opportunities beyond one may be challenging for time-or cost-based measures (Levinson & King, 2020). Furthermore, travel time alone may not fully capture people's needs or preferences (Levinson & King, 2020). For example, individuals may prefer to shop at a supermarket that is not necessarily the closest one to their home.

In this study, the cumulative opportunity accessibility measure will be selected to estimate transit accessibility to jobs, since it is easier to compute and interpret in practice and therefore more likely to be adopted by planning agencies.

2.2.1.2 Spatial resolution & time resolution of transit accessibility

The accuracy of accessibility calculations usually depends on two factors: spatial resolution and time resolution.

The spatial resolution of origins and destinations is an essential factor that could affect the results of accessibility studies. Many prior studies use the centroid points of arbitrary zones as the origin to calculate transit accessibility (Cui & Levinson, 2020b; El-Geneidy et al., 2016b). However, the transit accessibility of the centroid point might not represent the average transit accessibility level in that zone. In response to this problem, some methods now use a higher spatial resolution in which origins and destinations can be a rectangular grid cell for each region, which is the case with an open-source “Analysis” platform that is utilized in this study (Conway et al., 2017). To improve the accuracy and representativeness of citywide transit accessibility, this paper utilized every rectangular grid cell in the region as the origin of the calculation.

Another essential factor that could affect accessibility results is time resolution (Levinson & King, 2020). Transit accessibility is schedule-dependent (Levinson & King, 2020) and could be highly variable over time (Owen & Murphy, 2020b). Some prior studies only consider the service frequency (e.g., number of vehicle trips per week) (Aman & Smith-Colin, 2020; Delbosc & Currie, 2011; Ricciardi et al., 2015) or the transit accessibility at a single departure time (Cui & Levinson, 2020b; El-Geneidy et al., 2016b). However, the transit accessibility at a one-time point might not be representative. The common solution is to sample multiple time points and compute the average or the median travel time across the sample of time points (Levinson & King, 2020). To prevent the results from being influenced by a specific time point, this study utilized a schedule-based accessibility measurement that takes the median among results from multiple time points (Conway et al., 2017).

2.2.2 Transit equity of affordable housing

Equity is generally divided into two categories: **horizontal equity**, which emphasizes the equal distribution of resources between individuals and groups, and **vertical equity**, which suggests that the supply of resources should be based on needs and abilities (Litman, 2017). In the field of transit, vertical equity aims to provide transit access to those with the greatest need (Delbosc & Currie, 2011). Many prior studies related to transit vertical equity evaluate the distribution of transit accessibility among disadvantaged groups, which are categorized by demographic

characteristics such as low income households, no-car households, or elderly groups (Delbosc & Currie, 2011; Manaugh et al., 2015; Sharma et al., 2020). Limited prior studies consider the transit equity of affordable housing units where low income populations often reside.

The purpose of affordable housing programs is to make the rent for low income households more affordable. However, it is often unknown if affordable housing programs provide equitable transit access. Hence, the transit equity of affordable housing programs (region-wide) and the transit equity of affordable housing locations (specific locations within a region) should be measured. One relevant previous study evaluated region-wide transit equity across affordable housing programs in Baltimore by applying Lorenz curves and Gini coefficients (Welch, 2013). Lorenz curves are commonly applied in a range of disciplines to graphically represent a quantity that can be accumulated across a population (Delbosc & Currie, 2011). The Gini coefficient can be used as a mathematical metric to quantify the system-wide degree of inequity by calculating the ratio of the area between the line of equity and the Lorenz curve (Gini, 1912) and has been used in some prior studies (Chen et al., 2019; Delbosc & Currie, 2011; Kaplan et al., 2014; Ricciardi et al., 2015). This paper adopts a similar method to evaluate transit equity of affordable housing programs at the city level. However, the above-mentioned Baltimore study (Welch, 2013) only used the Lorenz curve and Gini coefficient and lacks a measurement of transit equity for specific affordable housing locations. To fill this gap, this paper expands the analysis of transit inequality to consider specific locations of affordable housing units within a region.

The key point of measuring transit equity for specific locations within a region is to understand the relationship between the transit supply and transit demand of specific locations. A place with high demand and low supply will be defined as inequitable (Aman & Smith-Colin, 2020). Transit demand in this analysis is measured as the percentage of existing affordable housing units at a specific location, which has rarely been considered in previous studies. Therefore, this paper proposes a simple inequity index that calculates the ratio of the percentage of existing affordable housing units and the percentage of jobs accessible within a 60-minutes transit trip for each affordable housing location. This inequity index is a straightforward measure of the relative relationship between transit demand and transit supply and can be easily applied in practice.

2.3 Objectives

The following summarizes the three objectives of this study.

- Objective 1: Evaluate transit equity of existing affordable housing programs at the city level.
- Objective 2: Evaluate transit equity of specific affordable housing locations and identify specific affordable housing locations that have inequitable transit access within the city.
- Objective 3: Propose short-term transit service modifications to potentially increase transit accessibility for existing affordable housing locations.

2.4 Background and case studies

2.4.1 Background on affordable housing

Housing costs have the highest share (34.9% in 2020) of average annual expenditures for U.S. households (U.S. Bureau of Labor Statistics, 2021). To help alleviate the burden of housing costs for low income households, numerous affordable housing programs are administered by the U.S. federal government. One well-known program is known as Low-Income Housing Tax Credits (LIHTC) (2022a), also known as Section 42, which issues tax credits for the development of affordable housing for low income households. Two other programs considered in the following analysis are Multifamily Subsidized Housing (Multifamily) and Public Housing (PH), which are both rental assistance programs administered by the U.S. Department of Housing and Urban Development (HUD) that provide decent and safe rental housing for eligible low income households (2022b; 2022c). These are the three largest federally funded supply-side programs (Preston & Reina, 2021) with the overall purpose of making rent for low income households more affordable and geospatial datasets for these affordable housing programs are publicly available from the HUD-eGIS Storefront (U.S. Department of Housing and Urban Development, 2020). Therefore, they have been selected for analysis in this study.

The Qualified Allocation Plan (QAP) is the federally mandated standard for evaluating all housing projects that apply the federal Low Income Housing Tax Credit (LIHTC) program (Gramlich, 2014). Each state in the United States is required to design and implement its QAP that specifies the sociospatial selection criteria of affordable housing for low income people (Gramlich, 2014; Johnson, 2014). For example, three points will be awarded to a housing building if it is located within 1,500 feet of a regular public bus stop or rapid transit system stop in some states (Johnson, 2014). Because many low income people depend on transit for their transportation needs (Pendall et al., 2006), scoring criteria related to transit accessibility (e.g., proximity to transit stops

and transit access to jobs) are used in some states (such as California, Connecticut, Virginia, Georgia, etc.) (Johnson, 2014; Palm & Niemeier, 2018).

2.4.2 Background on the case studies

Previous studies on transit accessibility and housing affordability primarily focused on dense cities with robust transit networks, such as recent studies of Baltimore (*Welch, 2013*), Chicago (*Liu et al., 2021*), San Diego (*Duncan, 2011*), Orange County, California (*Houston et al., 2013*), and Houston (*Park & Choi, 2021*). However, additional research is needed about low income populations living in lower-density, heavily automobile-oriented cities, such as those in Tennessee. According to the U.S. Census Bureau, about 60 percent of transit commuters in Tennessee are low-income workers earning less than \$24,999 per year (U.S. Census Bureau, 2019), which suggests that transit plays a vital role in providing critical transportation services to low income communities.

Moreover, this paper is particularly relevant in Tennessee because the Tennessee Housing Development Agency's most recent Qualified Allocation Plan (QAP) for Low-Income Housing Credits does not consider transit access in the process of allocating credits for affordable housing (Perrey, 2022). This suggests the need to develop a method for policy-makers and practitioners to systematically evaluate the transit accessibility levels of existing affordable housing units. The proposed case studies demonstrate the significance of the work and the potential applicability to other urban areas in the United States facing similar issues.

This research focuses on three large cities in Tennessee (Nashville, Chattanooga, and Memphis) that all have predominantly automobile-oriented transportation systems with bus-based public transit systems. However, these three cities differ from one another in terms of population size, housing policies, demographics, and economic characteristics. Nashville is a very large population center experiencing significant economic growth and gentrification over the last decade, and it currently ranks as the 21st most populous city in the United States according to the most recent data from the U.S. Census Bureau (Bureau, 2021). It should also be noted that Public Housing is not included among the affordable housing programs in Nashville. Chattanooga is a relatively small-sized city that has experienced economic growth and gentrification – particularly in its downtown area – in recent years (Lambe & de Zeeuw, 2016). Compared to the other two cities, Memphis has a higher rate of poverty, a higher rate of crime, and a slower rate of economic

growth (Bureau, 2021; Federal Bureau of Investigation, 2019).

In the remainder of this paper, the transit equity of existing affordable housing programs in these three cities is first evaluated and compared across cities. Then, for each city, specific affordable housing locations with inequitable transit accessibility are identified and ranked by inequity index values. Last, a specific affordable housing location with inequitable transit in the city of Memphis is selected to demonstrate the process of proposing and evaluating short-term transit service modifications.

2.5 Data

This section discusses the data used to measure transit accessibility and transit equity of affordable housing units. **Figure 2** presents maps of the three case studies, including the transit network (shown as green lines), the locations of affordable housing (including LIHTC, Multifamily, and Public Housing (PH)), and the total number of housing units in each census block.

2.5.1 *Origins data (affordable housing locations)*

The affordable housing programs selected in this study include LIHTC, Multifamily, and PH. Geocoded affordable housing locations with the number of housing units were extracted from HUD (2020).

2.5.2 *Destination data (job locations)*

Various datasets provide job information nationally or regionally. The Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) dataset provides the home and work locations of employed people living in the U.S. at the Census Block level. It is commonly used to obtain information about workers and jobs (Bertolaccini, 2018; Blanchard & Waddell, 2017; El-Geneidy & Levinson, 2006; Zuo et al., 2020). For this study, the geospatial locations of the jobs were obtained from the latest version of LODES, which was from 2018. Because more recent data was not available, it was assumed that job locations were stable from 2018 to 2022.

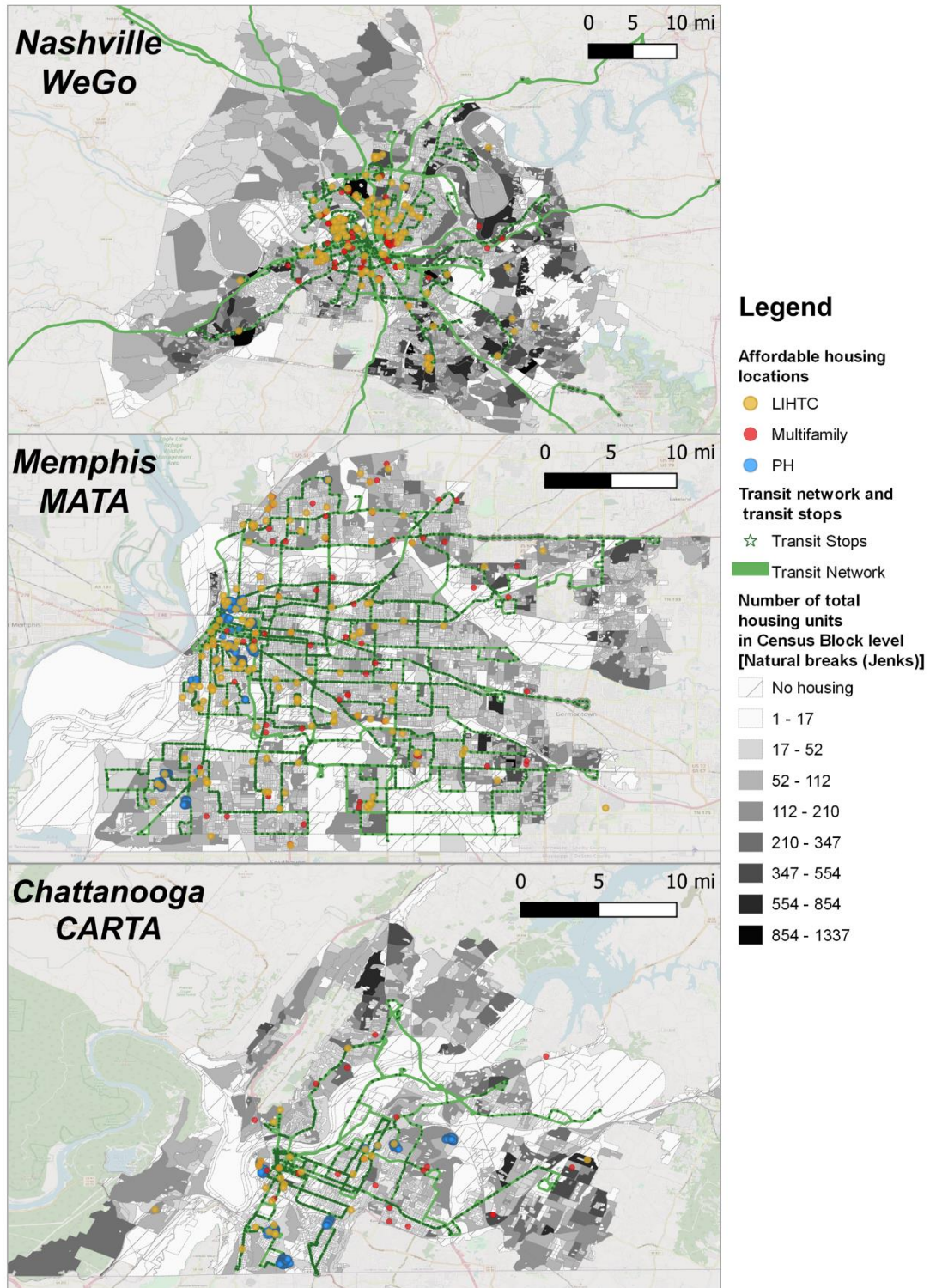


Figure 2 Maps of the three study areas (Nashville, Memphis, Chattanooga) showing the transit networks, locations of affordable housing, and the total number of housing units in each census

2.5.3 Transit network

The General Transit Feed Specification (GTFS) is applied in previous literature on transit accessibility to estimate travel times from one point to another at different times of the day (Fransen et al., 2015). Furthermore, the standardization of GTFS data makes it possible to analyze transit accessibility across different cities (Bok & Kwon, 2016; Owen & Murphy, 2020b). The GTFS datasets, including static transit schedules and geospatial transit networks in 2022 for three Tennessee cities (Nashville, Memphis, and Chattanooga), were collected from the Nashville Metropolitan Transit Authority (WeGo), Memphis Area Transit Authority (MATA), and Chattanooga Area Regional Transportation Authority (CARTA).

2.5.4 Geographic layer for measuring citywide transit accessibility

To measure the transit accessibility for citywide total housing units, the 2020 TIGER/Line shapefile of census block boundaries (the finest level recording the number of housing units) was obtained (U.S. Census Bureau, 2020b). The origins for measuring citywide transit accessibility are grid cells (with a resolution of 306 m (1002 ft.) cell width (measured at the equator) or 216 m (709 ft.) cell width (measured at the 45° latitude)). The transit accessibility for total housing units within a census block was derived by calculating the average transit accessibility of each grid cell within the block.

2.6 Methodology

This section discusses the proposed method. **Figure 3** shows the conceptual framework, which is divided into three steps. Step 1 measures transit accessibility for affordable housing locations and citywide transit accessibility for all housing units in a city. Step 2 evaluates transit equity of affordable housing programs at the city level by applying Lorenz curves and Gini coefficients, and it also identifies specific affordable housing locations within the city that have inequitable transit access by applying a simple inequity index. Step 3 demonstrates the process of proposing and evaluating possible transit service changes that can be implemented in the short term (e.g., for buses) for an existing affordable housing location with a high inequity index. The method is applied to three cities with primarily bus-based transit systems in Tennessee (Nashville, Memphis, and Chattanooga).

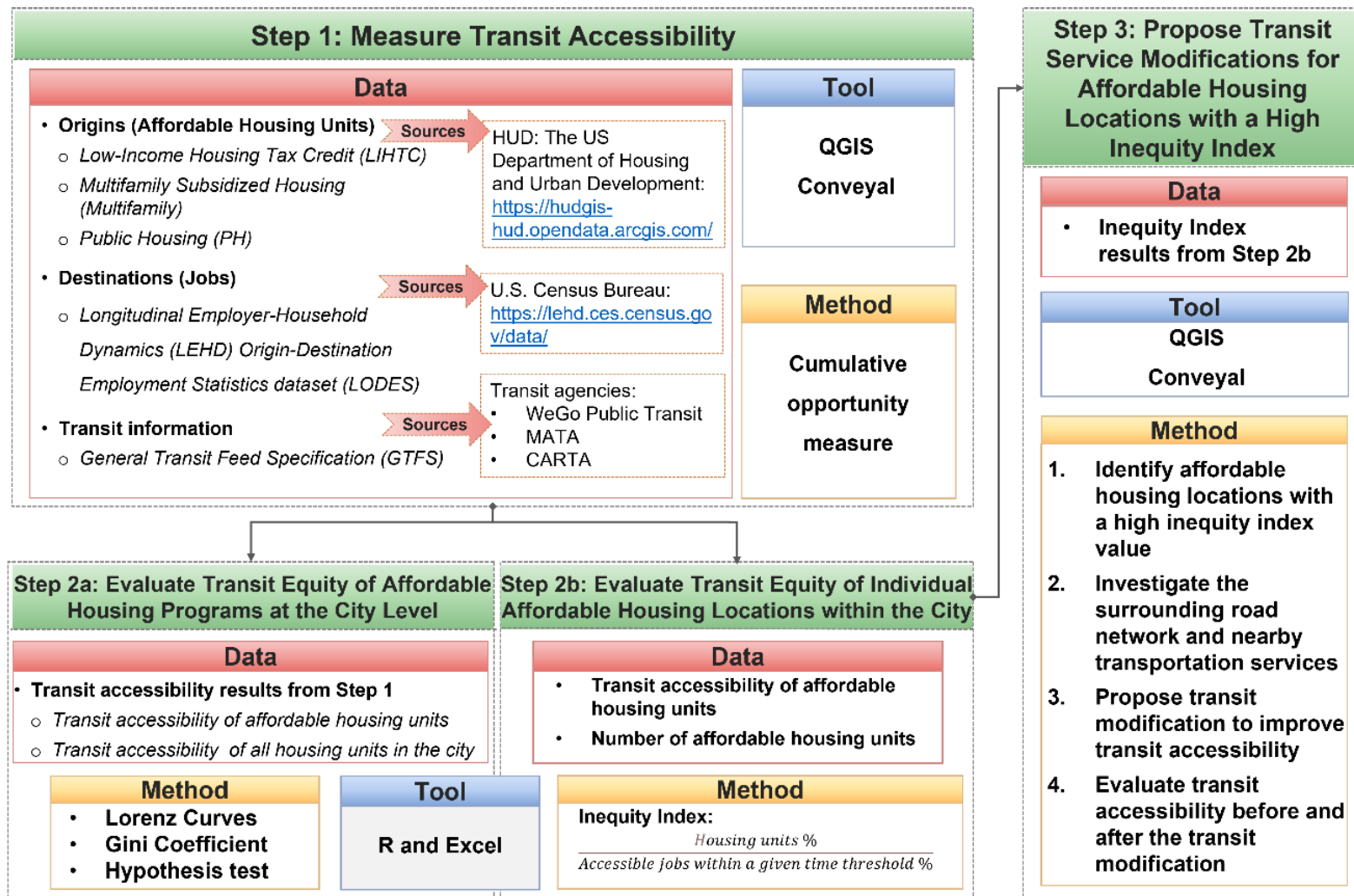


Figure 3 Conceptual framework of the methodology

2.6.1 Step 1: measure transit accessibility

Figure 4 shows the configuration of measuring transit accessibility in the Conveyal Analysis platform. Two origin sets were used in the transit accessibility analysis. One was affordable housing locations; the other was grid cells of each of the three cities. The spatial resolution (cell width) of grid cells is 306 m (1002 ft.) (measured at the equator) or 216 m (709 ft.) (measured at the 45° latitude). The following assumptions were made: transit vehicle departures were between 7 a.m. to 10 a.m. on a weekday; transit stops were accessed by walking; fixed route transit trips were taken with a maximum of three transfers (considered to encompass most practical trips (Conway & Stewart, 2019)); and walking was used to egress from transit stops to the destination. The maximum travel time was a total of 60 minutes, which was selected because 74% of Tennessee's transit commuters travel for less than 60 minutes to get to work (U.S. Census Bureau, 2019). The maximum walking time was set at 20 minutes, and the walking route followed the street network developed by OpenStreetMap. A schedule-based algorithm in the Analysis platform calculated the number of jobs accessible via walking and transit from each origin at every minute between 7 a.m. to 10 a.m. and then exported the median value of transit accessibility for all minutes as the result.

This paper applied the cumulative opportunity measure that calculated the number of jobs accessible via transit from given origins within a specific time threshold, as shown in equations (1) and (2) below.

$$A_i = \sum_j O_j f(C_{ij}), \quad (1)$$

$$f(C_{ij}) = 1, \text{ when } C_{ij} \leq t, \text{ else } f(C_{ij}) = 0 \quad (2)$$

A_i is the transit accessibility from origin i , O_j is the number of opportunities available at destination j , C_{ij} is the travel cost from i to j , and $f(C_{ij})$ is an impedance function, which equals 1 when travel costs less than the given time threshold t and equals 0 otherwise. In pedestrian access analysis, walking speed is generally assumed as 5 km/h (3 mph) based on prior experience (Levinson & King, 2020).

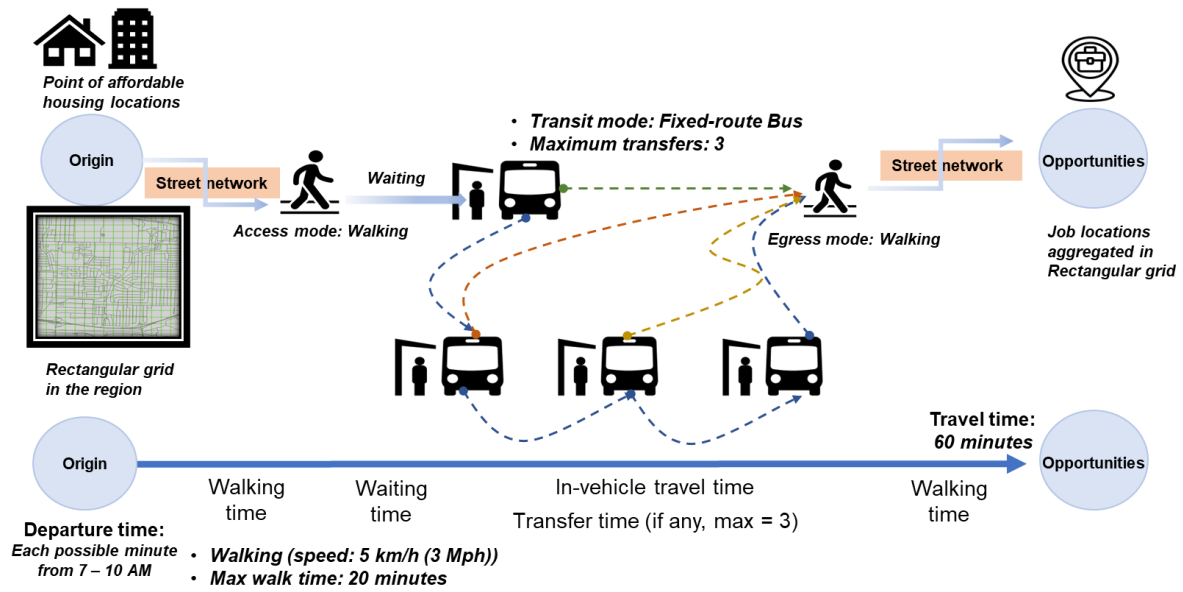


Figure 4 Configuration for transit accessibility calculation

2.6.2 Step 2a: evaluate transit equity of affordable housing programs at the city level

The aim of this step is to 1) evaluate horizontal equity that investigates whether there is an equal distribution of transit accessibility among affordable housing units in different subsidized housing programs, and 2) evaluate vertical equity that determines if affordable housing programs provide more equitable transit accessibility compared to the citywide total housing or randomly selected housing units.

Transit equity of affordable housing programs at the city level was evaluated by applying Lorenz curves and Gini coefficients. **Figure 5** shows an example of a Lorenz curve for the transit accessibility distribution among a population. The diagonal is the equity line that presents the equal distribution of cumulative transit access among the population. The curved line is an example of a Lorenz curve that represents an inequitable distribution of transit access among the population. In this example, 70% of the population shares only about 15% of the population's transit supply. The ratio of the area between the equity line and the Lorenz curve (dot shaded area *m* in **Figure 5**) divided by the total area under the equity line (dot shaded area *m* plus slash shaded area *n* in **Figure 5**) is mathematically presented by the Gini coefficient (Gini, 1912).

Equation (3) approximately shows the mathematical calculation of the Gini coefficient (Brown, 1994):

$$G_j = 1 - \sum_{i=1}^n (Y_i + Y_{i-1}) * (X_i - X_{i-1}) \quad (3)$$

Where:

Y_i is the cumulative proportion of the transit accessibility, $i = 0, \dots, n, Y_0 = 0, Y_n = 1$,

X_i is the cumulative proportion of the population, $i = 0, \dots, n, X_0 = 0, X_n = 1$,

G_j is the Gini coefficient for a sample j .

In the case of measuring transit equity among affordable housing programs, the Lorenz curve represents the cumulative distribution of transit-accessible jobs across the citywide total housing and affordable housing units, respectively.

To analyze the transit equity of affordable housing programs at the city level, a hypothesis test was used to determine if the Gini coefficient of affordable housing units was significantly different from the mean Gini coefficient of randomly selected housing units in a specific city. Citywide total housing includes houses, apartments, mobile homes, groups of rooms, and single rooms occupied or intended for occupancy as separate living quarters (U.S. Census Bureau). The number of housing units randomly selected from citywide total housing was set equal to the

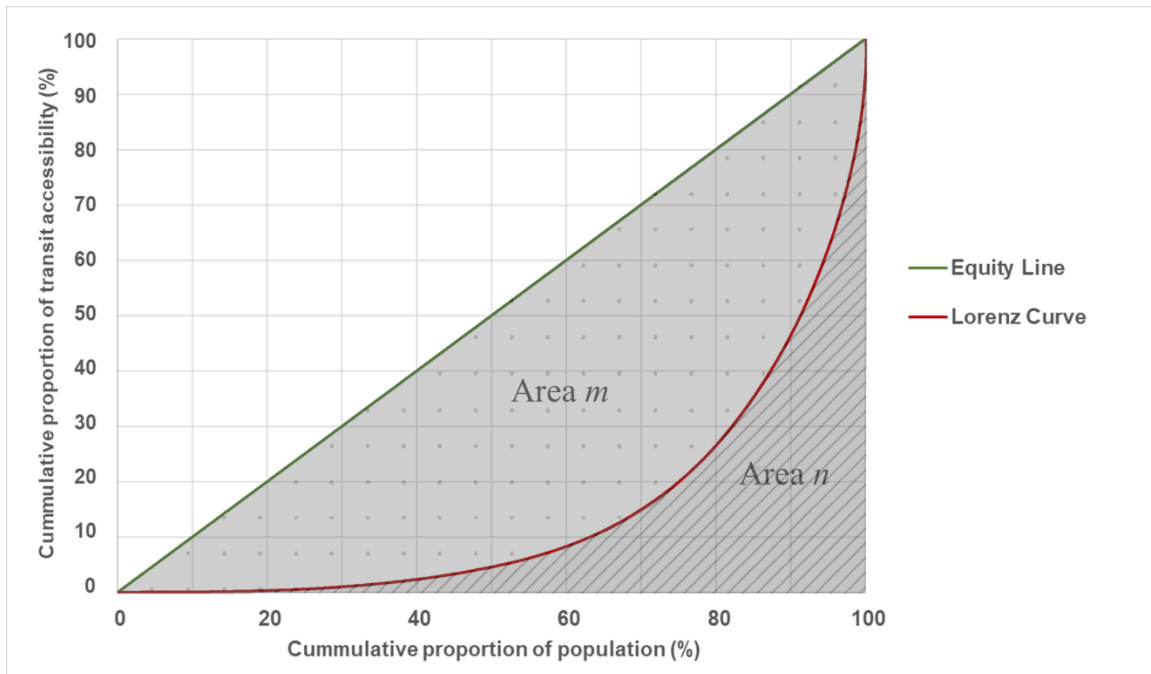


Figure 5 Example of Lorenz curves of transit accessibility distribution among a population

combined total number of housing units in the three affordable housing programs (LIHTC, Multifamily, PH) in that city. Fifty random samples were created for each city. The hypothesis test applied the 99% confidence interval and the two-tailed T -test. The null hypothesis H_0 was that the mean Gini coefficient of randomly selected housing units is equal to the Gini coefficient of affordable housing units, and the alternative H_1 was that the mean Gini coefficient of randomly selected housing units is not equal to the Gini coefficient of affordable housing units.

Based on the context of this study and objectives for this step of the method, a desirable outcome in terms of vertical equity would be that the Gini coefficients are lower for affordable housing units compared to the citywide total or randomly selected housing, and that the Lorenz curve of affordable housing units is closer to the equity line (above the Lorenz curves of citywide total housing or randomly selected housing).

2.6.3 Step 2b: evaluate transit equity of specific affordable housing locations within the city

The numerator (the percent of housing units for a specific location i) was defined as the number of affordable housing units at location i (e.g., within a large apartment complex) divided by the total number of affordable housing units in the city. The denominator (the percent of jobs accessible with a 60-minute transit trip) was defined as the number of transit-accessible jobs from the affordable housing location i divided by the cumulative number of transit-accessible jobs in all affordable housing locations within the city. This inequity index is a straightforward measure of the relative relationship between transit demand and transit supply and can be easily applied in practice. A higher inequity index indicates a higher demand (a higher number of affordable housing units) and a lower transit supply (a lower number of transit-accessible jobs).

$$\text{Inequity index}_i = \frac{\text{Percent of affordable housing units at location } i}{\text{Percent of transit accessible jobs within a given time threshold at location } i} \quad (4)$$

2.6.4 Step 3: propose transit service modifications for affordable housing locations with a high inequity index

This method aims to propose short-term transit service changes that can be easily applied in practice to existing affordable housing locations with limited transit access. Within the Conveyal Analysis platform tool, the following transit service modification types can be selected: converting frequency, adding a trip pattern, adjusting dwell time, adjusting speed, removing stops, removing trips, and rerouting (Conveyal User Manual, 2022). The “converting frequency” modification can

modify the transit vehicle's headway by editing the timetables. The "add trip pattern" modification enables the addition of new trip patterns to a scenario. The "adjust dwell time" modification allows for changes in the dwell time at a specific stop or along a route. The "adjust speed" modification can adjust the transit vehicle's speed on an entire route or just a route segment. The "remove stops" modification can remove some of the stops from a route. The "remove trips" modification is used to remove entire routes or remove specific trip patterns on a particular route. The "reroute" modification can be used to represent detours, extensions, and curtailments (Conveyal User Manual, 2022).

The surrounding road network and nearby transit services were investigated before selecting one or more of these transit service changes in the software. For example, increasing the frequency would be selected if the walking distance to the nearest transit stop from the housing unit was relatively short but the headway of transit service was poor. For the specific affordable housing locations under consideration, various transit service modifications can be selected from this list and then analyzed in relation to a "comparison scenario" as the baseline. For the example used in this paper to demonstrate the method, the "converting frequency" modification was selected. Then, the transit accessibility level from the affordable housing location under the new scenario (e.g., increased transit frequency for the example shown in the results section) was calculated by applying the method described in Step 1. The platform then provides an isochrone map and numerical outputs for the change in the number of accessible job opportunities after each transit service modification. This simulation process in Conveyal's analysis tool makes it easy to evaluate many different possible transit modifications before one is selected for implementation.

2.7 Case studies and results

This section presents the results of the three-step method applied to the case studies of Nashville, Memphis, and Chattanooga, Tennessee.

2.7.1 Results of Step 1: transit accessibility results

Figure 6 provides a visual representation of the distribution of transit accessibility levels at all affordable housing locations by displaying citywide transit accessibility levels and affordable housing locations in the three cities. The darker the purple area, the lower the transit accessibility in that area. Transit accessibility was grouped by quantile (equal count) classification. The housing

Affordable housing programs

LIHTC-Number of housing units

- 1 - 25
- 26 - 50
- 51 - 100
- 101 - 150
- 151 - 200
- 201 - 250
- 251 - 300

Multifamily-Number of housing units

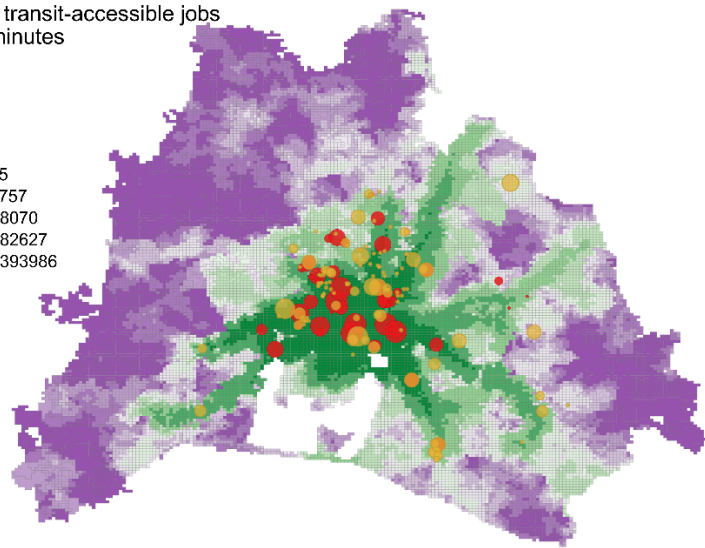
- 1 - 25
- 26 - 50
- 51 - 100
- 101 - 150
- 151 - 200
- 201 - 250
- 251 - 300
- >300

0 5 10 mi

Regional transit accessibility (2022)

Number of transit-accessible jobs within 60 minutes

- 0 - 11
- 11 - 31
- 31 - 77
- 77 - 157
- 157 - 368
- 368 - 1125
- 1125 - 13757
- 13757 - 78070
- 78070 - 182627
- 182627 - 393986



(1). Nashville

Affordable housing programs

LIHTC-Number of housing units

- 1 - 25
- 26 - 50
- 51 - 100
- 101 - 150
- 151 - 200
- 201 - 250
- 251 - 300
- >300

Multifamily-Number of housing units

- 1 - 25
- 26 - 50
- 51 - 100
- 101 - 150
- 151 - 200
- 201 - 250
- 251 - 300
- >300

PH-Number of housing units

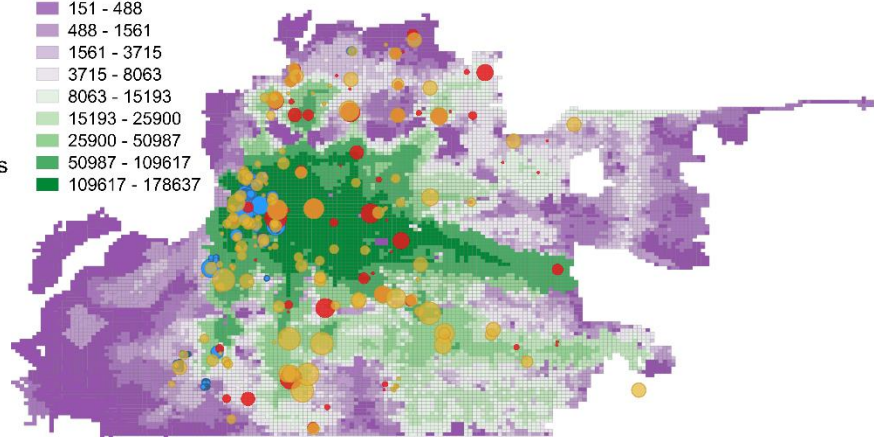
- 1 - 5
- 6 - 10
- 11-100 (small complex)
- >100 (big complex)

0 5 10 mi

Regional transit accessibility (2022)

Number of transit-accessible jobs within 60 minutes

- 0 - 151
- 151 - 488
- 488 - 1561
- 1561 - 3715
- 3715 - 8063
- 8063 - 15193
- 15193 - 25900
- 25900 - 50987
- 50987 - 109617
- 109617 - 178637



(2). Memphis

Figure 6 Transit accessibility and affordable housing locations in three cities

Affordable housing programs

LIHTC-Number of housing units

- 1 - 25
- 26 - 50
- 51 - 100
- 101 - 150
- 151 - 200
- 201 - 250

Multifamily-Number of housing units

- 1 - 25
- 26 - 50
- 51 - 100
- 101 - 150
- 151 - 200
- 201 - 250

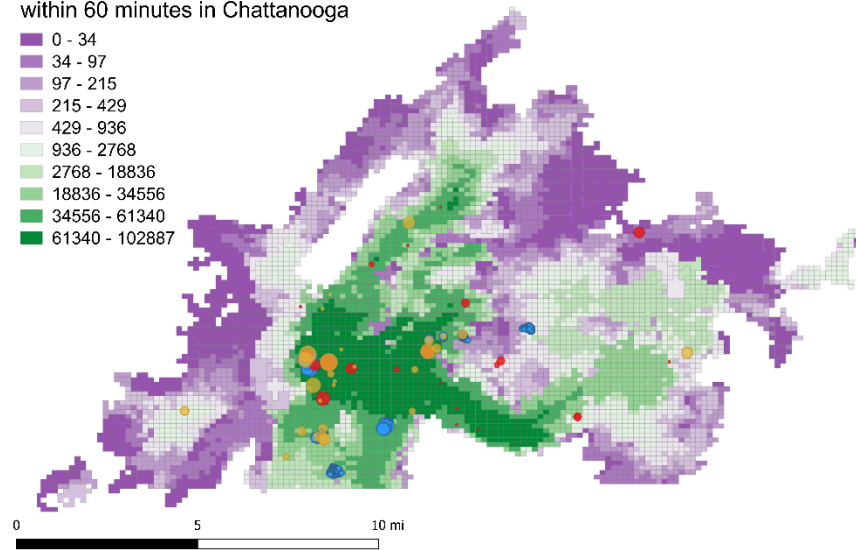
PH-Number of housing units

- 1 - 5
- 6 - 10
- 11-100 (small complex)
- >100 (big complex)

Regional transit accessibility (2022)

Number of transit-accessible jobs within 60 minutes in Chattanooga

- 0 - 34
- 34 - 97
- 97 - 215
- 215 - 429
- 429 - 936
- 936 - 2768
- 2768 - 18836
- 18836 - 34556
- 34556 - 61340
- 61340 - 102887



(3). Chattanooga

Figure 6 continued

locations of LIHTC units, Multifamily units, and PH units are shown as yellow circles, red circles, and blue circles, respectively. As can be seen in the figure, compared to other cities, Nashville had the greatest range of variation in transit accessibility throughout the city, which may be related to the fact that Nashville is a consolidated city-county that also contains large areas of rural and undeveloped land. It should also be noted that compared to Chattanooga, Memphis had a higher number of affordable housing units.

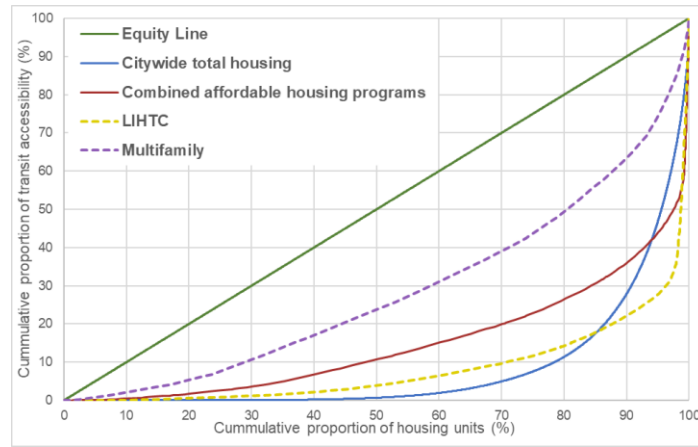
These maps suggest that even though the majority of affordable housing was located in green areas with relatively good access to transit, there were still some affordable housing units located in purple areas with relatively low access to transit.

2.7.2 Results of Step 2a: Lorenz curves and Gini coefficients

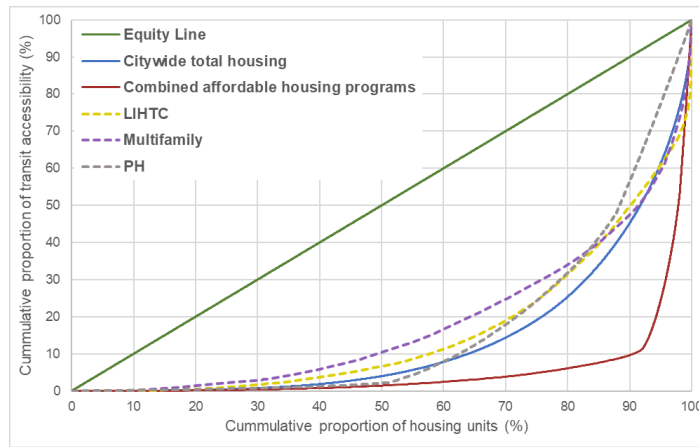
Table 1 shows the results of transit accessibility calculations and the Gini coefficient for citywide total housing, random samples, and affordable housing units in Nashville, Memphis, and Chattanooga. The number of housing units randomly selected from citywide total housing is equal to the combined total number of affordable housing units in all three housing programs (LIHTC, Multifamily, PH) in that city. Generally, affordable housing units had higher transit accessibility on average than both citywide total housing and randomly selected housing units. Comparing the Gini coefficient of each affordable housing program separately, transit accessibility was more equitably distributed among Multifamily units than among units of other programs (LIHTC or PH). In Memphis and Chattanooga, the distribution of transit accessibility of the combined total of affordable housing units was less equitable than that of affordable housing units in any single program. This result indicates that transit resources were unevenly distributed among different affordable housing programs in Memphis and Chattanooga. This same result is shown in **Figure 7**, where the red solid line (which represents the Lorenz curve for combined affordable housing programs) lies below all dashed lines (which represent the Lorenz curves for LIHTC units, Multifamily units, or PH units) for Memphis and Chattanooga, while the red solid line lies between the two dashed lines for Nashville. The closer the Lorenz curve is to the equity line, the more equitable the transit accessibility distribution. **Table 2** provides the hypothesis test results within the 99% confidence interval and two-tailed *T*-test. The results of rejecting the null hypotheses and comparing the Gini coefficients indicate that transit access is distributed more equitably among each affordable housing program than if the housing units were randomly distributed within the

Table 1 Results of transit accessibility and Gini coefficient

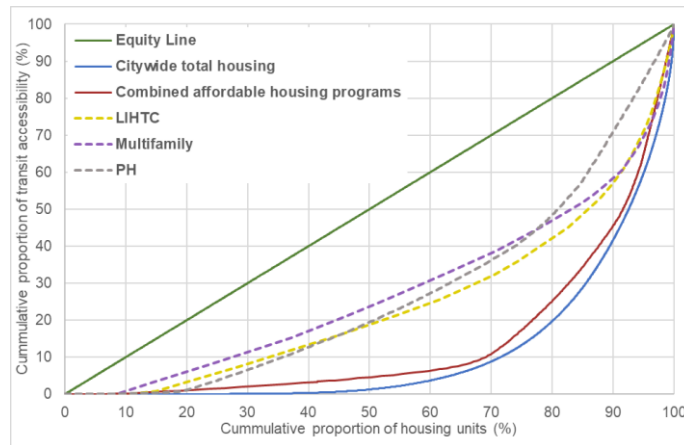
	Housing types	Number of housing units	Average transit accessibility	Gini coefficient
Nashville	Citywide total housing	316,363	116,979	0.8370
	Random samples	15,509	117,123	0.8338
	Combined affordable housing programs^	15,509	160,665	0.7039
	LIHTC	6,482	144,222	0.8350
	Multifamily	9,027	204,414	0.4299
Memphis	Citywide total housing	286,713	64,101	0.7230
	Random samples	26,657	64,473	0.7241
	Combined affordable housing programs	26,657	93,270	0.8950
	LIHTC	15,602	76,890	0.6817
	Multifamily	6,905	64,635	0.6379
	PH	4,150	96,745	0.6703
Chattanooga	Citywide total housing	85,266	46,719	0.7711
	Random samples	6,099	46,650	0.7646
	Combined affordable housing programs	6,099	53,140	0.7154
	LIHTC	2,267	68,173	0.5138
	Multifamily	1,685	57,643	0.4502
	PH	2,147	51,959	0.4596
^Nashville does not have public housing.				



(1). Nashville



(2). Memphis



(3). Chattanooga

Figure 7 Transit accessibility Lorenz curves by type of affordable housing programs in three cities

Table 2 Transit equity hypothesis test within 99% confidence interval

	Combined affordable housing programs (AHs)	LIHTC	Multifamily	PH
H_0	$\mu_G = G_{AHs}$	$\mu_G = G_{LIHTC}$	$\mu_G = G_{Multifamily}$	$\mu_G = G_{PH}$
H_1	$\mu_G \neq G_{AHs}$	$\mu_G \neq G_{LIHTC}$	$\mu_G \neq G_{Multifamily}$	$\mu_G \neq G_{PH}$
In Nashville: n = 50, $\bar{x} = 0.833815$, $\sigma = 0.019478$				
T-value	46.689483	-0.425891	145.160974	
P-value	<0.00001	0.672052	<0.00001	
Result	Reject H_0	Do not reject H_0	Reject H_0	
In Memphis: n = 50, $\bar{x} = 0.724131$, $\sigma = 0.015135$				
T-value	-79.028206	19.624625	39.88245	24.89721
P-value	<0.00001	<0.00001	<0.00001	<0.00001
Result	Reject H_0	Reject H_0	Reject H_0	Reject H_0
In Chattanooga: n = 50, $\bar{x} = 0.764597$, $\sigma = 0.032522$				
T-value	10.589294	53.981842	67.671158	65.647894
P-value	<0.00001	<0.00001	<0.00001	<0.00001
Result	Reject H_0	Reject H_0	Reject H_0	Reject H_0

city (with the exception of LIHTC units in Nashville). Given the results in **Table 1**, the Gini coefficient of the combined total of the affordable housing programs is higher than the sample mean of random housing units in Memphis, suggesting that transit accessibility is distributed less equitably among affordable housing units than if the housing units are randomly selected; however, the opposite is true for Nashville and Chattanooga. This suggests that affordable housing units in Memphis may be more dispersed, with some housing in areas with good transit access and others in areas with poor transit access, and that some of the affordable housing locations may have high levels of transit inequity.

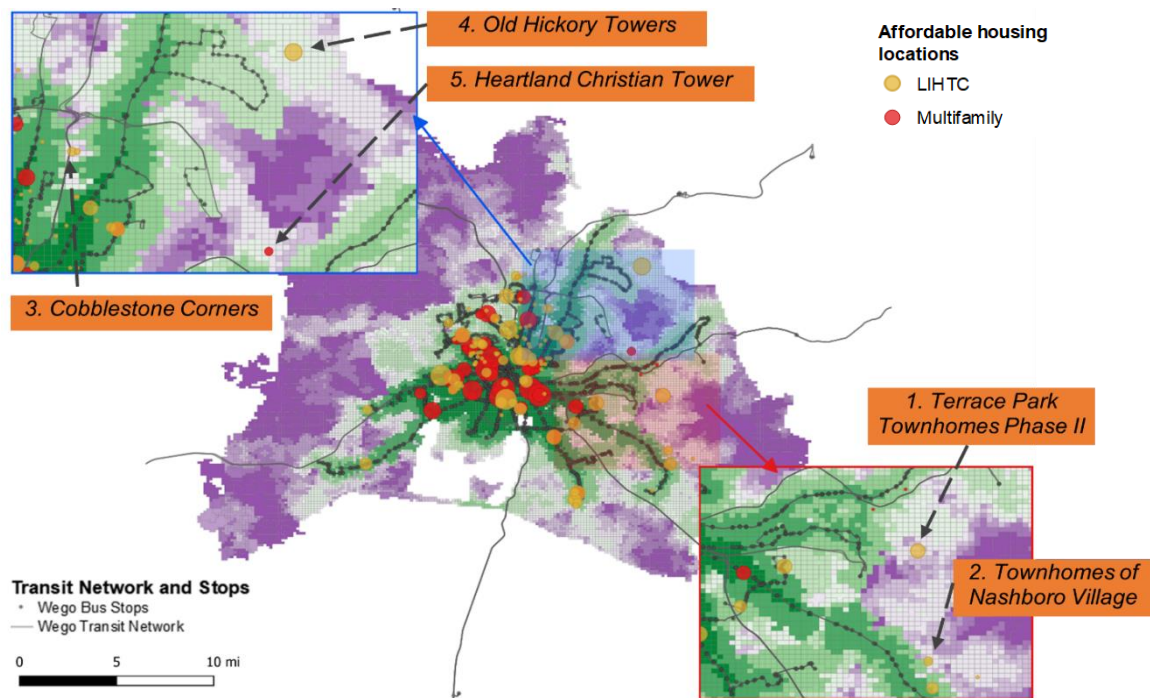
2.7.3 Results of Step 2b: identify affordable housing locations with inequitable transit accessibility

Next, the inequity index was calculated for each affordable housing location within the city to identify specific locations that have inequitable transit access. **Table 3** lists the five affordable housing locations with the highest inequity indices in each of the three cities. Overall, Nashville had a higher level of inequitable transit accessibility among these affordable housing locations.

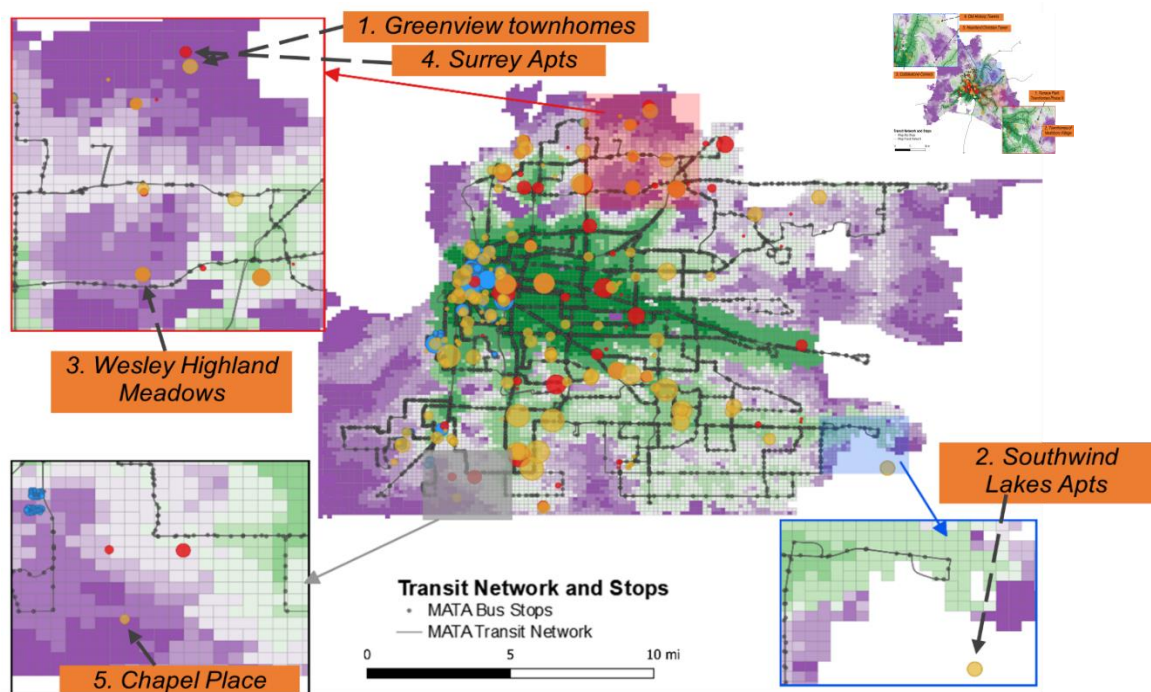
Figure 8 shows the five affordable housing locations listed in **Table 3** on a map for each city; also included are the transit network (stops and routes) and transit accessibility levels (shaded in green to purple, as in previous figures). **Figure 8** reveals that many of the affordable housing locations that scored poorly on the inequity index were in areas with low transit accessibility that also had substantial walking distances to the nearest transit stop. For affordable housing located away from transit stops, rerouting or extending transit routes may be a reasonable modification to improve accessibility. However, rerouting is funding-dependent, requires long-term planning, and can diminish overall transit operational efficiency. For affordable housing locations near transit stops (e.g., Wesley Highland Meadows in Memphis, shown in (2). Memphis of **Figure 8**), limited transit service frequency may be the cause of low transit accessibility levels, and a short-term schedule modification that increases frequency can be applied to improve transit accessibility in practice. In the following example, the results of Step 3 illustrate the process of proposing and evaluating a short-term schedule modification (specifically, increasing frequency/decreasing headway) to an existing affordable housing location with a high inequity index.

Table 3 Affordable housing locations with top five inequity index in three cities

Index Rank	Nashville			Memphis			Chattanooga		
	Housing Program	Measures		Housing Program	Measures		Housing Program	Measures	
1	Terrace Park Townhomes Phase II (LIHTC)	Inequity Index	1,496	Greenview Townhomes (LIHTC)	Inequity Index	1,092	Silvertree Seniors Apts (Multifamily)	Inequity Index	2,264
		Accessible jobs	258		Accessible jobs	94		Accessible jobs	30
		Housing units	172		Housing units	158		Housing units	124
2	Townhomes Of Nashboro Village (LIHTC)	Inequity Index	819	Southwind Lakes Apts Phase I (LIHTC)	Inequity Index	1,057	Cromwell Hills Apts (PH)	Inequity Index	205
		Accessible jobs	200		Accessible jobs	123		Accessible jobs	533
		Housing units	73		Housing units	200		Housing units	200
3	Cobblestone Corners (LIHTC)	Inequity Index	680	Wesley Highland Meadows (LIHTC)	Inequity Index	963	Eastwood Manor (Multifamily)	Inequity Index	123
		Accessible jobs	317		Accessible jobs	135		Accessible jobs	438
		Housing units	96		Housing units	200		Housing units	98
4	Old Hickory Towers (LIHTC)	Inequity Index	577	Surrey Apts I (Multifamily)	Inequity Index	709	Orange Grove II (Multifamily)	Inequity Index	38
		Accessible jobs	840		Accessible jobs	99		Accessible jobs	457
		Housing units	216		Housing units	108		Housing units	32
5	Heartland Christian Tower (Multifamily)	Inequity Index	396	Chapel Place Homes (LIHTC)	Inequity Index	331	Walden Group Home (Multifamily)	Inequity Index	6
		Accessible jobs	323		Accessible jobs	171		Accessible jobs	850
		Housing units	57		Housing units	87		Housing units	10

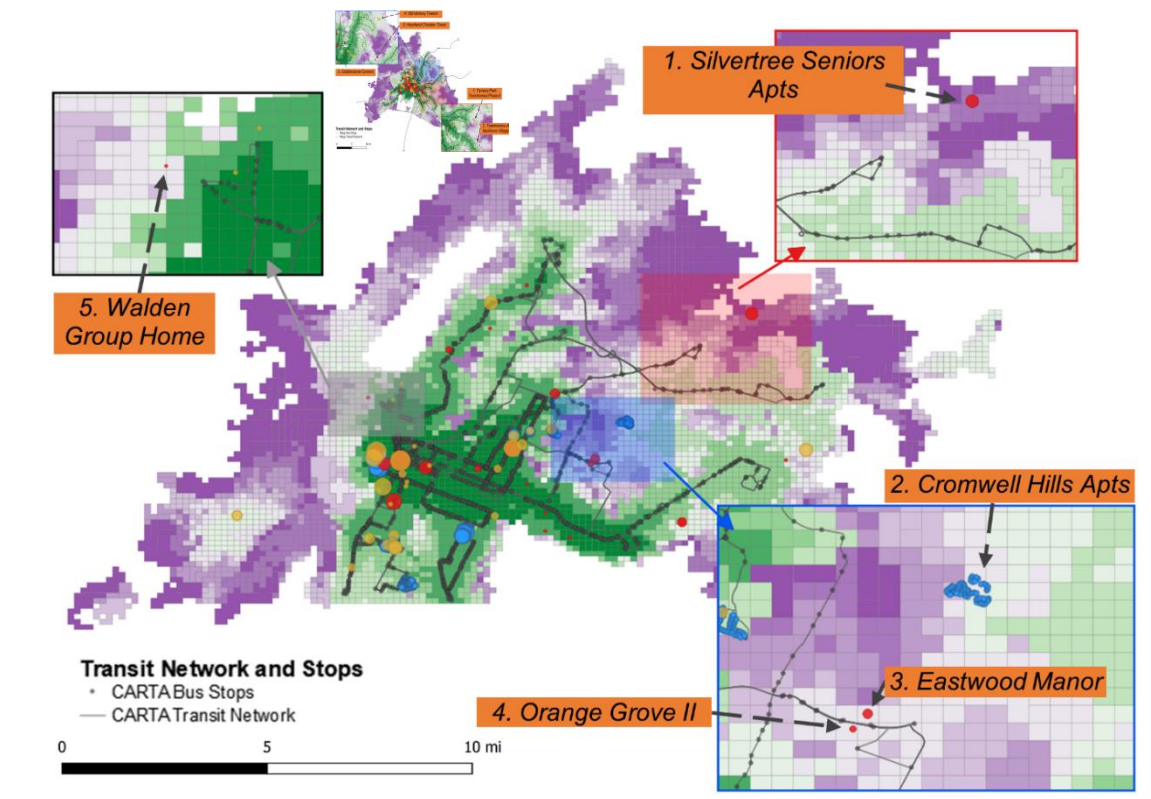


(1). Nashville



(2). Memphis

Figure 8 Top five affordable housing locations with limited transit access in three cities



(3). Chattanooga

Figure 8 continued

2.7.4 Results of step 3: propose and evaluate transit service modifications for existing affordable housing locations with a high inequity index

This section demonstrates the process of proposing and evaluating transit service modifications for a single affordable housing location in Memphis known as Wesley Highland Meadows. One of the reasons this affordable housing location was chosen for in-depth study is that the nearest transit route (#40) has proposed modifications in a local planning document known as the Memphis Transit Vision (City of Memphis, 2022). The Memphis Transit Vision includes a redesign of the existing transit system and was produced with significant involvement from the public, stakeholders, and elected officials who believe that, if funded, the proposed transit system redesign will significantly improve transit accessibility to jobs (City of Memphis, 2022). The Wesley Highland Meadows example was chosen not only to demonstrate the methodology for researchers, but also to show its real-world applicability to help transit agencies, local planners, and policy-makers assess proposed transit modifications.

Figure 9 shows a map of Wesley Highland Meadows relative to the nearby MATA Route 40 (red line), the nearby transit stops (black squares), and the walking path between the closest transit stop and the affordable housing location (black dashed line). Wesley Highland Meadows is 0.4 miles (8 minutes walking) from the nearest transit stop, indicating relatively good spatial access to transit. Route 40 has a headway of 90 minutes during the AM peak hour (7:00 a.m. to 10:00 a.m.), during which three buses depart from and two buses depart towards the downtown direction. Therefore, it could be concluded that a large headway of transit vehicles may be one cause of low accessibility levels.

The draft recommended transit network developed by the Memphis Transit Vision proposes decreasing the headway of Route 40 from 90 minutes to 60 minutes. Therefore, in this example, the proposed transit service modification is to decrease the headway of Route 40 in AM peak from 90 minutes to 60 minutes, which increases the number of trips departing Wesley Highland Meadows from five (three in one direction and two in the opposite direction) to seven during the AM peak hour (which is an additional trip in either direction). The results of this transit service modification are displayed in **Figure 10**, which shows overlapping isochrones in which blue indicates the isochrones under the baseline scenario (with existing transit service) and red indicates

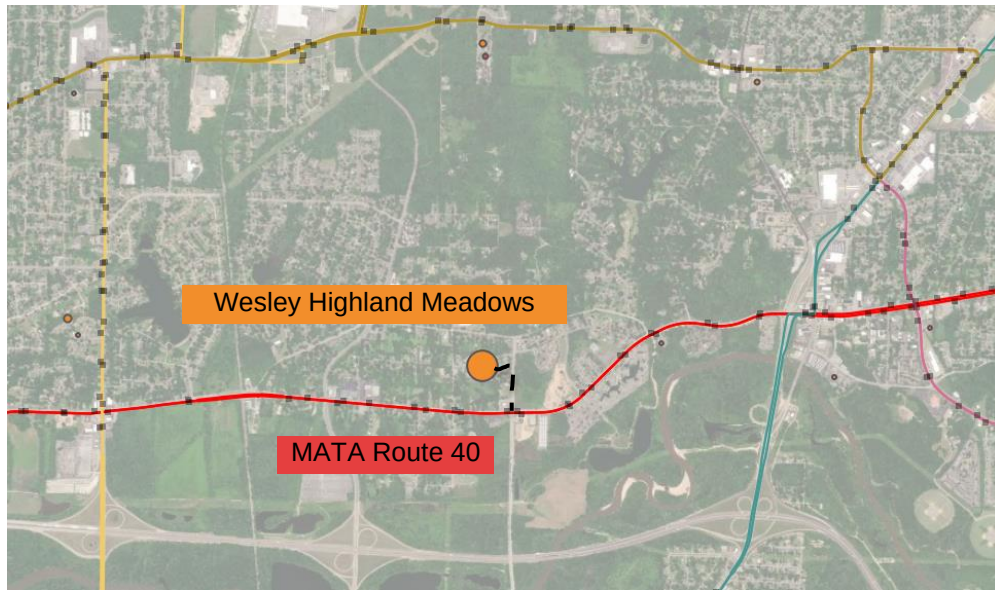


Figure 9 Satellite view of Wesley Highland Meadows and the surrounding road network and transit network

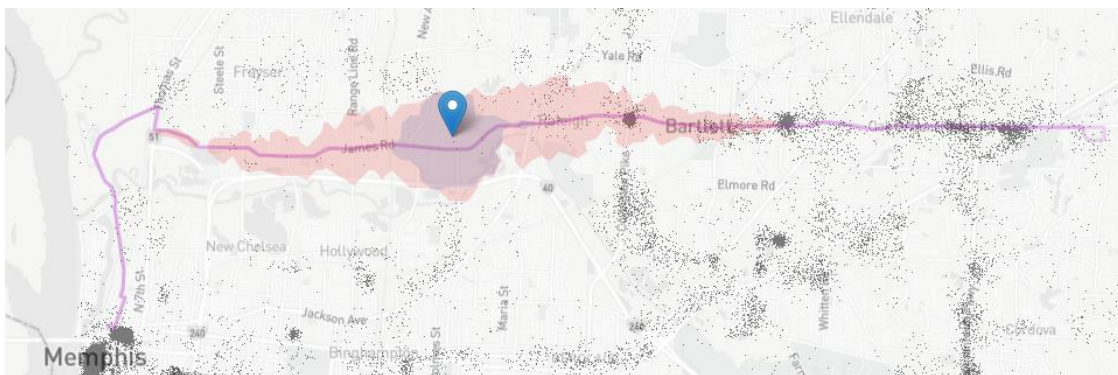


Figure 10 Overlapping isochrones before and after modifying the frequency of MATA transit route 40 for Wesley Highland Meadows

the isochrones under the comparison scenario (with increased frequency/decreased headway). The location of Wesley Highland Meadows is indicated as a blue icon in **Figure 10**. The red isochrone covers a larger area than the blue isochrone, which means that people from Wesley Highland Meadows can travel farther within an hour under the improved transit network. Specifically, people from Wesley Highland Meadows can reach 6,400 jobs (as opposed to just 135 jobs) within an hour after decreasing the headway of route 40 from 90 minutes to 60 minutes in the AM peak. The results suggest that a short-term transit service change can substantially improve the transit accessibility from this affordable housing location.

2.8 Discussion and conclusions

In this study, a three-step method to evaluate transit equity of existing affordable housing units was proposed, with case studies from Nashville, Memphis, and Chattanooga, Tennessee which have primarily bus-based transit systems. Transit accessibility is not considered in the process of allocating low income housing credits for affordable housing planning in Tennessee (Perrey, 2022). This suggests that there may be a need to develop a method for policy-makers and practitioners to systematically evaluate the transit accessibility levels of affordable housing units.

In Step 1, affordable housing and transit accessibility were visualized. In Step 2a, the results of the Gini coefficient showed that the overall transit accessibility of the combined total of affordable housing units (in the LIHTC, PH, and Multifamily programs) in Memphis and Chattanooga was less equitable than that of the affordable housing units in any single program. The citywide evaluations suggested that transit accessibility levels were distributed less equitably among affordable housing units (a Gini Coefficient of 0.895 for the combined total from three housing programs) than randomly selected housing units (with a Gini Coefficient of 0.724) in Memphis. The aforementioned findings showed that the transit equity of affordable housing units in different cities within a state can vary.

Step 2b identified Wesley Highland Meadows in Memphis as an affordable housing location with a high inequity index of 963 because residents at this location could only reach 135 jobs within an hour on transit but there is high potential demand for transit (specifically, 200 affordable housing units at this location). It is important to note that the goal of this step is to

compare transit access (supply) and the number of affordable housing units (potential demand) across different existing affordable housing locations to identify those locations with the most inequitable transit access. By identifying these locations and bringing them to the attention of the relevant authorities, planners and policy-makers can better prioritize serving neighborhoods with high levels of affordable housing when making future transit service changes.

In Step 3, a frequency/headway modification (specifically, changing 90 minutes to 60 minutes for Route 40 in AM peak) was proposed for the Wesley Highland Meadows location. It is noted that the transit modification evaluated in this study aligns with local planning recommendations in a proposed Transit Vision for the city of Memphis. After modification, the number of jobs accessible via transit to the housing location was shown to increase from 135 to 6,400 jobs. The results of the three-step method suggest that short-term transit service changes can improve the transit accessibility of existing affordable housing locations with limited transit access. After conducting this analysis, it can be concluded transit agencies and housing authorities may avoid transit inequity by collaborating to ensure that transit resources are distributed evenly across different affordable housing programs and the transit accessibility of affordable housing units is higher than the regional average.

This paper contributes to the literature by proposing a three-step method that helps transit agencies and their partners to (1) assess transit equity of affordable housing programs at the city level; (2) evaluate transit equity of specific affordable housing locations within a city; and (3) consider possible transit modifications before actual implementation. It is noted that the method primarily relies on open datasets; specifically, GTFS data and geospatial affordable housing locations from HUD make this method widely applicable in other regions of the U.S. with fixed transit service.

The three-step method presented in this study provides useful insights for housing authorities and transit agencies to guide their efforts toward enhancing transit equity and serving their local communities.

This study offers transit agencies a framework for assessing the equity of transit services for low income groups, aligning with the Federal Transit Administration's (FTA) overarching objectives that seek to integrate environmental justice goals into programs, policies, and activities

(FTA, 2012). By identifying affordable housing locations with higher demand and lower transit supply, transit providers can then prioritize service to these communities when making transit planning decisions. This approach could help improve transit access for residents in these areas, potentially leading to better mobility and connectivity. The proposed approach may be applicable for housing authorities in evaluating transit accessibility of affordable housing locations at both the citywide and location-specific level, particularly in instances where transit access is not already incorporated into the federally mandated Qualified Allocation Plan (QAP).

It is important to note that efforts to coordinate transit service planning and affordable housing development are ongoing in many US cities. For example, transit agencies in Raleigh, NC and Austin, TX each have plans to preemptively acquire land adjacent to transit corridors for affordable housing development. Both cities have dedicated funding to minimize the displacement of existing affordable housing units near new transit developments. The Equitable Development Around Transit plan in Raleigh uses zoning around transit stations to encourage the development and preservation of affordable housing units. This type of policy could be considered in other cities to facilitate the coordination of affordable housing and transit service in the future (City of Austin; City of Raleigh, 2020).

It is also important to highlight the ongoing efforts of many transit agencies to evaluate transit equity, including efforts in the case studies evaluated in this paper. For instance, in Nashville, TN, the WeGo transit agency regularly employs the Transit Boardings Estimation and Simulation Tool (TBEST) software to assess transit equity for minority and low-income populations, typically as part of Title VI service equity analyses (National Academies of Sciences Engineering and Medicine, 2022a). However, WeGo transit planners have noted in a recent survey that the percentage change in access to jobs could serve as a suitable accessibility metric for analyzing the impacts of proposed service plans under their Better Bus initiative (National Academies of Sciences Engineering and Medicine, 2022a). They further expressed a desire to incorporate transit accessibility into their planning activities in collaboration with key community partners in the future (National Academies of Sciences Engineering and Medicine, 2022a). This study proposes an approach that could be utilized by transit agencies such as WeGo in Nashville, TN to assess the impact of transit modifications while promoting coordination between transit

planning and local partners, particularly housing authorities.

Broadly speaking, it is generally recommended that local transit agencies and housing authorities in the United States coordinate transit planning and affordable housing development. For example, transit agencies could give priority to affordable housing communities when planning new transit services and/or offer free or discounted fare programs to encourage affordable housing residents to take transit. In addition, housing authorities could consider locating new affordable housing construction in areas with good transit access. Other planning and policy options could also be considered to facilitate housing and transit coordination in the future.

2.9 Limitations and future research

There are at least three notable limitations to this study: (1) the applicability to other areas beyond the United States, (2) the absence of low-wage jobs in the transit accessibility indicator, and (3) the lack of a decay function for job attractiveness and potential competition among affordable housing residents in the transit accessibility measure.

First, the applicability of the method proposed in this study may be limited to the United States because housing policies, transit planning practices, and the availability of data vary significantly between different countries. The next two limitations are associated with different factors that can lead to variations in the results of the transit accessibility analysis, potentially influencing the conclusions.

A second limitation relates to the selection of the destinations in the calculation of transit accessibility levels. Some studies suggest that people living in low income communities are more likely to work in or be qualified for low-wage jobs (Benner & Karner, 2016; Delmelle et al., 2021; Klumpenhower & Huang, 2021). The absence of an analysis of transit accessibility to low-wage job destinations could lead to an underestimation of the transit inequity issues faced by affordable housing units, since their residents are typically low-income individuals and may be more likely to be employed in low-wage jobs. The goal of this paper was to provide a general understanding of transit accessibility to all jobs for affordable housing locations; however, future research should consider the unique challenges faced by individuals in low-wage jobs.

An additional limitation pertains to the type of transit accessibility measure used in this study. The use of the cumulative opportunity measure did not consider the decay function of job attractiveness and potential competition among affordable housing residents and other populations within the same area to access job opportunities. These limitations are particularly noteworthy since previous research on travel behavior has shown that individuals are less likely to travel to jobs that are farther away. Previous research also suggested that competition for job opportunities may occur among low-income people, with numerous persons potentially competing for the same job position. Consequently, this limitation may result in an underestimation of the transit inequity faced by affordable housing residents. Notably, the conclusions drawn from a study are contingent on the measure of transit accessibility employed, and different measures can potentially yield varying results and implications (Giannotti et al., 2022; Tiznado-Aitken et al., 2021).

There are several areas where future research could contribute to a deeper understanding of transit equity in affordable housing.

First, although providing access to jobs is an important function of public transit, some travelers – especially low income populations who may be transit-dependent – rely on transit to get to grocery stores, healthcare facilities, schools, outdoor recreational areas, or other essential services (Klumpenhower & Huang, 2021). Therefore, transit access to other essential services is a future focus for research.

Second, this paper measured the transit accessibility of fixed-bus routes in dense urban areas. However, on-demand services (e.g., dial-a-ride routes) are available in many suburban and rural areas that do not have fixed-bus routes. Therefore, measuring access using on-demand transit services among affordable housing units could be considered in future research.

Third, the proposed method considered the impact of transit service changes on the transit accessibility of a single affordable housing location along the transit route being modified; however, future research could expand the method to consider the impacts of transit service changes on all affordable housing locations in the vicinity.

Fourth, this paper proposed short-term transit modifications for existing affordable housing locations. Future research could consider long-term coordination between transit service planning and affordable housing development (e.g., where to locate new housing developments).

In summary, this study highlights several significant areas for future research. Moreover, the findings offer important policy implications for practitioners seeking to enhance transit equity and potentially improve the accessibility of affordable housing locations. By implementing this methodology, housing authorities and transit agencies can work towards creating more equitable and connected communities.

CHAPTER 3.
EVALUATING SPATIOTEMPORAL TRANSIT ACCESSIBILITY AND
TRANSIT EQUITY OF ESSENTIAL SERVICES

This chapter is based on a research paper by Jing Guo and Candace Brakewood titled "Analysis of spatiotemporal transit accessibility and transit inequity of essential services in low-density cities, a case study of Nashville, TN". This paper is in review at the Transportation Research Part A: Policy and Practice.

Abstract

Evaluating the accessibility and equity of transit service to essential services that fulfill people's fundamental needs is critical, especially in lower-density areas with limited transit services. Although numerous studies have analyzed the inequity of transit accessibility in dense, urban areas with robust transit networks, few of them evaluated transit inequity across multiple essential service categories (e.g., food stores, healthcare facilities, schools, etc.). This paper fills this research gap by focusing on a low-density, automobile-oriented city (Nashville, TN) to evaluate spatial transit inequities across essential service deserts and sociodemographic groups. The results of the case study show that many areas with higher transit-dependent demand (i.e., populations with limited personal vehicles, those living in poverty and minority populations) tend to experience more restricted transit access to food, healthcare, school, and childcare facilities; interestingly, this is not the case for transit access to green space (specifically, parks). This study further identified essential service deserts by Local Indicator of Spatial Association (LISA) clustering and analyzed the correlation among them. The correlation results suggest that food deserts, healthcare deserts, school deserts, and childcare deserts are highly correlated with each other, while they have a lower correlation with park deserts. The findings of spatial transit inequity and the identification of essential service deserts provide crucial policy implications that can be used by transit agencies and local planning departments to prioritize their resources and target interventions to improve transit equity. This study contributes to the existing literature by proposing a systematic process that utilizes publicly available datasets to measure spatiotemporal transit supply, identify essential service deserts, and explore the correlation among these areas in a low-density city.

3.1 Introduction

There is a growing body of research investigating transit accessibility, which refers to the capacity of individuals to reach various destinations via public transportation (El-Geneidy et al., 2016b; Owen & Murphy, 2020a; Stewart, 2017; Welch, 2013; Yan et al., 2022). Providing transit access to essential services is critical for promoting health and enhancing overall quality of life, particularly for populations that rely on transit for their transportation needs (Brondeel et al., 2014; Jin et al., 2022; Mao & Nekorchuk, 2013; Martens et al., 2019; National Academies of Sciences Engineering and Medicine, 2022b; Taylor & Morris, 2014; USDA, 2023; Walker et al., 2010; Wood & Horner, 2016; Zhang & Mao, 2019; Zhang et al., 2022). The assessment of transit equity, which examines the geographical distribution of transit services and the provision of transit services to populations with the highest transit needs, has recently gained attention in the transit literature (Aman & Smith-Colin, 2020) and has emerged as an important aspect of the discourse on Environmental Justice for low-income and minority populations, particularly in the United States (FTA, 2012). Despite the growing body of research on transit accessibility and transit equity, there are still significant gaps that need additional attention and further investigation.

Firstly, most previous studies focused on single destination types, such as job opportunities, overlooking other essential services like healthcare facilities, food stores, schools, and childcare services. Secondly, temporal variations in transit services due to departure times and service frequency have been underemphasized, necessitating the development of a comprehensive spatiotemporal transit supply index. Thirdly, while social equity has been explored in previous research, spatial disparities in transit accessibility across diverse essential service types and potential spatial correlations in service deserts have received limited attention. Lastly, many transit equity studies have evaluated densely populated urban areas (Hess, 2005; Kawabata & Shen, 2006), while transit equity is no less important in lower-density areas (like Nashville, Tennessee) that are characterized by limited transit resources and unique urban structures. Addressing these gaps contributes significantly to the transit equity literature.

Therefore, this paper aims to contribute to the literature by (1) analyzing transit accessibility and transit equity to food, healthcare, education (schools), childcare, and green space (parks); (2) proposing a spatiotemporal transit supply index; (3) evaluating the spatial correlation

between transit-dependent demand and transit supply and identifying essential service desert clusters; and (4) estimating the correlation among various types of essential service deserts. The proposed method will be applied in Nashville (the capital city of Tennessee), a sprawling city with a bus-oriented transit system, as a case study. The proposed method primarily relies on open datasets, specifically General Transit Feed Specification (GTFS) data, Census data, and public geospatial location data of essential service facilities from federal or local departments, which makes this method widely applicable to other regions of the United States with fixed route transit service.

The subsequent sections of the paper are organized as follows. The first section provides a comprehensive review of relevant literature, highlighting previous studies that have examined transit accessibility and equity to essential services. This is followed by an introduction to the study area and the data required for this study. The proposed methodology is summarized in the subsequent section. The results of the study are then presented, followed by a policy discussion. The conclusion section provides a summary of the study findings, and the potential limitations and future research are discussed in the final section.

3.2 Literature review

This section provides a review of related literature pertaining to transit access to essential services and transit equity in the context of reaching essential services.

3.2.1 Transit accessibility to essential services

A growing number of studies published in the last decade have focused specifically on accessibility via transit, which refers to one's ability to reach opportunities by taking transit (El-Geneidy et al., 2016b; Owen & Murphy, 2020a; Stewart, 2017; Welch, 2013; Yan et al., 2022). The most extensively researched topic in these studies is transit accessibility to jobs (Hess, 2005; Karner, 2018; Kawabata & Shen, 2006; Yan et al., 2022). However, the critical role of accessibility to essential services to improve the quality of life of individuals and evaluate the operational efficiency of transit systems has received less attention in the literature. Some travelers use transit to get to other essential services, such as food stores, healthcare facilities, schools, childcare services, green spaces, etc. Accessibility to these other essential services that meet the needs of

people, especially minority populations and low-income people who rely on transit, is a key consideration for transit planners and stakeholders and is an important evaluation of the level of transit equity.

Numerous recent studies have suggested the importance of providing accessible food sources for residents, as a lack of access to affordable and nutritious food has been linked to a range of negative health outcomes and is often indicative of broader systemic issues related to poverty and inequality (USDA, 2023; Walker et al., 2010; Wood & Horner, 2016; Zhang & Mao, 2019). Similarly, prior research focusing on transit accessibility to healthcare has emphasized the significance of such access for vulnerable populations and has highlighted the need for policymakers to take action to enhance transit access to healthcare facilities (Brondeel et al., 2014; Jin et al., 2022; Mao & Nekorchuk, 2013; Zhang et al., 2022).

While food and healthcare are widely recognized as fundamental needs that play a critical role in people's lives, education and childcare services have received comparatively less attention in the literature. One prior study evaluated transit access to schools and found that highly educated people typically have better access to schools than other destinations (Ermagun & Tilahun, 2020). Some studies found that low-income parents frequently rely on transit for childcare trips, suggesting that transit access to childcare should be a significant factor in transit evaluation (Wang & Xu, 2020).

Additionally, parks offer a range of benefits for physical and mental well-being, community building, and environmental sustainability (Park et al., 2021). As such, parks are an important component of a well-functioning city and should not be overlooked in efforts to address service deserts and promote equitable access to essential services. One prior study analyzed transit accessibility levels to parks for disadvantaged populations and suggested that accessibility to parks has an important effect on both human health and social justice (Park et al., 2021).

Last, previous studies have predominantly concentrated on transit accessibility to one specific type of essential services, and only a few prior studies have considered multiple destinations, thereby creating a gap in the literature in which multiple essential service destinations are considered and compared. To address this gap, this study will calculate the transit accessibility to five types of essential services and provide insights into the variations in transit accessibility

among these essential service destinations, enabling policymakers and urban planners to make informed decisions for enhancing overall accessibility and equity.

3.2.1.1 Measurement of transit accessibility to essential services

Transit accessibility measurements can be broadly classified into two categories: opportunity-based (primal) and time/cost-based (dual) measurements (Cui & Levinson, 2020a). Opportunity-based measurements rely on predefined travel time thresholds that have no standard value under different scenarios (Levinson & King, 2020). Such measurements are typically used in scenarios where individuals have multiple options, like accessing job opportunities. However, compared to jobs, essential services tend to be fewer in number and more dispersed in distribution. Consequently, prior research commonly employed a time-denominated approach to measure transit access to these essential services, as it mirrors the actual travel behaviors of accessing essential services. In contrast to the opportunity-denominated approach, which calculates the number of accessible opportunities within a specified time threshold, time-denominated measurements assess the travel time required to access a fixed number of opportunities (Cui & Levinson, 2020a). This measurement is particularly valuable when the emphasis is on the significance of time in reaching these opportunities (Levinson & King, 2020). For instance, Farber et al. (Farber et al., 2014) utilized this method when measuring accessibility to food stores in Cincinnati, determining the travel time from each census block to the nearest supermarket. This approach has also found successful application in evaluating the accessibility of other essential services, such as a recent study examining healthcare accessibility in Florida (Ghorbanzadeh et al., 2020). Another key advantage of utilizing travel time as the accessibility metric is its capacity to facilitate direct comparisons of transit accessibility levels among different types of essential services and various groups of transit users. Moreover, measuring access in travel time offers a user-friendly and easily interpretable scale, making it more comprehensible to the public (Levinson & King, 2020). Therefore, in this study, the time-denominated approach will be applied in the transit accessibility calculation.

3.2.1.2 Temporal variation of transit accessibility to essential services

Another important consideration in the analysis of transit accessibility to essential services

is the temporal variation caused by differences in departure times or the variation in transit service frequency across different times of the day (Yan et al., 2022; Zhang et al., 2022). A growing body of literature incorporates temporal variation into the calculation of transit accessibility, either by calculating the average accessibility over multiple time windows (Allen, 2019; Boisjoly & El-Geneidy, 2016; Fransen et al., 2015) or by weighting accessibility by the percentage of time windows that reach a predetermined threshold (Farber et al., 2014). While commuting trips may be more concentrated during the AM and PM peaks on weekdays, trips to access essential services may be more likely to occur at other times of the day (Allen, 2019). Neglecting temporal variations in evaluating transit access to essential services may lead to inaccurate results, potentially resulting in incomplete and inadequate planning for future transit development.

This paper will first follow the method in previous studies (Allen, 2019; Farber et al., 2014; Fransen et al., 2015; Lei & Church, 2010; Yan et al., 2022; Zhang et al., 2022) in measuring transit accessibility in four time period on weekdays (AM peak during 7-10 a.m., midday during 11 a.m.- 3 p.m., PM peak during 4 p.m. – 7 p.m., early-evening during 8 p.m. – 11 p.m.). Then, time variation is calculated based on the variance of transit accessibility over these different time periods. Based on the time variance, one previous study that evaluated transit services categorized traffic analysis zones into different scenarios based on the temporal dynamics of transit accessibility (Yan et al., 2022). This previous study also argued that consistently high accessibility throughout the day (i.e., high accessibility with low variance) is a more favorable scenario than a situation with generally high accessibility but occasional sharp drops (i.e., high accessibility with high variance) (Yan et al., 2022). Building on this prior research, this study proposes a comprehensive spatiotemporal transit supply index that weights transit accessibility by the effects of temporal variations on transit accessibility observed within the study area.

3.2.2 Transit equity

3.2.2.1 Transit-dependent demand

An important step in evaluating transit equity is to identify disadvantaged groups that may be dependent on transit more than the general population. Socially disadvantaged groups typically have less access to resources and goods than the general population and thus are commonly

considered in measuring a variety of equity issues (Townsend et al., 1988). Social indicators, which have been widely used to identify socially disadvantaged groups in prior research (Foth et al., 2013; Sánchez-Cantalejo et al., 2008; Townsend et al., 1988), have been extensively applied in transit equity studies (El-Geneidy et al., 2016a; El-Geneidy et al., 2016b; Foth et al., 2013).

In terms of specific indicators, many prior studies have found that individuals with limited access to vehicles are more likely to rely on public transit to meet their transportation needs (Steiss, 2006). In recognition of this relationship, the U.S. Department of Transportation developed a formula for measuring the car-limited population based on data regarding household drivers and vehicle ownership (Steiss, 2006). This formula has subsequently been employed by numerous studies focused on transit equity as a means of quantifying transit-dependent demand (Cai et al., 2020; Jiao, 2017; Jiao & Dillivan, 2013; Lee et al., 2021; Li & Fan, 2020).

Among demographic variables, low-income and minority populations are frequently identified as groups with a higher potential need for transit because they may not be able to afford vehicles and are therefore more likely to rely on transit for travel. Previous studies (El-Geneidy et al., 2016b; Ermagun & Tilahun, 2020; Foth et al., 2013) suggested that individuals with lower incomes may find the cost of owning and operating a vehicle prohibitive and are therefore more likely to use public transit when it is available (Martens et al., 2019; Taylor & Morris, 2014). Race or ethnicity is often considered as a potential factor because some minority groups may have relatively lower income levels and experience lower levels of car ownership, leading to increased reliance on transit (Di Ciommo & Shiftan, 2017; Lucas et al., 2016; McCray & Brais, 2007).

Last, one prior study specifically conducted in rural regions of Tennessee indicated that rural transit riders in Tennessee are more likely to belong to minority groups, have lower income levels, and possess fewer or no personal vehicles (Yang & Cherry, 2017). Therefore, this study will consider potential car-limited populations with limited personal vehicle access, low income levels, and minority populations for the transit equity analysis that follows.

3.2.2.2 Transit equity of essential services

Previous studies examining transit equity to essential services have yielded varied findings. For instance, one transit equity study conducted in the Detroit metropolitan region demonstrated that minority and low-income households had favorable levels of transit accessibility to hospitals,

yet faced disadvantages accessing supermarkets (Grengs, 2015). In another study conducted in Chicago, it was found that low-income households encountered restricted transit accessibility to grocery stores, while the Hispanic population experienced increased transit accessibility to grocery stores but faced limitations in accessing hospitals (Ermagun & Tilahun, 2020). Notably, these studies focused on dense areas with well-established transit networks. Therefore, the following analysis conducted in Nashville provides a valuable addition to the existing literature by examining the transit equity of essential services specifically in a low-density urban area.

The term “transit desert” has been extensively discussed in prior literature and is generally defined as geographic areas or locations that have limited transit accessibility to a specific type of service, such as “food deserts” (Forsyth et al., 2010; Walker et al., 2010) and “healthcare deserts” (Brondeel et al., 2014; Jiao & Dillivan, 2013; Mao & Nekorchuk, 2013). However, few prior studies have quantified transit equity for accessing multiple essential services that are important to fulfill people’s many fundamental needs (Cui & Levinson, 2020a; Zheng et al., 2019). Therefore, the concept of “essential service deserts” is proposed in this paper to identify areas with limited access to numerous essential services.

The literature on transit equity typically employs comparative or statistical approaches to measure transit equity. Comparative approaches include simple gap identification methods to identify transit deserts by the difference or ratio of demand and supply (Aman & Smith-Colin, 2020; Jiao, 2017; Jiao & Dillivan, 2013). In terms of statistical approaches, various indicators have been used to quantify transit equity, such as the Gini coefficient (Liang et al., 2023) and the Theil index (Jin et al., 2022). Some studies involving spatial analysis of transit equity have utilized the bivariate local indicator of spatial association (bi-LISA) to evaluate the spatial disparity of the relationship between transit supply and demand (Jin et al., 2022; Liang et al., 2023).

Despite numerous studies conducted on transit equity analysis, a potential gap exists as few of them have considered the spatial inequity of transit with regard to different types of essential services and the potential spatial correlations between different essential service deserts. This highlights the need for further research to consider the interconnectivity between transit accessibility and essential service facilities in order to better understand the spatial patterns of transit inequity.

3.3 Study area and data

3.3.1 Study area

Nashville is the capital city of the state of Tennessee located in the southeastern United States. According to the U.S. Census Bureau, as of 2020, Nashville had an estimated population of approximately 690,000 people, making it the 21st most populous city in the United States (U.S. Census Bureau, 2021b). However, due to its extensive land area, Nashville is listed as the third least densely populated large city (with 350,000 or more population) and ranks 24th out of the 318 least densely populated US cities (with a population above 100,000) (Heacock, 2019). Demographic data for Nashville show that about 15% of residents are below the poverty line, 38% of residents are minorities (non-white), and 14% of residents are Hispanic or Latino (U.S. Census Bureau, 2020b).

Regarding transportation, Nashville is an automobile-oriented city with only 6% of households without vehicles. Nashville Metropolitan Transit Authority (Nashville MTA, rebranded as "WeGo Public Transit" (WeGo) in 2018 (Pair, 2018)) was established in 1973 to provide public transit services for Nashville's Davidson County (Nashville MTA, 2019). The American Public Transportation Association (APTA) Public Transportation Factbook noted that the transit agency in the Nashville area is listed among the smaller transit agencies nationwide, with the Metropolitan Transit Authority (MTA) being the 84th-ranked transit agency evaluated by Unlinked Passenger Trips (APTA, 2022). However, transit equity is no less important in lower density areas (such as Nashville, Tennessee) where transit service may be limited. In such contexts, it is especially important to allocate limited transit resources to those who need it most. The most recent onboard surveys conducted by Nashville's MTA in 2017 revealed that over half of riders belonged to minority groups and had limited access to personal vehicles, with approximately 44% of Black/African American and 36% of Hispanic/Latino riders indicating a lack of personal vehicle ownership (Nashville MTA, 2019).

3.3.2 Data

This section discusses the data used to measure transit accessibility and transit equity. GTFS data including static transit schedules and geospatial transit networks for 2022 were collected from the

Nashville Metropolitan Transit Authority (WeGo Transit). For the transit accessibility calculations, origin locations were the centroid of each Census block; the 2020 TIGER/Line shapefile of Census blocks and Census block groups was obtained from the U.S. Census Bureau (U.S. Census Bureau, 2020b). The Census block level was aggregated to the Census block group level to evaluate transit equity. The demographic information used to estimate transit-dependent demand was downloaded at the Census block group level from the U.S. Census Bureau (U.S. Census Bureau, 2020b). Location data for essential services, including food stores, healthcare facilities, schools, childcare facilities, and parks, were assembled from various online datasets. These sources are from nationally available programs such as the Supplemental Nutrition Assistance Program (SNAP), Department of Homeland Security (DHS), National Center for Education Statistics (NCES), and The Trust for Public Land. A description of these datasets is shown in **Table 4**. Last, since the entrance locations of parks were not available from the Trust for Public Land, the locations of park entrances were estimated by the intersection of park boundaries and roads using OpenStreetMap with no restriction to pedestrians, and to ensure the road intercepts the park boundaries, a 100-ft (30.48-meter) buffer was created. The 100-foot (30.48-meter) buffer was implemented based on insights derived from a prior study. This considered the potential for the road centerline to not align precisely with a park boundary, even when they are spatial close enough, along with the possible existence of pedestrian pathways between them, which are not included in the TIGER/Line® shapefiles (Park et al., 2021).

3.4 Methodology

3.4.1 Research questions and conceptual framework

Based on the literature review, the following research questions and methods have been proposed for the case study of Nashville, TN.

- Question 1: Does the level of transit supply to access different essential services facilities vary?
- Question 2: Does the level of transit-dependent demand vary among different socio-demographic groups?
- Question 3: Are there spatial inequities in transit supply to access different types of essential services? If so, does transit inequity vary among transit-dependent demand groups?

Table 4 Data sources and data descriptions

Data	Categories	Data source	Data description
Transit information	GTFS	WeGo transit	WeGo transit schedule, routes
Geographic information	TIGER/Line Shapefile	U.S. Census Bureau	2020 TIGER/Line shapefile of census block and census block group boundaries
Demographic information	Car-limited population	U.S. Census Bureau	2021 ACS data: Household Type (Including Living Alone) by Relationship; Tenure by Vehicles Available; Sex by Age
	Poverty population	U.S. Census Bureau	2021 ACS data: Ratio of Income to Poverty Level in the Past 12 Months
	Minority (Race and ethnicity) population	U.S. Census Bureau	2021 ACS data: Race; Hispanic or Latino Origin by Race
Essential service facility locations	Food stores	Supplemental Nutrition Assistance Program (SNAP) from the U.S. Department of Agriculture (USDA)	The locations of food stores were exported from SNAP the USDA website. An interactive mapping program on the USDA website provides a GIS dataset of authorized SNAP retailers including supermarkets, grocery stores, and convenience stores.
	Healthcare facilities	Department of Homeland Security (DHS)	The locations of healthcare facilities including hospitals and pharmacies were exported from the Homeland Infrastructure Foundation-Level Data (HIFLD) Open Data website provided by DHS.
	Schools	National Center for Education Statistics (NCES)	GIS datasets for educational institutions including colleges, universities, and public and private elementary and secondary schools were downloaded from the NCES Edge Open Data website.
	Childcare facilities	Department of Homeland Security (DHS)	A list of childcare services in the State of Tennessee was downloaded through an interactive tool from the Homeland Infrastructure Foundation-Level Data (HIFLD) Open Data website provided by DHS.
	Parks	ParkServe® data (The Trust for Public Land, 2019)	A list of parks that has open access (no restricted access)

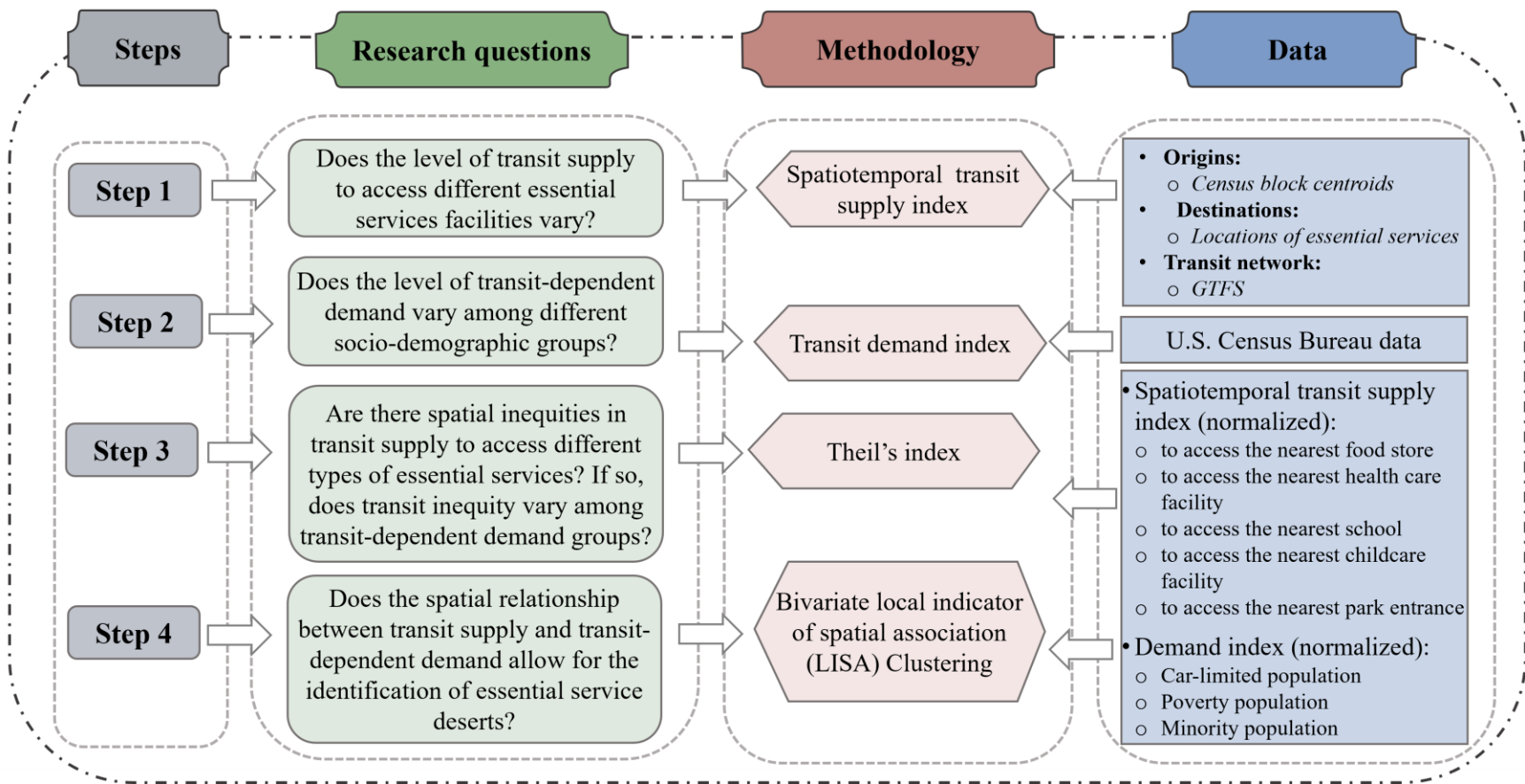


Figure 11 Conceptual framework

- Question 4: Does the spatial relationship between transit supply and transit-dependent demand allow for the identification of essential service deserts?
- Question 5: Is there a spatial relationship among different types of essential service deserts?

To answer these research questions, this paper proposed a five-step method shown in **Figure 11**, which provides a framework for the remainder of the paper. In the first step, a spatiotemporal transit supply index was developed to incorporate travel time-based transit accessibility and the temporal variation of accessibility across different times of the day. The second step involved the creation of a demand index for three potential groups that historically rely on transit utilizing sociodemographic data obtained from the U.S. Census Bureau. The third step used Theil's index to evaluate spatial transit inequity. To identify the spatial clustering of transit inequity of essential services, the fourth step investigated the spatial disparity of the relationship between transit supply to access different essential services and transit-dependent demand using the bivariate local indicator of spatial association (LISA). After identifying essential service deserts in the fourth stage, the final step involved conducting further analysis of the relationships between different deserts by generating a correlation matrix and co-location maps.

Each of these steps is described in more detail in the following section.

3.4.2 Step 1: measure spatiotemporal transit supply index

3.4.2.1 Step 1a: measure transit accessibility

A time-denominated measure was used to calculate the transit travel time required for accessing the nearest essential service facility via transit at a given departure time point. This method assumes that users opt for the nearest essential service location due to the unavailability of actual travel behavior data showing essential service selection. The calculation of transit travel time was done in the Conveyal Analysis platform. The transit travel time includes walking time to access to and egress from transit stops, waiting time at the stop, and in-vehicle travel time. In the Conveyal Analysis platform, the maximum walking time was set at 20 minutes, the walking route followed the street network developed by OpenStreetMap, and a maximum of three transfers is assumed. In addition, a time percentile needs to be selected to represent the arrival process of riders at the stop based on transit schedules. A lower percentile indicates that riders are accustomed to

relying on schedules and that they adjust their departure time to minimize waiting times at the stop and overall travel times, which often is the case in areas with less frequent service. A higher percentile suggests that riders are less reliant on schedules, potentially starting trips randomly, which is typical in areas with high frequency transit service. In this study, the time percentile was set at the median (50th percentile), which represents a mix of both timed arrivals and random arrivals at the transit stop.

The equation for calculating the travel time is shown in **Equation (1)**.

$$Transit_access_{ijt} = \min_{\forall k \in K, \forall t \in T} (Travel_time_{ijtk}) \quad (1)$$

Where:

$Travel_time_{ijtk}$ is the travel time via transit from the block centroid i to the k^{th} location of the essential service j at departure time t ;

k is the location of essential service j ;

j is the type of essential service facility including food stores, healthcare facilities, schools, childcare facilities, and park entrances;

t is the departure time within the time window T .

Time windows include the AM peak during 7:00 - 9:59, midday during 11:00 - 13:59, PM peak during 16:00– 18:59, and early evening during 19:00 - 21:59 on a weekday. Therefore, $Transit_access_{ijt}$ is the minimum transit travel time needed to travel from origin i to the nearest essential service facility j at time window T . Then the average transit accessibility for a day is calculated using **Equation (2)**.

$$Transit_access_{ij} = \frac{\sum_T Transit_access_{ijt}}{Number\ of\ T} \quad (2)$$

Where $Transit_access_{ij}$ is the average travel time from the block centroid i to the essential service facility j and T is equal to 4.

3.4.2.2 Step 1b: measure time variation of transit accessibility

The time variation of transit accessibility is calculated using **Equation (3)**.

$$Time_Variation_{ij} = \frac{\sum_T (Transit_access_{ijt} - Transit_access_{ij})^2}{(Number\ of\ T) - 1} \quad (3)$$

Where T represents time windows and $Time_Variation_{ij}$ is the time variation from the

block centroid i to the essential service facility j .

3.4.2.3 Step 1c: measure transit supply index: spatiotemporal transit supply to access essential services

Equation (4) was developed to measure the spatiotemporal transit supply index, which assigns weights to travel time-based transit accessibility. First, the travel time-based transit accessibility was normalized to a range of 0 to 1. For ease of interpretation and consistency with common conventions, the transformation, represented as one minus the normalized travel time-based transit accessibility, was employed. This transformation ensures that a higher transit supply index value corresponds to a larger value level of accessibility and lower values show worsening access. The assignment of weights was determined by the effects of temporal variations on transit accessibility observed within the study area.

$$Transit_supply_{i,j} = (1 - [Transit_access_{ij}]_{normalized}) * Weight_{i,j} \quad (4)$$

Where:

$$[Transit_access_{i,j}]_{normalized} = \frac{(Transit_access_{i,j} - \min(Transit_access_j))}{(\max(Transit_access_j) - \min(Transit_access_j))};$$

$Transit_supply_{i,j}$ is the transit supply to access the essential service facility j for the block i ;

$Weight_{i,j}$ represents the weight that is determined based on the temporal variation of transit accessibility to the essential service facility j for the block i .

To determine the weights in the context of Nashville, the distribution of the results in the study area from the previous two steps (step 1a and step 1b) were visualized through scatter plots and box plots (as illustrated in **Figure 12**). The x-axis denotes the average transit accessibility represented by the average travel time in minutes, and the y-axis denotes the temporal variation of transit accessibility. The blue box plots provide a summary of average transit accessibility, and the pink box plots depict a summary of the temporal variation of transit accessibility. Additionally, the orange box plots display the distribution of non-zero temporal variation of transit accessibility. As can be seen in **Figure 12**, the pink box plots generally have narrow boxes and short whiskers that extend toward the lower end of the plots, which suggests that the majority of the data points have values near zero. This indicates that the time variation of transit accessibility across the four

time periods is minimal, suggesting that most transit services maintain a consistent schedule across different time periods. Therefore, the time variation value of zero was categorized as low variation. For those cases with time variation value greater than zero, time variation was categorized into low and high variation based on the third quantile value instead of the median value (the third quantile value was computed after separating zero-time variation cases). The transit accessibility results were categorized based on the quantile threshold values into four categories, namely high transit accessibility (travel time less than the first quantile), moderate-high transit accessibility (travel time ranging from the first quantile to the median), moderate-low transit accessibility (travel time ranging from the median to the third quantile), and low transit accessibility (travel time greater than the third quantile).

Weights were proposed for various combinations of transit accessibility and time variation, as illustrated in **Figure 13**. The highest weight was assigned to areas with high transit accessibility and low variation, indicating consistently high transit accessibility and the highest level of the transit supply index. The second-highest weight was assigned to areas with high transit accessibility and high variation, indicating overall high transit accessibility with occasional dips in accessibility. Conversely, the lowest weight was assigned to areas with low transit accessibility and low variation, indicating consistently low transit accessibility and the lowest level of the transit supply index. The second-lowest weight was assigned to areas with low transit accessibility and high variation, indicating overall low transit accessibility with occasional increases in accessibility. Consequently, six weights were assigned with a linear progression from 1/6 to 1 (Fransen et al., 2015). This progression guarantees that the transit supply index falls within the range of 0 to 1, offering a meaningful scale for interpretation while also facilitating a comprehensive spatiotemporal assessment of transit supply to access essential services.

3.4.3 Step 2: measure transit-dependent demand index

Drawing on prior research, three sociodemographic groups were selected for evaluation in Nashville. The first group was car-limited populations, and the formula for this was adapted from research conducted by the U.S. Department of Transportation (USDOT) (Steiss, 2006). Car-limited populations were identified as those individuals who are unable to operate a vehicle or

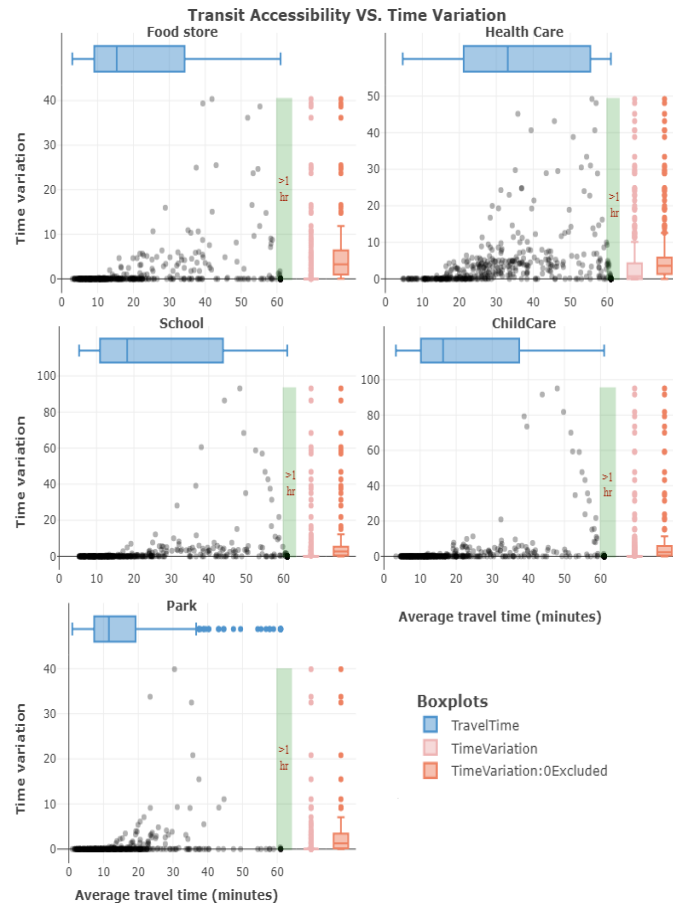


Figure 12 Scatter plots and box plots of transit accessibility and time variation

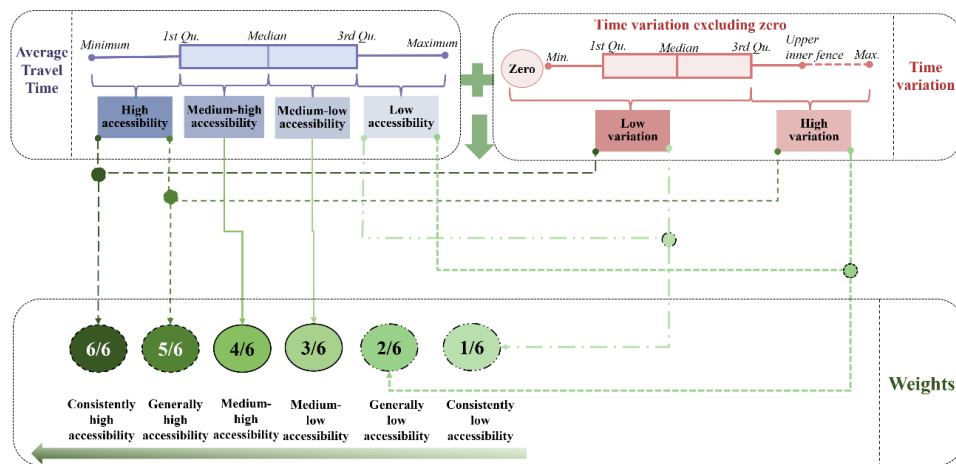


Figure 13 Proposed weights for the estimation of spatiotemporal transit supply to access essential services

have limited vehicles available to use and, consequently, are more likely to rely on transit for their daily transportation needs. It is noted that individuals living in group quarters were deducted from the car-limited population calculation formula because the entity or organization that owns or manages the group quarters provides housing and/or other services for the residents (U.S. Census Bureau, 2021a), which may affect their reliance on transit.

Based on the USDOT formula, prior studies further considered potential car-limited populations who are not able to drive but sometimes might need to go out on their own (Jiao, 2017; Jiao & Dillivan, 2013; Li & Fan, 2020). This paper utilized the formula adapted by a previous study (Li & Fan, 2020) that included the population aged 10-15 as potentially car-limited. It is important to note that while there is no universal legal age at which children may be allowed to travel independently, the Tennessee State Courts (Tennessee State Courts) recommend against leaving children under the age of 10 unattended.

Accordingly, **Equations (5) to Equations (7)** were developed for this study to calculate the car-limited index at the i_{th} census block group:

- $Driving - age_population_i = (populations\ over\ age\ 16)_i - (people\ living\ in\ group\ quarters)_i$ (5)

- $Car - limited_population_i = (Driving\ age\ population)_i - (Number\ of\ available\ vehicles)_i + (Total\ population\ between\ 10 - 15)_i$ (6)

- $Car - limited_index_i = [Car - limited_population_i]_{normalized}$ (7)

The normalization process in **Equation (7)** followed the same min-max method as applied in **Equation (4)**.

Before continuing, it should be noted that a lack of data specifically showing the difference in the number of drivers and available vehicles at the household level may potentially result in an underestimation of the transit-dependent population.

The remaining two potential transit-dependent demand groups are comprised of poverty and minority populations, which are recognized as protected groups entitled to equitable transit access under Title VI of the Civil Rights Act of 1964. Poverty is defined as individuals with incomes below the poverty threshold (U.S. Census Bureau) at the Census block group level, and

minority populations encompass nonwhite and Hispanic origin populations at the Census block group level. Accordingly, **Equations (8) to (9)** and **Equations (10) to (11)** were developed for this study to calculate indexes for the population in poverty and for minority populations at the i_{th} Census block group, respectively.

- $Poverty_population_i = population\ below\ poverty\ threshold_i$ (8)

- $Poverty_index_i = [Poverty_population_i]_{normalized}$ (9)

- $Minority_population_i =$
 $(NonWhite\ population\ (Black, Asian, American\ Indian, Alaskan))_i +$
 $(Hispanic\ origin\ population_i)$ (10)

- $Minority_index_i = [Minority_population_i]_{normalized}$ (11)

Last, the populations from these three groups were then summed to measure the combined transit-dependent demand, as shown in **Equation (12)**. All demand indexes had a range of 0 to 1.

- $Combined\ Transit - dependent\ demand\ index_i = (Car - limited_population_i +$
 $Poverty_population_i + Minority_population_i)_{normalized}$
(12)

The normalization process in **Equation (9)**, **Equation (11)** and **Equation (12)** followed the same min-max method as applied in **Equation (4)**.

In accordance the findings of prior research (Grengs, 2001; Li & Fan, 2020), it is pertinent to note that due to the inherent overlapping characteristics present in Census data across these demographic factors, there is a potential for unavoidably double-counting some people when aggregating to the combined transit-dependent demand index.

3.4.4 Step 3: quantify spatial transit inequity using the Theil index

This step utilized the Theil index to estimate the spatial inequity associated with transit supply to access essential services. The overall Theil index, which measures the total spatial inequity in the study area, can be decomposed into within-group and between-group components. The advantage of this decomposition is that it helps identify inequality within and between different defined population subgroups with different levels of transit demand. The Theil index ranges between 0 and 1, where 0 indicates that transit supply to access essential services is equally

distributed in the whole region and a higher Theil index indicates a wider disparity among Census block groups, suggesting a greater inequity. The equations are shown below in **Equations (13), (14), and (15)**:

$$T = \left(\frac{1}{N}\right) \sum_{i=1}^N \left(\frac{TS_i}{\overline{TS}}\right) \ln \left(\frac{TS_i}{\overline{TS}}\right) \quad (13)$$

$$T_{WG} = \sum_{k=1}^K TS_k \left[\sum_{i \in g_k} \frac{TS_{ki}}{\overline{TS}} \ln \frac{TS_{ki}/TS_k}{1/n_k} \right] \quad (14)$$

$$T_{BG} = \sum_{k=1}^K TS_k \ln \left(\frac{TS_k}{n_k/N} \right) \quad (15)$$

Where:

T is the overall Theil index;

T_{WG} is the within-group component of the Theil index, which evaluates the inequity within each transit demand subgroup;

T_{BG} is the between-group component of the Theil index, which evaluates the inequity across different transit demand subgroups;

N is the total number of Census block groups;

TS_i is the transit supply index of Census block group i ;

$\overline{TS}$ is the average level transit supply to access essential services of all the Census block groups in Nashville;

K is the number of transit demand subgroups;

g_k is the set of Census block groups within the k_{th} level;

n_k is the number of g_k ;

TS_{ki} is the percent share of the total transit supply index of Census block group i ;

TS_k is the percent share of the total transit supply index of the transit demand subgroup k .

3.4.5 Step 4: identify essential service deserts using the bivariate local indicator of spatial association (bi-LISA)

To identify essential service deserts characterized by low transit supply and high transit-dependent demand, the bivariate local indicator of spatial association (bi-LISA) was utilized to evaluate the spatial disparity of the relationship between transit supply to access essential services and transit-dependent demand across Census block groups and to identify spatial clustering of

transit inequity. The bi-LISA calculates the local Moran's I statistic for each Census block group i , as shown below in **Equation (16)**:

$$I_i = D_i \sum_j W_{ij} S_j \quad (16)$$

Where:

D_i is the standardized transit demand index (*standardization of demand index obtained from Equation (9), Equation (11) and Equation (12)*) for the Census block group i ;

S_j is the standardized transit supply index (*standardization of supply index obtained from Equation (4)*) for the Census block group j ;

W_{ij} are the elements of the neighborhood weight matrix that was generated by queen contiguity weight to assess the spatial relationship between Census block group i and Census block group j in which $W_{ij} = 1$ if i and j are neighbors; $W_{ij} = 0$ if i and j are not neighbors.

D_i and S_j represent the standardized index, which can encompass both positive and negative values. Consequently, the values for the local Moran's I range between -1 and 1 , where positive values represent positive spatial association patterns and negative values indicate the opposite direction. The absolute values of the local Moran's I correspond to the strength of the spatial correlation. A 5% significance level was used to determine the statistical significance of the calculation, with Census block groups having a p-value above this threshold considered not significant. The outputs of this step included the bi-LISA clustering maps showing the local spatial correlation patterns for different transit-dependent demand groups and different transit supply categories. The spatial correlation patterns can help to identify the spatial match and mismatch between transit-dependent demand and transit supply to access essential services by categorizing the census block groups into four clusters: High-High clusters (Census block groups with high transit-dependent demand and high transit supply to access essential services), High-Low clusters (Census block groups with high transit-dependent demand and low transit supply to access essential services), Low-High clusters (Census block groups with low transit-dependent demand and high transit supply to access essential services), and Low-Low clusters (Census block groups with low transit-dependent demand and low transit supply to access essential services). Specifically, High-Low clusters were identified as ***essential service deserts***.

3.4.6 Step 5: correlation analysis and co-location maps of essential service deserts

This step further analyzed areas with inequitable transit supply that were identified as essential service deserts in the previous step. The analysis method for this step consists of two parts. First, the tetrachoric correlation measure was employed to estimate the correlation among various types of essential services, which were identified by the binary variables indicating whether a Census block group was classified as an essential service desert (1) or not (0). The tetrachoric correlation measures the Pearson product-moment correlation between two binary variables, with values ranging from -1 to 1. A value of -1 indicates a strong negative correlation, 0 indicates no correlation, and 1 indicates a strong positive correlation between the two variables. A 2x2 table containing two binary variables for “food store desert” and “school desert” is shown in **Table 5** as an example, and the corresponding formula for calculating the tetrachoric correlation between the two variables is shown in **Equation (17)**:

$$Cor = \cos \left[\frac{\pi}{(1 + \sqrt{ad/bc})} \right] \quad (17)$$

Where:

a is the number of Census block groups that are neither food store deserts nor school deserts;

b is the number of Census block groups that are school deserts but not food store deserts;

c is the number of Census block groups that are food store deserts but not school deserts;

d is the number of Census block groups that are food store deserts and school deserts.

The outcome of this is a correlation matrix that displays the direction, strength, and statistical significance of the correlation among five identified essential service deserts.

In the second part of this step, areas with overlapping essential service deserts were identified by conducting a co-location analysis. The anticipated outcome comprises co-location maps that demonstrate the areas with multiple categories of essential service deserts with a high correlation value.

3.5 Results

This section presents the results of this study in five parts. The first two parts map the distribution of the transit supply index and transit demand index for the study area. The third part

Table 5 Example of two binary variables

		<i>Variable: School desert (binary)</i>	
		No (0)	Yes (1)
<i>Variable: Food store desert (binary)</i>	No (0)	a	b
	Yes (1)	c	d

quantifies the spatial transit inequity for the five essential service categories and compares the transit inequity across and within different transit-dependent demand groups. The fourth part assesses the spatial match and mismatch between transit supply to access essential services and transit-dependent demand and identifies underserved areas as essential service deserts. The last part presents the correlation analysis results across different types of essential service deserts and the co-location maps of areas with overlapping essential service deserts.

3.5.1 Transit supply index

This part applied the method discussed in section 4.2 to compute the spatiotemporal transit supply index for the five essential service categories. To enable comparison between maps for the city of Nashville, **Figure 14** employed equal interval classifications to visualize the transit supply index at the Census block group level. The map in the bottom right corner displays Nashville's WeGo transit network, and the remaining maps depict the transit supply index with overlaid essential service facility locations (e.g., one map showing food stores, one showing healthcare facilities, etc.). These transit supply index maps utilized a consistent reference scale and legend, with darker shades of blue representing higher levels of transit supply to access essential services.

The maps in **Figure 14** reveal several noteworthy spatial patterns. First, the downtown area of Nashville has the highest transit supply levels regardless of the essential service category. Second, areas with denser transit stops and more essential service facility locations generally correspond to higher transit supply levels (as would be expected). Third, there is a consistent trend of decreasing transit access to food, healthcare, school, and childcare as one moves away from the city center and towards the outskirts of Nashville. Finally, the distribution of transit supply to access parks is somewhat different, with higher transit supply levels concentrated in the central and south/east areas of Nashville. This is likely because recreational amenities and green spaces, such particularly larger parks, are often located in suburban areas of the city. Based on these findings, it can be noted that certain areas in Nashville encounter limited access to one or several types of essential services via transit.

3.5.2 Transit demand index

This part applied the method discussed in section 4.3 to compute the transit-dependent

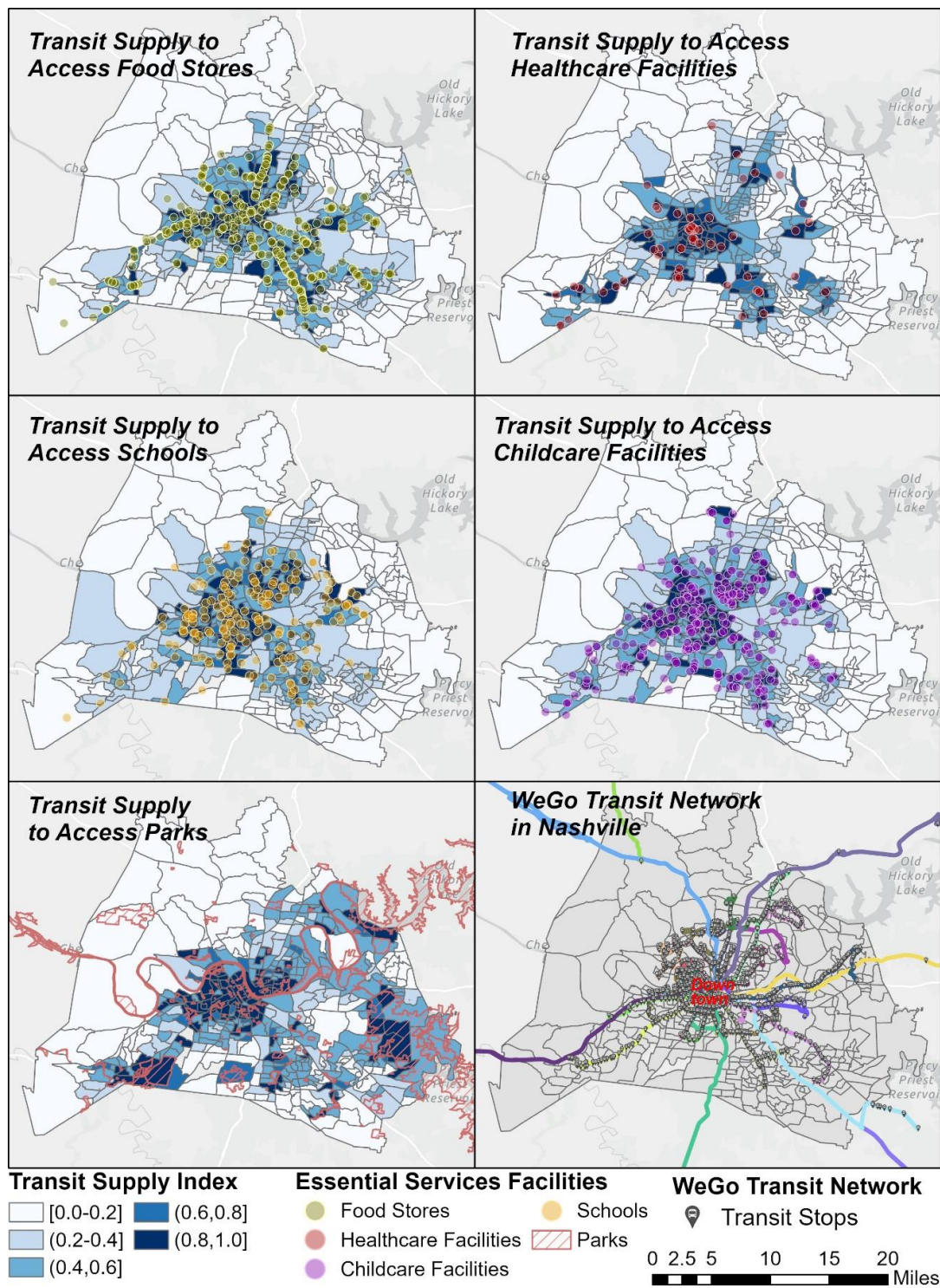


Figure 14 Distribution of the transit supply index to the five essential service categories in Nashville

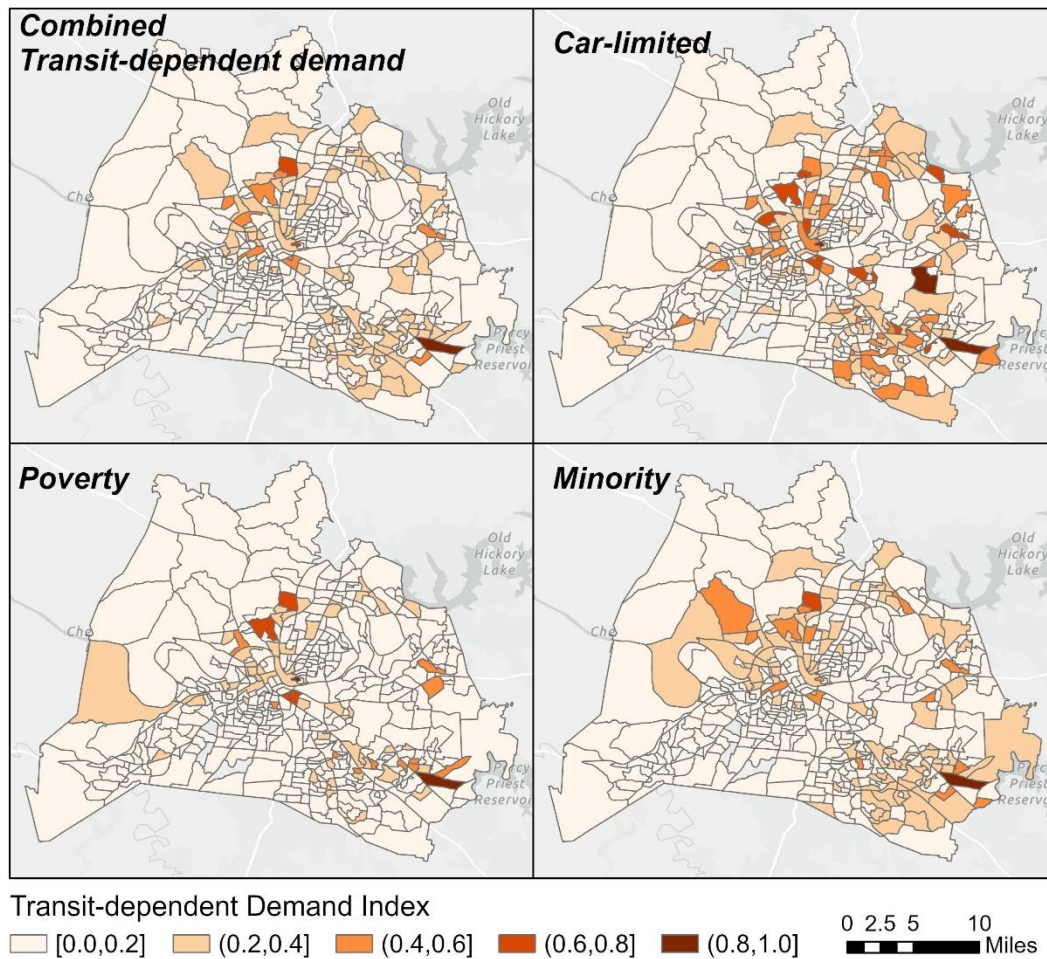


Figure 15 Distribution of the transit-dependent demand index in Nashville

demand index for three transit-dependent groups (car-limited, poverty, minority) in the city of Nashville. **Figure 15** displays the distribution of the transit-dependent demand index at the Census block group level, utilizing the equal interval classification method. The color scheme was created based on the value of the normalized transit-dependent demand population, with darker shades of orange-brown indicating higher levels of transit-dependent demand. As can be seen in **Figure 15**, most areas in Nashville exhibit relatively low levels of transit-dependent demand, as indicated by the lightest orange color. This finding aligns with the sociodemographic characteristics of Nashville, where approximately 15% of residents fall below the poverty line, 38% of residents are minorities (non-white), 14% of residents identify as Hispanic or Latino, and only 6% of households do not own vehicles. Despite variations in the distribution of different transit-dependent groups, there are some areas of overlap among them. For instance, one block group located in southeast Nashville has the highest transit-dependent demand index level for all three transit-dependent groups, indicated by the darkest orange shade.

3.5.3 Spatial transit inequity using the Theil index

The Theil index was applied to evaluate the spatial inequity of transit supply to access essential services in Nashville. The overall spatial inequity index of transit supply to access essential services is presented in the second column in **Table 6**. The average transit supply to access five essential services for the total population and for the five population subgroups with different levels of combined transit-dependent demand index are shown in the parentheses in **Table 6**. The Theil index for transit supply to access healthcare facilities (0.38) is the highest among all essential services, indicating that transit accessibility to healthcare has the greatest level of inequity. Furthermore, when compared to transit supply to access the other four essential services, the average transit supply to access healthcare facilities (which is also 0.38) is notably the lowest. This is mainly because, compared to other essential services, healthcare facilities are fewer in number and more concentrated in certain areas, as shown in **Figure 14**. Conversely, transit accessibility to parks has the lowest total level of spatial inequity and transit supply to access parks has the highest average level across the city, as reflected by the smallest Theil index value (0.20) and the largest transit supply index value (0.51). This can be attributed in part to the fact that parks

are more evenly distributed throughout the city than other essential service facilities. The level of spatial inequity in transit accessibility to other essential services in descending order of the Theil index is as follows: transit supply to access schools (0.32), transit supply to access childcare facilities (0.30), and transit supply to access food stores (0.28). Transit accessibility to these three essential services has similar levels of spatial inequity, which is consistent with **Figure 14**, where the transit supply index to these essential services has a similar spatial distribution pattern. This observation is further supported by the citywide average transit supply index values, which are very similar (0.47, 0.47 and 0.48, respectively) for these essential services.

In terms of transit inequity in different population subgroups with different levels of combined transit-dependent demand, the results from the third to the seventh column of **Table 6** indicate that population subgroups with low to moderate levels of transit demand (with the combined transit-dependent demand index below 0.6) have more equitable transit access to parks (indicated by the Theil index of 0.20, 0.21, and 0.09). However, population subgroups with higher transit demand levels (with the combined transit-dependent demand index above 0.6) have more equitable transit access to food stores and healthcare facilities (indicated by the Theil index values of 0.02 and 0.03). Nevertheless, there are varying equity trends within subgroups, with some having an average transit supply index higher than the citywide average and others having an average transit supply index lower than the citywide average, even when the overall larger group shares a uniform level of equity. For example, the subgroup with the combined transit-dependent demand index between 0.0 to 0.2 and the subgroup with the combined transit-dependent demand index between 0.2 to 0.4 have the same Theil index value (0.28) for transit supply to access food stores. However, the former subgroup has an average transit supply index higher than the citywide average (as shown by $0.49 > 0.48$) while the latter subgroup has an average transit supply index lower than the citywide average (as shown by $0.46 < 0.48$). The subgroup with a combined transit-dependent demand index ranging from 0.6 to 0.8 exhibits a high level of spatial transit equity in accessing food stores and healthcare facilities, with Theil index values of 0.02 and 0.03, respectively. However, transit supply to access these two services differs within this subgroup, with higher-than-citywide transit supply level for food stores ($0.49 > 0.48$) and lower-than-citywide transit supply level for healthcare facilities ($0.35 < 0.38$). The Theil index for the transit-

Table 6 Theil index, T_{BG} and T_{WG} of relative transit supply to access essential services for population subgroups with different combined transit-dependent demand index

	Theil index							
	Combined transit-dependent demand index						T_{BG}	T_{WG}
	Total	(0.0, 0.2]	(0.2, 0.4]	(0.4, 0.6]	(0.6, 0.8]	(0.8, 1.0]		
Transit supply to access food store	0.28 (0.48)	0.28 (0.49)	0.28 (0.46)	0.24 (0.56)	0.02 (0.49)	0 (0.03)	0.77%	99.23%
Transit supply to access healthcare	0.38 (0.38)	0.37 (0.39)	0.42 (0.35)	0.50 (0.37)	0.03 (0.35)	0 (0.03)	0.71%	99.29%
Transit supply to access school	0.32 (0.47)	0.30 (0.49)	0.40 (0.38)	0.23 (0.66)	0.12 (0.67)	0 (0.03)	2.36%	97.64%
Transit supply to access childcare	0.30 (0.47)	0.28 (0.49)	0.35 (0.41)	0.27 (0.58)	0.11 (0.66)	0 (0.03)	1.52%	98.48%
Transit supply to access park	0.20 (0.51)	0.20 (0.51)	0.21 (0.50)	0.09 (0.69)	0.35 (0.55)	0 (0.38)	0.55%	99.45%
<i>Average transit supply index for each population group is shown in parentheses</i>								

dependent demand index of (0.8, 1.0] is zero, which is because only one block group belongs to this level. The residents of this block group experience notably limited transit access to all these five essential services, with particularly poor accessibility to food, healthcare facilities, schools, and childcare services.

Furthermore, it is worth noting that even among subgroups with lower levels of equity, they may exhibit a higher average transit supply. For instance, when considering transit supply for accessing food stores and healthcare facilities, subgroups with a combined transit-dependent demand index ranging from 0.4 to 0.6 show lower spatial equity, indicated by Theil index values of 0.24 and 0.5, compared to subgroups with a combined transit-dependent demand index between 0.6 to 0.8, which have Theil index values of 0.02 and 0.03. However, despite the lower equity levels, the former subgroups have higher average transit supply for accessing food stores (0.56 compared to 0.49) and greater average transit supply for accessing healthcare (0.37 compared to 0.35). Therefore, further analysis of the spatial match and mismatch between the transit-dependent demand and transit supply to access essential services is developed in the next section.

The last two columns on the righthand side of
present the between-group and within-group components of the Theil index. The within-group inequity is much more pronounced than between-group inequity, primarily due to the disparities caused by a large number of block groups that were categorized within a single group (the group with the lowest range of (0.0, 0.2]). Regarding between-group inequity, transit supply to access schools has the highest level of inequity (2.36%), indicating that between-group inequity for transit accessibility to schools made a higher contribution to the overall inequity when compared with between-group inequity for transit accessibility to other categories. However, it still is a very small contribution compared to the within-group inequity.

3.5.4 Spatial correlation between transit-dependent demand and transit supply and identification of essential service deserts

The bi-LISA maps in **Figure 16** visualize the spatial match and mismatch between the transit-dependent demand and transit supply to access essential services by categorizing block groups into four types of significant spatial correlation clusters. It is noted that a 5% significance

level was used to determine the statistical significance of the calculation of local Moran's I , with block groups having a p-value above this threshold classified as not significant. The matched correlation consists of H-H clusters (shown in red), indicating high transit-dependent demand and high supply areas, and L-L clusters (indicated in blue), representing areas with low transit-dependent demand and low transit supply to access essential services. The mismatched pattern includes two types, namely the H-L clusters (indicated as pink), which highlights underserved areas with high levels of transit-dependent demand but limited access to essential services via transit, and the L-H clusters (indicated as indigo), indicating areas with low transit-dependent demand but high transit accessibility, which are considered overserved areas.

In general, the majority of H-H clusters (high demand and high supply) and L-H clusters (low demand and high supply) are concentrated in the central city area characterized by a high density of transit stops and numerous essential service facilities. In contrast, most H-L clusters (high demand and low supply) and L-L clusters (low demand and low supply) are distributed on the peripheries of the city. However, different distribution patterns can be observed between clusters of transit supply to access parks and clusters of transit supply to access the other four essential services. As an illustration, in terms of combined demand groups (shown in the first column), it is noted that the number of H-L clusters is higher for food stores, healthcare, schools, and childcare facilities compared to parks. This indicates that communities with high transit-dependent demand have less access to food stores, healthcare facilities, schools, and childcare facilities than to parks. Furthermore, within the southeastern region of the city, H-L clusters can be observed for food stores, healthcare, schools, and childcare facilities, whereas there are few H-L clusters.

The cross-sectional comparison reveals spatial disparities in transit supply to access essential services for different demand groups. Specifically, in terms of transit accessibility to food stores, healthcare facilities, schools, and childcare facilities (represented in the first four rows in **Figure 16**), H-L clusters (pink areas) were identified on the southeast edge and in the mid-northwest areas for minority groups, while these areas were classified as L-L clusters (blue areas) for car-limited groups and poverty groups. These findings imply that the southeast and mid-northwest areas of Nashville, with limited transit access, have a higher transit-dependent demand

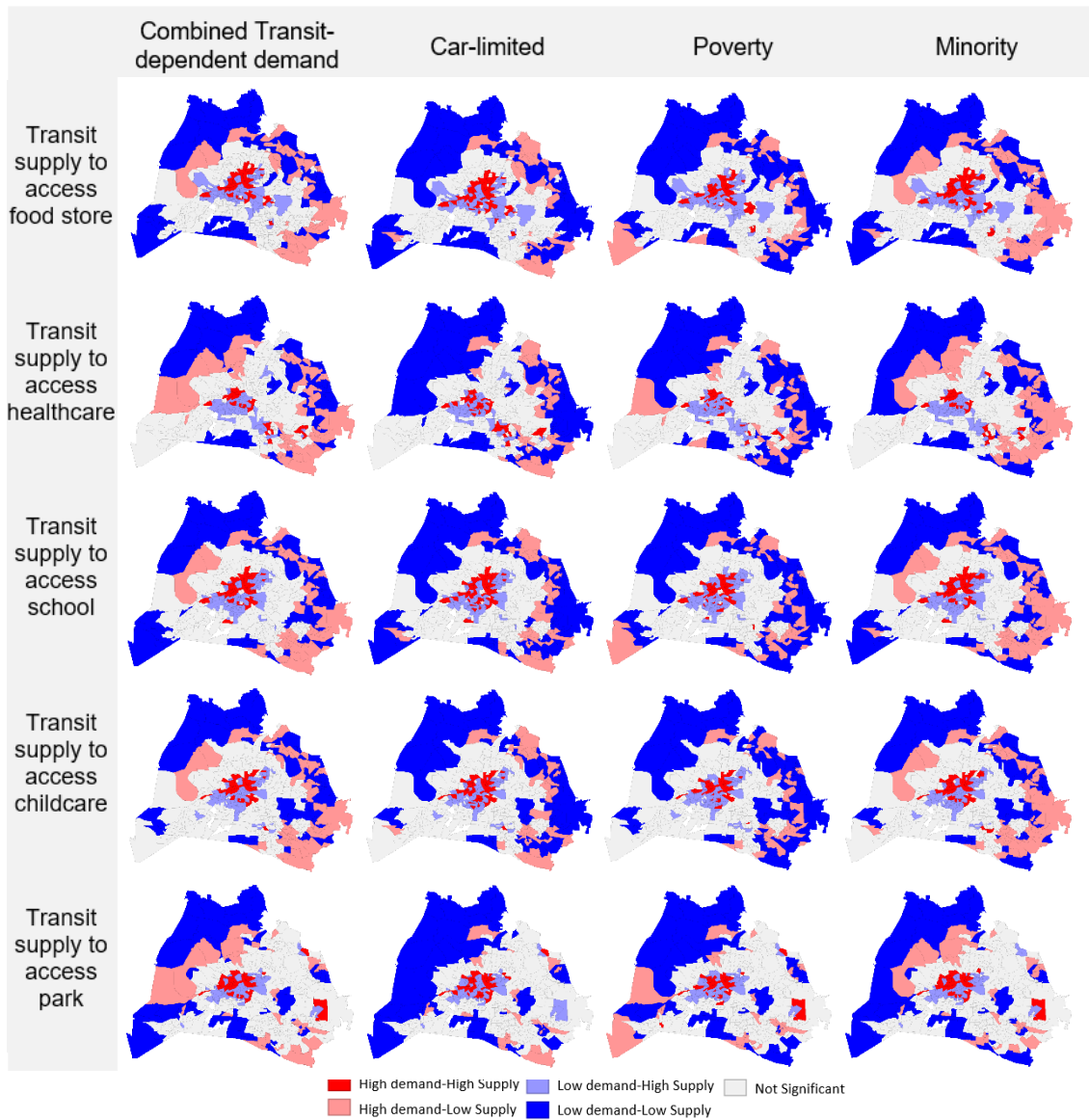


Figure 16 Bi-LISA cluster maps for different combinations of transit supply categories and transit-dependent demand groups

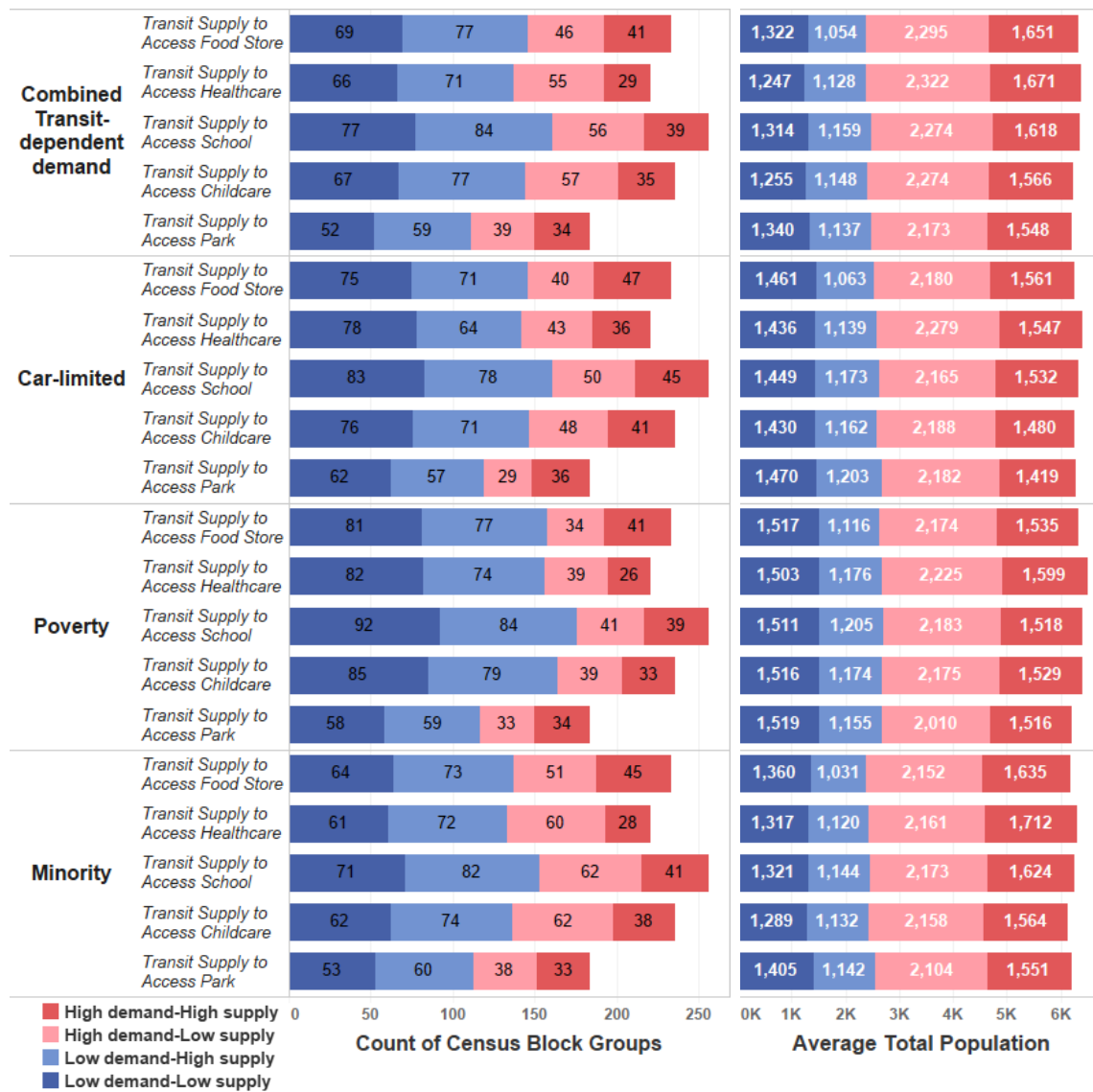


Figure 17 Bar plot of summary of bi-LISA clusters

from minority populations. The H-L clusters for food store access, school access, and park access were observed for the poverty group in the southwest corner of the city, whereas the same communities were classified as L-L clusters for car-limited groups and minority groups. This implies that the underserved regions in the southwest corner of the city exhibit a greater demand from the poverty group.

The summary of the four bi-LISA clusters was visualized in a bar plot shown in **Figure 17** for the different transit-dependent demand groups and different transit supply access to essential service categories. By examining the count of block groups in each cluster, it becomes apparent that there is a larger proportion of H-L clusters (indicated by the pink bar) in the food store, healthcare, school, and childcare categories than in the park category. Moreover, the healthcare, school, and childcare categories have a greater number of H-L clusters than the food store category. This implies that there are greater levels of transit inequity regarding access to healthcare facilities, schools, and childcare facilities, as opposed to food access and park access. In terms of transit-dependent demand, a greater proportion of H-L clusters was observed within minority groups, indicating that compared to those who are car-limited and in poverty, minority groups encounter more pronounced transit inequity. The average population for each category is also shown on the right side of **Figure 17**. The average population suggests that while the count of Census block groups in H-L clusters (highlighted by the pink bar) is lower than that in low-demand clusters (represented by indigo and blue bars), the total population within the H-L clusters surpasses all other clusters. This population visualization highlights an inequitable distribution of transit supply, with a concentration of population within these H-L clusters.

This section further identifies H-L clusters, which refer to areas with overall high transit-dependent demand but low transit supply, as *essential service deserts*. To determine if a block group was considered an essential services desert, five binary variables were coded to indicate whether the block group was included in each of the five essential service categories of H-L clusters. The outcomes of this step were used to examine the correlation of essential service deserts in the subsequent section.

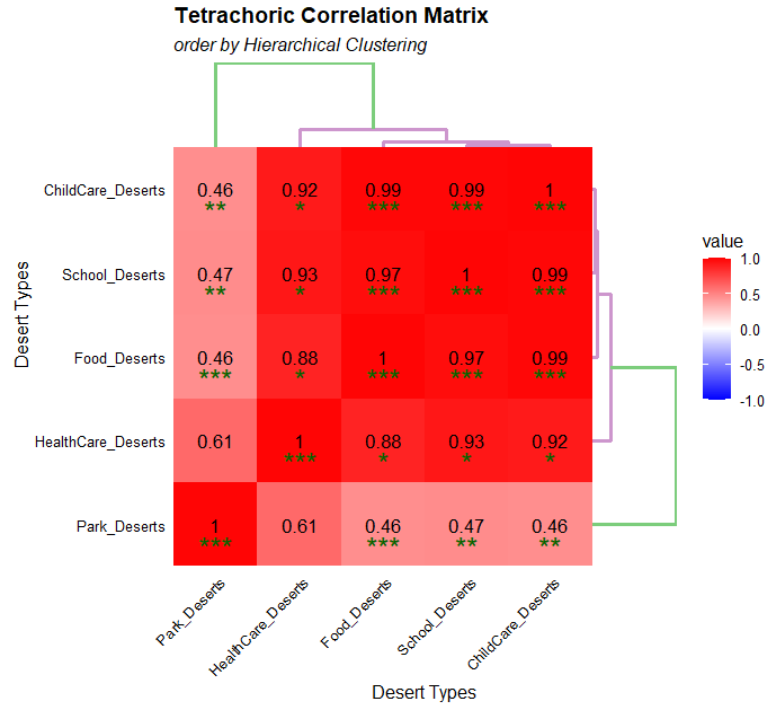


Figure 18 Tetrachoric correlation matrix for different types of essential service deserts

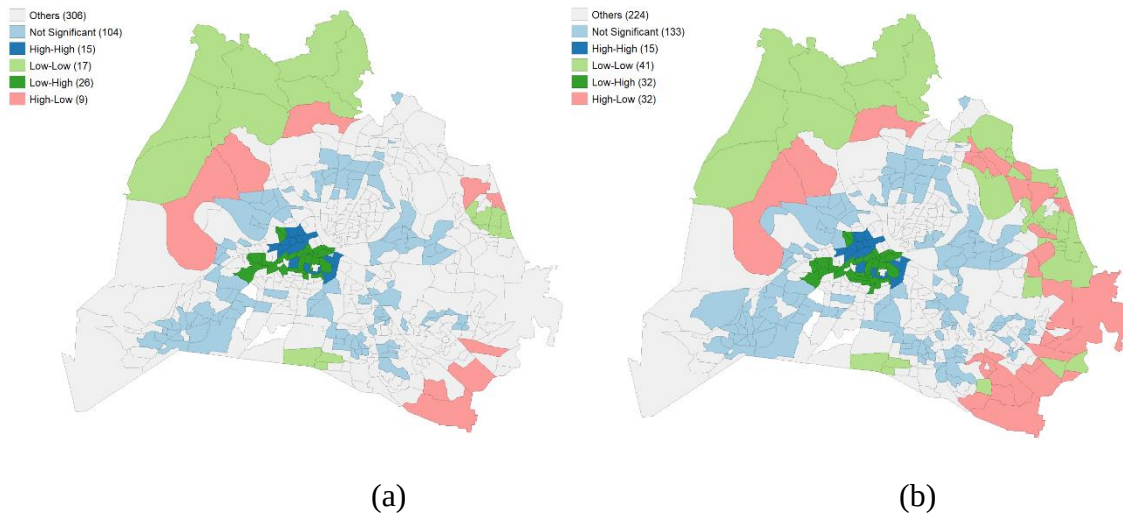


Figure 19 Co-location maps of (a) food deserts, healthcare deserts, school deserts, childcare deserts, and park deserts; (b) food deserts, healthcare deserts, school deserts, and childcare deserts (excluding parks)

3.5.5 Correlation analysis and co-location maps of essential service deserts

The preceding section focused on the association between transit-dependent demand and transit supply, which identified essential service deserts that have high demand for transit but limited access to it. This section subsequently analyzed the statistical and spatial correlation between distinct categories of underserved essential service deserts using a tetrachoric correlation matrix and co-location maps.

Figure 18 displays the tetrachoric correlation matrix that examines the significance and strength of the relationship between each pair of essential service deserts. The green stars indicate significance, with at least one star denoting a statistically significant correlation at the 95% level, two stars representing 99% of confidence level, and three stars indicating 99.9% of confidence level. The red color denotes a positive association, with darker shades of red indicating a stronger association. The figure reveals that food deserts, healthcare deserts, school deserts, and childcare deserts are highly correlated with each other, but they have a lower correlation with park deserts (except healthcare deserts, which show no significant correlation with park deserts). To classify essential service deserts, hierarchical clustering was employed using the correlation distance. The clustering outcomes were also visualized in **Figure 18** by the dendrograms, with two clusters represented by green branches and purple branches, respectively. The findings indicate that food deserts, healthcare deserts, school deserts, and childcare deserts have a high correlation, and therefore were grouped as a cluster, while park deserts have a lower correlation with other essential services and were classified as a separate cluster.

This section further investigated the spatial correlation of different types of essential service deserts by utilizing co-location maps to identify the most underserved areas with overlapping essential service deserts. Based on the correlation results, two co-location maps were generated: one to identify the co-location of bi-LISA clusters for all five essential service deserts, and the other to identify the co-location of bi-LISA clusters for food deserts, healthcare deserts, school deserts, and childcare deserts (excluding parks), since these have high correlation with each other.

The shaded pink communities in **Figure 19** represent areas with essential service deserts. **Figure 19 (a)** shows nine block groups were found to be transit deserts with respect to all five

essential services, distributed across the mid-northwest, northeast edge, and southeastern edge of Nashville. When excluding park deserts, the overlapping transit deserts increased to thirty-two block groups and extended to some eastern communities with good transit access to parks but limited transit access to food, healthcare, schools, and childcare.

3.6 Discussion and conclusions

This research contributes to literature in four important ways. First, this study proposed a spatiotemporal transit supply index that considers the temporal variation of transit accessibility, specifically in the context of Nashville, Tennessee. Second, this study identified essential service deserts as areas with a spatial mismatch between transit supply to access essential services and transit-dependent demand and compared the spatial disparities of transit inequity across essential service categories and potential transit-dependent demand groups. Third, this research further investigated the correlation between different categories of essential services and identified communities with overlapping essential service deserts. Finally, this study enriched the existing literature by focusing on a low-density, automobile-oriented city and investigating the transit equity of essential services using publicly available datasets.

The analysis of the temporal transit accessibility revealed that transit services in Nashville exhibit low variance across various time periods of the day. Following that, a visualization was created to analyze the spatial distribution of the transit supply index and transit-dependent demand index. The spatial distribution of the transit supply index to parks was different from that of food, healthcare, school, and childcare. Based on the maps of the transit-dependent demand index, many areas in Nashville exhibit relatively low levels of transit-dependent demand for transit. However, there are certain areas where an overlap exists among different transit-dependent groups (e.g., car-limited, those in poverty, and/or minority groups).

The results of the Theil index suggested that transit accessibility to healthcare had the greatest level of inequity and that parks were more evenly distributed throughout the city than other essential service categories. This generally aligns with the pattern observed in the distribution of healthcare facilities and parks in Nashville. Most healthcare facilities are privately provided and concentrated in the central city, whereas parks, being predominantly public facilities, have a more

balanced distribution throughout the city. This result may also be attributed to the greater availability of land for parks at the outskirts of the city compared to the densely developed downtown area. The components of the Theil index suggested that groups with a higher level of transit-dependent demand have more equitable transit access to food stores and healthcare facilities while groups with low to moderate levels of transit-dependent demand have more equitable transit access to parks. The findings could potentially be attributed to decisions made by individuals to prioritize transit access to essential resources such as food and healthcare over other factors like recreational or leisure facilities. The bi-LISA spatial clustering further found that areas with high transit-dependent demand are more likely to have limited transit access to food stores, healthcare, school, and childcare categories than to have limited transit access to parks. The clustering results also implied a different distribution of demand groups in underserved areas. A higher transit-dependent demand from minority populations was found in the southeast and mid-northwest areas, and a greater demand from the poverty group was located in the southwest corner of the city. The minority populations in mid-northwest areas have limited transit access to all five essential services and the poverty groups within the underserved regions in the southwest corner of the city have limited transit access to food stores, schools, and parks. Last, H-L clusters were identified as essential services deserts that have overall high transit-dependent demand but low transit supply. Among the five essential service deserts, food deserts, healthcare deserts, school deserts, and childcare deserts were highly correlated with each other, while they had a lower correlation with park deserts.

The findings of spatial transit inequity and the identification of transit deserts of essential services hold crucial policy implications that can be used by transit agencies and local planning departments to prioritize their resources and target interventions to improve transit access to essential services for specific populations. For instance, the results revealed a greater level of transit inequity towards healthcare facilities compared to other essential services in Nashville. This finding underscores the importance for transit authorities to prioritize connections with healthcare facilities when formulating transit planning decisions. Additionally, the identification of different categories of essential service deserts through the clustering map provides a valuable resource for developing and implementing customized urban planning and transit planning strategies.

Specifically, the analysis identified that in the mid-northwest areas of Nashville, minority populations have limited transit access to all five essential services, necessitating efforts to improve transit access to all five categories of essential services or to locate more of these essential service facilities in the mid-northwest Nashville. On the other hand, populations in poverty located in the southwest corner of the city have limited transit access specifically to food stores, schools, and parks, highlighting the need for efforts to enhance transit accessibility to these specific destinations or the increase the number of food stores, schools, and parks in that area of the city. Accordingly, before initiating urban and transit planning processes, subsequent investigations are needed to differentiate whether transit deserts primarily result from a lack of nearby facilities or insufficient transit services.

3.7 Limitations and future research

There are some potential limitations and areas for future research that emerged from this study. First, the proposed study measured the transit accessibility of fixed-route transit service. However, on-demand services (e.g., dial-a-ride and microtransit routes) are available in some areas of Nashville. Therefore, measuring transit accessibility of on-demand transit services should be considered in future research. Second, this study only included five common essential service categories; other services such as libraries, various government services (e.g., courts), and restaurants could be added in future research. Third, this study only examined the time variation of transit accessibility on weekdays, primarily due to the high transit ridership observed during weekdays. However, investigating the time variation in transit accessibility between weekdays and weekends would provide a more comprehensive understanding of transit service distribution and potential disparities across different days of the week, further contributing to the body of knowledge in this field. Fourth, another limitation of this study is the modifiable areal unit problem (MAUP) due to the use of Census blocks; the MAUP is a common issue in spatial analysis that may influence the spatial patterns observed. Fifth, transit accessibility was estimated under the assumption that individuals choose to access the nearest essential service location; however, it is possible that people choose differently based on other criteria (e.g., a facility that is located farther away but is preferred for other reasons). Consequently, the identification of transit deserts

represents a potential supply-demand mismatch and future research using actual behavioral data could enhance precision of the analysis. Furthermore, future research could expand upon this study's focus on transit equity for car-limited, poverty, and minority populations by including an examination of transit accessibility for seniors or individuals with disabilities. This would contribute to a more comprehensive understanding of transit equity across a broader range of vulnerable and underserved populations.

CHAPTER 4.
ANALYZING GENDER AND AGE DIFFERENCES IN TRAVEL
PATTERNS AND ACCESSIBILITY FOR DEMAND RESPONSE TRANSIT
IN RURAL AREAS

This chapter is based on a research paper by Jing Guo, Sabyasachee Mishra, and Candace Brakewood titled "Analyzing gender and age differences in travel patterns and accessibility for Demand Response Transit in rural areas: a case study in Tennessee". This paper was submitted to the Journal of Transport and Land Use for review.

Abstract

Demand Response Transit (DRT) services play a crucial part in supporting rural transportation. However, the exploration of DRT trip patterns and accessibility, particularly the differences tied to demographics such as gender and age, remains an underdeveloped field. This study begins to fill this research gap by statistically and spatially analyzing real-world DRT trip data. DRT trip purposes were identified based on origin and destination land uses. Statistical analysis was conducted to evaluate DRT travel patterns for passengers of different genders and ages. Spatial analysis identified areas with higher DRT trip demand and limited DRT accessibility as potential essential destination deserts. The results show that women took more DRT trips across all purposes (e.g., Home-Healthcare, Home-Home, and Home-Leisure) except for Home-Work. About 36.8% of the DRT trips were made by the elderly, primarily for Home-Healthcare trips (67%), and they preferred shorter DRT trips. Spatial analysis revealed disparities in potential essential destinations deserts for the elderly and females, as well as differences in possible deserts by trip purpose (e.g., healthcare-related trips). This study contributes to the literature by proposing a methodological framework for assessing DRT travel patterns and accessibility, which has been excluded from most of the prior literature on accessibility.

4.1 Introduction

Public transit services provide an important mobility option, particularly for individuals who either lack access to private vehicles or are unable to operate them. Demand response transit (DRT), also known as dial-a-ride or paratransit, refers to a mode of public transportation that operates on a reservation system to service trip requests (Durand et al., 2018). Within the field of public transportation research, considerable attention is given to fixed-route transit systems, which are largely prevalent in densely populated urban areas. However, dispersed travel demand in

suburban and rural communities often makes fixed-route transit systems ineffective. Therefore, DRT is an important transportation solution, especially for low-income, mobility-impaired, and elderly residents lacking alternative transportation options (Durand et al., 2018).

Understanding the demographics of travelers and their travel patterns can enhance the planning, performance evaluation, and efficiency of transportation systems. Age, gender, disability status, income level, race, education level, employment status, and vehicle ownership are typically considered important factors related to travel patterns (Jain et al., 2017; Wang et al., 2014). Although there is extensive research investigating travel patterns across various transportation modes and demographic groups, limited studies have focused specifically on DRT. Existing research on demographic differences in travel patterns has largely revolved around modes such as private vehicles, fixed-route buses, subways, walking, and bicycles, resulting in an underrepresentation of DRT in the literature.

Additionally, understanding accessibility and identifying potential areas of concern is critical in the assessment of transportation systems (Levinson & King, 2020). Although there is a growing body of research on transit accessibility, much of it has been conducted on fixed-route transit systems (Saif et al., 2019; University of Minnesota, 2023; Wessel & Farber, 2019). As a result, there is a gap in the literature on accessibility analyses for DRT system.

In DRT trip reservation systems, various characteristics such as trip distance and trip purpose are typically recorded, and some of these systems also collect a small number of demographic variables. The demographic information of travelers recorded in the DRT trip data used in the following analysis includes age and gender. Consequently, this paper focuses on how DRT travel patterns and accessibility vary by gender and age groups within the rural American context, exemplified by Morristown, TN. For the study area considered in this paper, trip distance was recorded in the trip data from the DRT reservation system. Hence, this research aims to measure DRT accessibility based on trip distance derived from actual trip data. This approach, referred to as an “actual accessibility approach” has been established in the existing literature (Niedzielski & Boschmann, 2014) and was employed in prior accessibility studies of other modes that directly incorporated actual travel behavior encompassing travel flows, trip distances, and trip time (Antipova, 2020; Casas, 2007; Horner & Schleith, 2012; Pérez et al., 2010). The analysis of

Morristown, TN presented in this paper is particularly pertinent given the characteristics of many rural communities, such as widespread destinations, limited public transit alternatives, and the prevalence of low-income groups, which highlight the important role of DRT in this region and other similar ones.

This paper proceeds in the following way. First, a brief literature review describes prior studies related to gender and age differences in transit travel patterns, transit accessibility, and transit deserts. Then, the study area and data for the case study are introduced. The next section describes the methodology, followed by the results of the case study. The conclusions, discussions, and future research are summarized in the last section.

4.2 Literature review

The following section reviews relevant literature pertaining to gender and age differences in transit travel patterns. This is followed by a brief review of literature on transit accessibility. Then, the research objectives for this study are introduced.

4.2.1 Literature on gender and age differences in transit travel patterns

Gender and age differences in travel behavior have been discussed in prior transportation research, and a growing body of literature has explored these differences across various locations using different data sources. It is imperative to acknowledge that the existing literature on DRT is notably scarce. Nonetheless, it is essential to emphasize the existence of studies dedicated to this subject within the U.S. context.

4.2.1.1 Gender differences in transit travel patterns

Travel mode preference is one of the critical topics in gender-focused studies. Travel survey data collected in the 2000s from Germany, the USA, and Australia indicated that women were more likely to use public transport modes than men (Buehler & Pucher, 2012; O'Hern & Oxley, 2015). A survey from 1994 in Montreal, Canada, on the other hand, suggested that women were less likely to use public transit for work trips (Patterson et al., 2005). Additionally, using data from the 2017 National Household Travel Survey (NHTS) in the U.S., men had a higher likelihood of utilizing both transit and ridesharing services than women (Deka & Fei, 2019). However, these

studies did not specifically include DRT as a travel mode in their analysis.

Trip purpose also has some typical differences by gender. Previous studies have found that women, who typically perform more of the household-related tasks, tend to have more complex trip-chaining activities than men, including frequent grocery shopping trips, child-serving trips, and household errand trips (Fan, 2017; Hanson & Johnston, 1985; McGuckin & Fucci, 2018; Metro Los Angeles, 2019). Previous studies also suggest that men are more likely to make work-related trips, whereas women make comparatively more non-work trips (McGuckin & Fucci, 2018; Metro Los Angeles, 2019). A summary of the 2017 NHTS data also pointed out that both men and women report a comparable number of social and recreational trips (McGuckin & Fucci, 2018).

The temporal aspects of trips and trip distance may also have differences by gender. A study conducted by LA Metro (Los Angeles County Metropolitan Transportation Authority) found that women tend to travel more during the midday when fixed-route transit service frequencies might be reduced (Metro Los Angeles, 2019). Other studies have found that women tend to travel shorter distances and for shorter durations than men in fixed-route transit systems (Chen & Akar, 2017; Crane, 2007; Jin & Yu, 2021; Metro Los Angeles, 2019).

In terms of gender differences in DRT usage, a survey conducted in Virginia suggested that women (61% of total respondents) were the dominant users of the DRT (Rosenbloom, 1998). A similar conclusion was drawn from a DRT rider survey conducted in Tennessee in 2012 (Yang & Cherry, 2017). This relationship was further confirmed by another study in Tennessee. In this study, the DRT trip data were collected and analyzed to demonstrate that higher demand for DRT services was observed in areas with more females (Sultana et al., 2018). The DRT trip data from the state of Tennessee also revealed that healthcare-related trips constituted the highest DRT demand (Sultana et al., 2018).

4. 2.1.2 Age differences in transit travel patterns

Prior literature has shown that age plays a significant role in mode choice and travel behavior. Overall, previous studies suggest a relatively low transit usage among older adults (Jamal & Newbold, 2020). However, a recent analysis of NHTS data reveals that transit use increased among older adults who lacked car access or were physically constrained from driving (Mattson, 2012). Additionally, a study based on the Nationwide Personal Transportation Survey suggests

that as travel becomes more physically demanding, elderly individuals tend to shift towards walking and traveling as passengers in privately owned vehicles (Giuliano et al., 2003).

For the trip purpose, prior studies revealed that the elderly make more non-work trips, including shopping, family visiting, social, recreation, and healthcare trips, when using fixed-route transit (Horner et al., 2015; Rashidi & Mohammadian, 2008). While numerous studies suggest that the elderly made fewer work-related trips than their younger counterparts, there were also studies indicating an increase in work-based travel among the aging population, possibly due to the recent trend of deferring the age of retirement (Horner et al., 2015; Srinivasan et al., 2006).

Age differences were also reflected in aspects of trip distance and travel time in fixed route transit systems. Numerous prior studies suggest that the elderly typically travel for shorter distances in fixed-route transit systems (Giuliano et al., 2003; Jamal & Newbold, 2020; Rashidi & Mohammadian, 2008; Yang et al., 2018). Additionally, according to a recent survey of transit riders in 17 US cities, older riders often shift their transit use from peak commuting hours to midday (TransitCenter, 2017).

Some prior studies have shown that age plays a significant role in DRT usage patterns. Based on the 2013 Rural National Transit Database (NTD) and survey data collected from rural transit agencies across the US, Mattson found that areas with more elderly corresponded with higher DRT ridership (Mattson, 2017). Higher DRT demand from the elderly was also observed in another study using NTD data (Nguyen-Hoang & Yeung, 2010) and studies using DRT trip data in Texas and Tennessee (LaMondia & Bhat, 2010; Sultana et al., 2018).

Despite numerous prior studies suggesting that gender and age groups have different travel patterns in other transportation modes, such as driving, walking, or fixed-route transit systems, this literature review has revealed few prior studies focused on gender and age differences in the travel patterns of DRT, particularly travel distance of DRT. Therefore, this study aims to enrich the existing literature by conducting a comprehensive analysis of gender and age differences in DRT travel patterns.

4.2.2 Literature on transit accessibility and transit deserts

This section briefly discusses relevant literature pertaining to transit accessibility measures

and transit desert identification, and their applicability to DRT.

4.2.2.1 Transit accessibility

Transit accessibility refers to the ability to reach trip destinations via transit (Manout et al., 2018). An increasing number of studies published in the last decade has been dedicated to the analysis of transit accessibility, particularly for fixed route transit systems (El-Geneidy et al., 2016b; Owen & Murphy, 2020b; Stewart, 2017; Welch, 2013; Wessel & Farber, 2019). However, there is a noticeable research gap in accessibility analysis for DRT.

Previous studies mostly relied on two types of metrics—travel costs or cumulative opportunities—to measure accessibility (Cui & Levinson, 2020b). In addition to these recognized metrics, there are different approaches for implementing accessibility measurements. In the literature on transit accessibility, one of the most significant differences exists between studies based on *potential accessibility* and *actual accessibility* (Niedzielski & Boschmann, 2014). Calculating potential accessibility requires making assumptions about travel behavior, such as travel thresholds or preferences for destinations. This approach is often used in situations where there is no reference to actual travel behavior (Niedzielski & Boschmann, 2014). Actual accessibility, on the other hand, is measured by the actual travel distance or travel time directly (Niedzielski & Boschmann, 2014).

In this study, DRT accessibility will be quantified as the travel distance that was recorded in real-world DRT trip data. The use of actual travel distance from DRT trip data ensures the repeatability of the methodology across DRT systems in other rural areas.

4.2.2.2 Transit deserts

The term “transit desert” has been extensively discussed in prior literature and is generally defined as geographic areas or locations that have high (fixed route) transit demand and limited (fixed route) transit accessibility (Brondeel et al., 2014; Forsyth et al., 2010; Jiao & Dillivan, 2013; Mao & Nekorchuk, 2013; Walker et al., 2010). The concept of transit deserts can be used to identify areas of concern by analyzing the relationship between transit demand and transit accessibility to important destinations (Aman & Smith-Colin, 2020; Jiao, 2017; Jiao & Dillivan, 2013; Ricciardi et al., 2015).

Based on prior research, transit demand refers to groups characterized by higher utilization of transit services or disadvantaged individuals who may rely on transit due to limited access to personal vehicles (El-Geneidy et al., 2016a; El-Geneidy et al., 2016b; Foth et al., 2013; Guo et al., 2023; Jeddi Yeganeh et al., 2018). In this study, DRT demand analysis will include total DRT demand, female DRT demand, and the elderly DRT demand; this will be quantified as the count of DRT trips made by total passengers, female passengers, and the elderly, respectively. This study specifically examined female and elderly demographic groups due to the availability of age and gender information in the recorded DRT trip data, as well as the recognition that women and the elderly make up a substantial proportion of DRT riders in the study area.

Previous studies identifying transit deserts also include evaluating transit accessibility to various types of important destinations (e.g., jobs, food stores, healthcare, etc.) for different demand groups. For example, a study conducted in the Detroit metropolitan area revealed that minority and low-income households had relatively good transit accessibility to hospitals, but encountered challenges to access supermarkets (Grengs, 2015). In another study conducted in Chicago, low-income households were found to have limited transit accessibility to grocery stores, while the Hispanic population experienced better transit accessibility to grocery stores but encountered difficulties in accessing hospitals (Ermagun & Tilahun, 2020). Moreover, previous studies on transit deserts commonly identified geographic areas or locations that have limited transit accessibility to different types of destinations, such as “*food deserts*” (Forsyth et al., 2010; Walker et al., 2010) and “*healthcare deserts*” (Brondeel et al., 2014; Jiao & Dillivan, 2013; Mao & Nekorchuk, 2013). However, these studies have primarily focused on urban areas with well-established fixed-route transit networks. Therefore, the following analysis in a rural area contributes to the literature by examining “essential destination” deserts in rural areas with widespread destinations and limited public transit alternatives.

Based on the prior literature on transit deserts, there are different methods to understand the relationship between transit demand and transit accessibility to identify areas of concern. For example, some studies identified transit deserts by using the difference or ratio of demand and accessibility (Aman & Smith-Colin, 2020; Jiao, 2017; Jiao & Dillivan, 2013). In another study, areas with high public transit demand but limited public transit accessibility were evaluated using

a quadrant classification method, which categorized regions into four classes based on their levels of transit demand and accessibility (Ricciardi et al., 2015). This classification method proved to be relatively simple to construct yet highly effective in producing meaningful outcomes (Ricciardi et al., 2015). Furthermore, it was easily comprehensible and feasible for transit agencies and policymakers to employ. Therefore, the proposed “essential destination” deserts analysis will employ a quadrant classification to spatially identify potential areas of concern with high DRT demand and limited DRT accessibility.

4.3 Research objectives

Based on this review of the literature, the following research objectives were proposed:

1. Identify differences in the DRT trip purpose (defined by origin and destination land uses) by gender and age.
2. Identify differences in the DRT trip distance by gender and age.
3. Identify spatial differences between DRT demand (represented by the number of DRT trips) and DRT accessibility (represented by DRT trip distance) to different trip purposes (defined by origin and destination land uses) to identify potential “essential destination” deserts.

To achieve these objectives, this study proposed a methodological framework, including statistical analysis and spatial analysis, which was applied to a rural area in Tennessee, as discussed in the following sections.

4.4 Study area and data

4.4.1 Study area

The study area focused on the rural city of Morristown, which is in Hamblen County located within the eastern region of Tennessee. Based on 2020 Census data, Morristown had a population of 30,431, making it the 27th largest city in Tennessee (U.S. Census Bureau, 2020a). However, in terms of population density, Morristown ranked 60th among cities in Tennessee, with a density of only about 1,097 individuals per square mile (ZIPAtlas). Data from the 2020 Census also showed a population composition of 48% male and 52% female in Morristown city.

Furthermore, individuals over 65 years old made up 17% of the population, and those between the ages of 30 and 64 represented 41.3% of the total population. In terms of income levels, Morristown city had a median household income of \$33,511 and a per capita personal income of \$19,457, both ranking 390th out of 504 cities in the state of Tennessee, as indicated by the 2016-2020 American Community Survey Data (U.S. Census Bureau, 2020c; U.S. Census Bureau, 2020d).

Morristown is primarily characterized as an automobile-dependent, rural city with limited public transportation options. Currently, Lakeway Transit operates three bus routes within the city, deploying only four vehicles for fixed route services (Lakeway Transit, 2023). These services are available from Monday to Friday until 6 p.m. In addition to the bus routes, Morristown has demand response transit (DRT) services facilitated by the East Tennessee Human Resource Agency (ETHRA) Public Transit (ETHRA). These DRT services aim to address the transportation needs of the community in a more flexible and on-demand manner. ETHRA Public Transit offers door-to-door transportation service to the general public, available through advanced reservations. The cost for a one-way trip is \$3, and trips crossing county lines incur an additional \$3 fee. **Figure 20** shows the geographic location of Morristown, accompanied by a map of the origins and destination points of the DRT trip data used in this paper and discussed in the subsequent section.

4.4.2 DRT trip data and variables

The DRT trips, collected from 2019 July to 2020 June, were obtained from ticket data from the ETHRA Public Transit reservation system. This system recorded the origins and destinations of passengers and the start time of the trip. The data was selectively filtered, retaining only the origin points situated within Hamblen County and its adjacent area, Jefferson County for the following analysis. The data was then cleaned to remove outliers. For example, two observations were flagged as temporal abnormalities because the trips occurred at the unusual hour of 2 a.m. and were therefore removed from the dataset. Regarding spatial abnormalities, a total of 16 observations were identified as having incorrect coordinates, as they were spatially mapped to locations outside of the state boundary. This inaccuracy primarily arose from ambiguous street addresses where multiple locations within the United States shared identical street names. To ensure precision, a meticulous geocoding process was employed to reassign the coordinates by

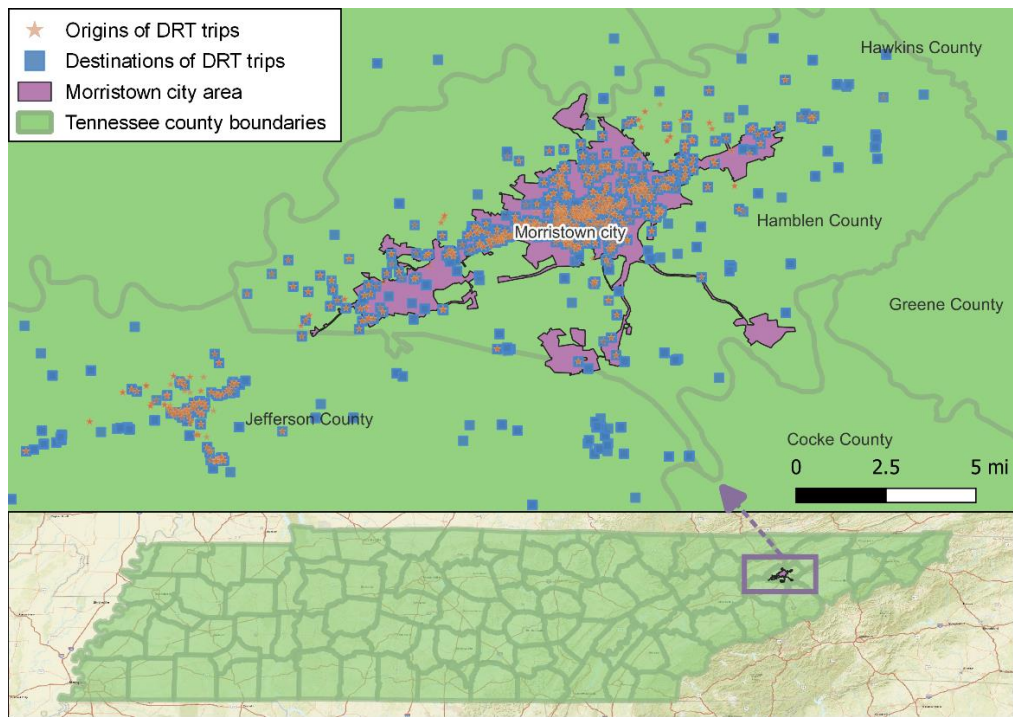


Figure 20 Study area and the origins and destinations of DRT trips in Morristown

Table 7 Variables creation and explanation

Category	Explanation	Count (%)
Gender	Passengers identified themselves as male or female, NA or “prefer not to say” records were removed from analysis	
Male		10,606 (46.79%)
Female		12,063 (53.21%)
Age groups	Passenger age range: [0 – 97] years old	
Children	Passengers aged between 0-12 years old	50 (0.22%)
Adolescent	Passengers aged between 13-18 years old	167 (0.74%)
Young Adult	Passengers aged between 19-29 years old	1,616 (7.13%)
Adult	Passengers aged between 30-64 years old	12,693 (55.99%)
Elderly	Passengers aged 65+ years old	8,143 (35.92%)
Time segments	Time range: 5 a.m. to 6 p.m.	
Early morning	Trips start between 5 a.m. to 6 a.m.	1,589 (7.01%)
AM peak	Trips start between 7 a.m. to 9 a.m.	5,736 (25.3%)
Midday	Trips start between 10 a.m. to 3 p.m.	11,783 (51.98%)
PM peak	Trips start between 4 p.m. to 6 p.m.	3,561 (15.71%)
Distance segments	Distance range: (0-89.42] miles	
Short distance	The trip distance falls within the first quartile (Q1) range (shortest distance to the median length of distance)	5,751 (25.37%)
Median-short distance	The trip distance falls within the second quartile (Q2) range (between the 25th and 50th percentiles of all recorded distances)	5,592 (24.67%)
Median-long distance	The trip distance falls within the third quartile (Q3) range (between the 50th and 75th percentiles of all recorded distances)	5,658 (24.96%)
Long distance	The trip distance falls within the fourth quartile (Q4) range (between the 75th percentile and the maximum value of the distances)	5,668 (25%)

incorporating comprehensive addresses, including zip codes. The data cleaning process was able to rectify the spatial locations of these observations and guarantee the integrity of the data.

The original dataset included 31,641 DRT trip records. Records that had no gender information (6,333 records), as well as those with blank or negative age information (6,501 records), were excluded from the analysis. Following the data-cleaning process, a total of 22,669 trip records were retained for analysis. Based on the cleaned data, several categorical variables were created for further analysis. The variable creation and explanation are shown in **Table 7**.

4.4.3 Identification of DRT trip purposes

Figure 21 shows a heatmap of the count and proportion of trips to/from varying origin and destination types in the initial DRT trip data. The intensity of the green color indicates the percentage of trips, with a darker hue representing a higher percentage. It can be inferred from **Figure 21** that trips predominantly originated from or terminated at the residential locations of clients. Specifically, trips made from clients' residences to employment areas are the most prevalent, closely followed by trips from physicians' locations to the residences of clients. Empty cells in the figure indicate the absence of trips linked to certain types of locations as origins or destinations. For instance, journeys starting from schools primarily terminated at clients' residences, with the destinations also including shopping locations and others; however, only one trip was recorded for each of these.

The classification provided in **Table 8** identified all trips across three distinct types. This followed the trip classification method employed in the typical transportation modeling trip generation process. Three types of Home-Based Work (HBW) included trips between home and work; Home-Based Other (HBO), representing trips with one end at home and not related to work; and Non-Home-Based (NHB), which represented trips that did not originate from or terminate at a home location. These were further divided into several distinct trip purposes based on the origin land use types and destination land use types. Specifically, locations such as hospitals, pharmacies, physicians, and dialysis centers were categorized as healthcare locations. Consequently, trips that either originated from or terminated at client residences to these locations were classified as Home-Healthcare trip purposes. Conversely, trips originating from locations other than client residences

to these healthcare locations were categorized as non-Home-Healthcare trip purposes. Similar classifications were observed with trips involving government services and banks, identified as either Home-Service or non-Home-Service trip purposes. Additionally, trips involving shopping locations and churches fell into the Home- or Non-Home-Leisure trip purpose category. The types and trip purpose, along with explanations for each classification, were presented in **Table 8**.

Table 8 reveals that the HBO category was the most common, with Home-Healthcare trips accounting for the highest count. The second most prevalent category was the Home-Work trip purpose, falling under the HBW trip type. However, NHB trips contributed a relatively small count, accounting for 996 out of a total of 22,669 trips, approximately 4.4%. As a result, the subsequent analysis excluded the NHB category, focusing solely on home-based trips (both HBO and HBW). This decision was due to the limited number of observations in the NHB category, which could lead to inadequate variability. Including such groups could significantly affect the accuracy and reliability of results in the subsequent logistic regression analysis.

4.5 Methodology

This section describes the method of this study. **Figure 22** shows the conceptual framework. The analysis includes two aspects of demographic categories: gender and age, and two aspects of travel patterns: DRT trip purpose and DRT trip distance.

The overall research objectives are to identify gender and age differences in DRT travel patterns and to investigate spatial differences between DRT demand and DRT accessibility to identify potential “essential destination” deserts. Accordingly, the method for the following analysis was done in two parts: statistical analysis and spatial analysis.

In the first part of the method, cross-tabulation analysis and binary logit regression models were employed to examine the differences in DRT use by gender and age for different DRT trip purposes. In addition to trip distance, the trip departure time was also introduced as the control variable for the trip pattern analysis. In the cross-tabulation analysis, the one-way Pearson chi-square test was performed to assess the statistical significance of the effect of gender and age on DRT trip patterns. Next, this study employed multiple binary logistic regression models to estimate the likelihood of a DRT trip having a specific trip purpose to further investigate the differences in

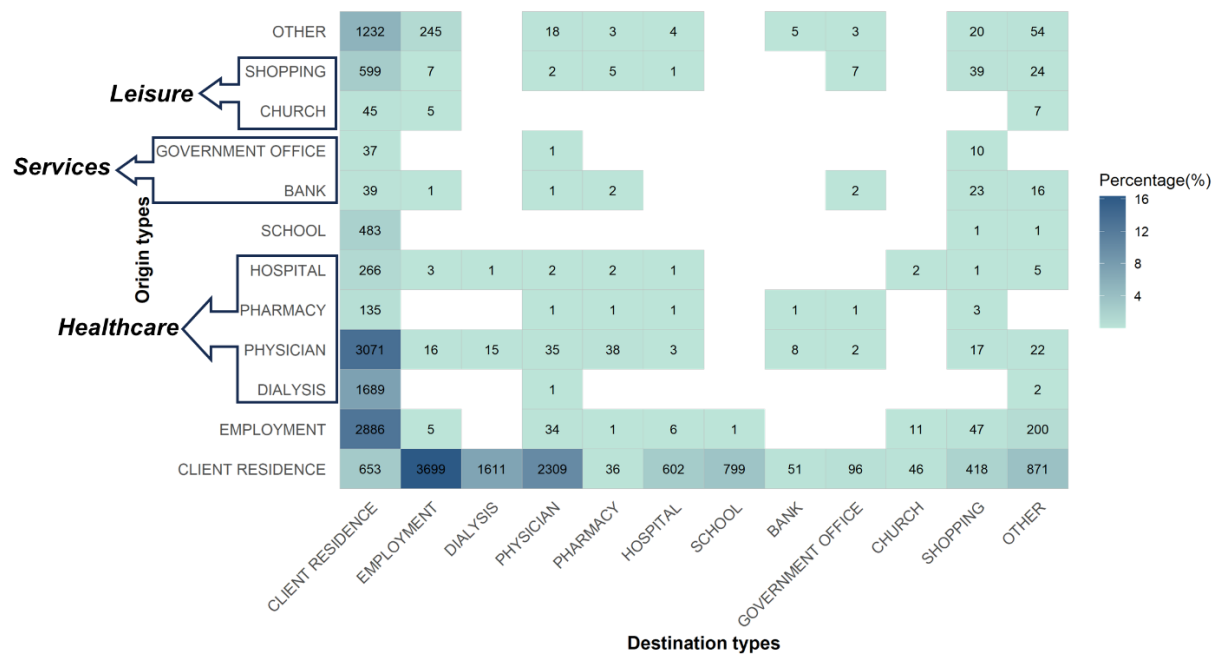


Figure 21 Heatmap for trips with different types of origins and destinations

Table 8 Types and trip purpose classification

Trip types	Trip purpose	Explanation	Count	Percentage (%)
HBW	Home-Work	Employment trips from (to) the client's residence	6,585	29.05%
HBO	Home-Healthcare	Trips from (to) hospitals, pharmacies, physicians, or dialysis places to (from) client residences.	9,719	42.87%
	Home-Home	Trips with both origin and destination being different client residence, recognized as home-visit trips	653	2.88%
	Home-Leisure	Trips from (to) churches or shopping places to (from) client residences	1,108	4.89%
	Home-School	Trips from (to) schools to (from) client residences	1,282	5.66%
	Home-Services	Trips from (to) banks or government offices to (from) client residences	223	0.98%
	Home-Other	Trips from (to) “other” to (from) client residences	2,103	9.28%
NHB	Non-Home-Healthcare	Trips from origins besides client residences to hospitals, pharmacies, physicians, or dialysis places	179	0.79%
	Non-Home-Leisure	Trips from origins besides client residences to churches or shopping places	174	0.77%
	Non-Home-School	Trips from origins besides client residences to schools	1	0.00%
	Non-Home-Services	Trips from origins besides client residences to banks or government offices	29	0.13%
	Non-Home-Other	Trips from origins besides client residences to “other”	331	1.46%
	Non-Home-Work	Employment trips from origins besides client residences	282	1.24%
Total			22,669	100%

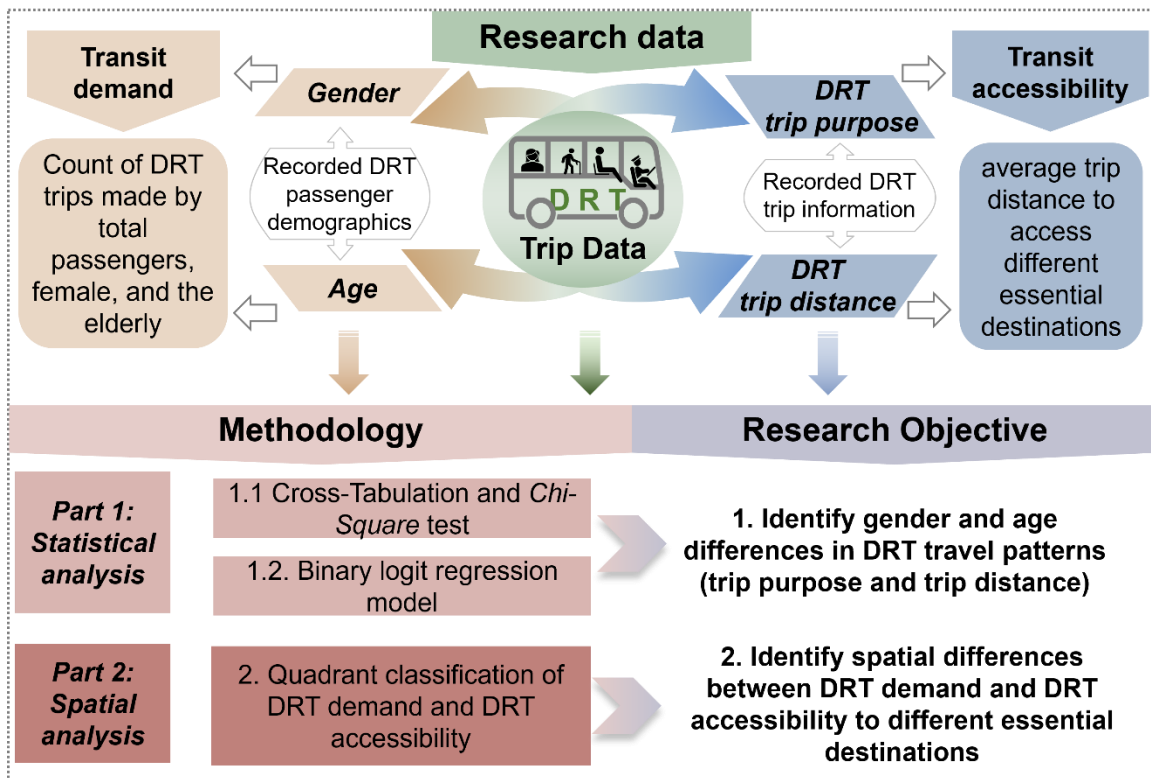


Figure 22 Conceptual framework

DRT trip purpose among genders and age groups, as well as the relationship between DRT trip purpose and temporal usage and trip distance. Trip purposes were converted into binary variables. For each trip purpose, a corresponding variable was created, which was coded as 1 if the trip fell into that specific trip purpose category and coded as 0 if it did not. These binary variables were subsequently used as dependent variables in separate binary logit regression models. The reference group for these models consisted of all other categories of trip purposes.

The binary logit models were estimated using **Equations (1) and (2)** where p represents the probability of the specific trip purpose y_i for individual trip i ; x_i represents the independent variables for individual trip i , including gender, age groups, trip departure time in segments, and trip distance in segments; and β_i are the coefficients for the independent variables, β_0 is the intercept term. The method of maximum likelihood was employed to estimate the parameters of the independent variables. **Equation (1)** represents the probability of a trip having a specific trip purpose. **Equation (2)** calculates the natural log of probability. The odds were then calculated from the probability shown in **Equation (3)**. In summary, **Equation (1)** represents the probability (likelihood) of a trip being classified as a specific trip purpose, **Equation (2)** calculates the logit of the probability, and **Equation (3)** calculates the odds from probability. The odds represent the ratio of the probability of a trip belonging to the specific trip purpose to the probability of it not belonging to that purpose.

$$p = \Pr(y_i = 1|x_i) = \frac{\exp(\beta_0 + \sum_{i=1}^n \beta_i x_i)}{1 + \exp(\beta_0 + \sum_{i=1}^n \beta_i x_i)} \quad (1)$$

$$\text{logit}(p) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \sum_{i=1}^n \beta_i x_i \quad (2)$$

$$\text{odds} = \frac{p}{1-p} \quad (3)$$

In the second part of the method, a spatial analysis was conducted to identify differences between DRT demand and DRT accessibility. It is noted that only home-origin DRT trips were included in the spatial analysis. The focus on home-origin trips was primarily driven by the need to illustrate the spatial distribution of DRT trip demand. By mapping out trips originating from individuals' residences, this study can gain valuable insights into the geographic distribution of DRT trips and identify areas with high demand. The following spatial analysis was performed at the geographical level of Census blocks.

First, the DRT demand within the i_{th} Census block was calculated by summing the total count of DRT trips originating from that block, as shown in **Equation (4)**.

$$Total_demand_i = number\ of\ total\ DRT\ trips_i \quad (4)$$

In addition to the total DRT demand, the number of DRT trips made by females and the elderly were calculated separately, as shown in **Equation (5)** and **Equation (6)**, respectively.

$$Female_demand_i = number\ of\ DRT\ trips\ made\ by\ female_i \quad (5)$$

$$Elderly_demand_i = number\ of\ DRT\ trips\ made\ by\ the\ elderly_i \quad (6)$$

The DRT demand was subsequently visualized on a map. To provide context and comparative insights, corresponding maps were created to visualize the distribution of the female and elderly populations using 2020 Census data.

Second, the DRT accessibility for each Census block was computed by averaging the travel distances of specific DRT trips originating from within the block, as shown in **Equation (7)** and **Equation (8)**. The overall DRT accessibility represented the average travel distance for total DRT trips. The average travel distances for DRT trips made by females and the elderly were also calculated separately. Moreover, to understand the DRT accessibility to access essential destinations, the average trip distance for DRT trips was calculated for three specific trip purposes: home-healthcare (trip with destination land use of healthcare facilities), home-leisure (trip with destination land use of shopping stores and churches), and home-service (trip with destination land use of government offices and banks). This was done using **Equation (7)** for each trip purpose type.

$$Transit_access_{ij} = \frac{\sum_N trip\ distance_{ijn}}{N} \quad (7)$$

$$Transit_access_i = \frac{\sum_j distance_{ij}}{J} \quad (8)$$

Where:

N is the number of DRT trips originating from the block i to access the specific trip purpose j ;

n is the n_{th} DRT trip;

$Trip\ distance_{ij}$ is the average trip distance from the block i to access the specific trip destination with purpose j ;

J is the number of DRT trip purposes;

j is the j_{th} trip purpose; and

$trip\ distance_i$ is the average trip distance of DRT trips with all trip purposes originating from the block i .

This analysis involved the visualization of DRT trip distances, where shorter distances were interpreted as indicative of higher accessibility and longer trip distances were indicative of lower accessibility.

Building on the outcomes of the two preceding parts, the final part of the spatial analysis aimed to classify the spatial relationship between DRT trip counts (demand) and trip distances (accessibility). Census blocks were classified into four categories (low or high) based on two criteria: the median value of DRT trip count and the median value of DRT trip distance, as illustrated in **Figure 23**. For example, a Census block was classified as “high demand-low accessibility” if it exceeded the median DRT trip count of all blocks, and the average DRT trip distance of this block exceeded the median value of the average trip distances for all blocks. Census blocks categorized as “high demand-low accessibility” were recognized as possible areas of concern, which were then deemed potential essential destination deserts.

4.6 Results

4.6.1 Results of gender and age differences in DRT trip patterns

4.6.1.1 Cross-tabulation results

Table 9 provides cross-tabulation results to evaluate the differences in gender and age by DRT trip purposes, trip time segments, and trip distance segments using Pearson chi-square tests. The results indicate that all attributes were highly significant with p-values less than 0.001.

Overall, women (54.5%) made more DRT trips than men (45.5%). This finding is not surprising, given that there are females than males residing in Morrison, TN according to Census data (U.S. Census Bureau, 2020a). The cross-tabulation of gender and trip purposes showed that women consistently took more DRT trips across all purposes with the sole exception of the Home-Work purpose where men recorded a higher number of trips. The segmentation of DRT trip start

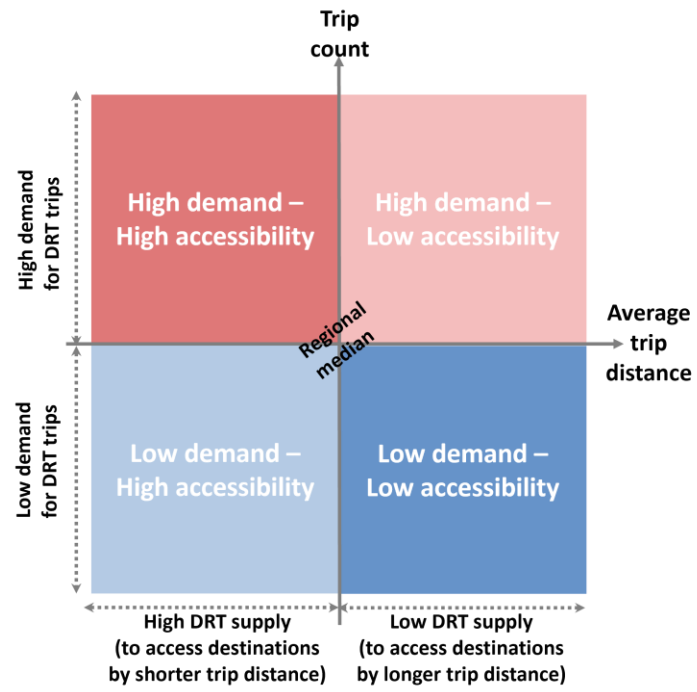


Figure 23 Classification of the number of DRT trips and DRT trip distance

times indicated that both women and men predominantly used DRT services during the midday, with over half of the trips occurring in this time segment. Furthermore, more DRT trips were observed during the AM peak than the PM peak for both genders. Regarding trip distance, women took more DRT trips that spanned between the first quartile and the median trip distance. However, men accounted for a slightly larger portion of trips that had a trip distance less than the first quartile. Additionally, men and women exhibited similar characteristics under long trip distances, specifically those exceeding the third quartile.

The statistical analysis of age groups revealed some noteworthy differences. First, adults between 30 and 64 years of age made up most DRT passengers, accounting for about 54.9% of total trips and utilized DRT for approximately 37% of Home-Work trips and around 35% of Home-Healthcare trips. Additionally, the elderly (over 65 years) made up a large percentage of DRT passengers: about 36.8% of the total DRT trips were made by the elderly. This result is interesting considering that the elderly constitutes only 17% of the total population according to Census data (U.S. Census Bureau, 2020a). The elderly prominently made Home-Healthcare trips (about 67%), and they also took about 20% of DRT trips for Home-Work purposes. Last, despite young adults only making up 7.3% of trips, they took 41% (527/1,282) of Home-School trips. Children and adolescents only comprised a small percentage of DRT trips (7.3%), and they primarily utilized DRT for Home-Healthcare trips and Home-School (41% of all home-school trips), respectively.

In terms of DRT trip time, except for adolescents, all other age groups were more likely to start their DRT trips at midday. All the early-morning DRT trips were made by adults and the elderly. In comparison to the PM peak, DRT trips were more likely to occur during the AM peak. Adults recorded 12.7% more DRT trips in the AM peak than in the PM peak, while the elderly reported a 6.3% increase in DRT trips during the AM peak compared to the PM peak. In terms of trip distance, the elderly showed a preference for shorter trips, with 31% of their journeys falling within the first quartile of all DRT trips. In contrast, younger adults tended to take longer trips where more than half of them exceeded the third quartile.

4.6.1.2 Binary logit results

Binary logit models were used to further explore gender, age, trip time, and trip distance differences for various DRT trip purposes. **Table 10** shows the estimation results (odds ratio value)

Table 9 Cross-Tabulation of gender and age groups for home-based DRT trips

		Gender		Age					Total
		Male	Female	Children	Adolescent	Young Adult	Adult	Elderly	
Trip purposes	Home-Healthcare	4,411 (44.8%)	5,308 (44.9%)	32 (66.7%)	21 (12.7%)	94 (5.9%)	4,191 (35.2%)	5,381 (67.4%)	9,719 (44.8%)
	Home-Home	29 (0.3%)	624 (5.3%)	0 (0%)	0 (0%)	7 (0.4%)	626 (5.3%)	20 (0.3%)	654 (3%)
	Home-Leisure	267 (2.7%)	841 (7.1%)	7 (14.6%)	0 (0%)	55 (3.5%)	749 (6.3%)	297 (3.7%)	1,108 (5.1%)
	Home-Other	1,032 (10.5%)	1,071 (9.1%)	1 (2.1%)	14 (8.4%)	345 (21.7%)	1,151 (9.7%)	592 (7.4%)	2,103 (9.7%)
	Home-School	577 (5.9%)	705 (6%)	8 (16.7%)	126 (75.9%)	527 (33.2%)	606 (5.1%)	15 (0.2%)	1,282 (5.9%)
	Home-Services	114 (1.2%)	109 (0.9%)	0 (0%)	2 (1.2%)	34 (2.1%)	147 (1.2%)	40 (0.5%)	223 (1%)
	Home-Work	3,423 (34.7%)	3,162 (26.7%)	0 (0%)	3 (1.8%)	525 (33.1%)	4,422 (37.2%)	1,635 (20.5%)	6,585 (30.4%)
Pearson Chi-Square (Asymptotic Significance)		774.115 p= <0.001***		6932.382, p= 0.000***					
Time segments	Early-Morning	680 (6.9%)	859 (7.3%)	0 (0%)	0 (0%)	0 (0%)	691 (5.8%)	848 (10.6%)	1,539 (7.1%)
	AM-peak	2,513 (25.5%)	2,959 (25%)	8 (16.7%)	81 (48.8%)	437 (27.5%)	3,306 (27.8%)	1,640 (20.6%)	5,472 (25.2%)
	Midday	5,269 (53.5%)	5,976 (50.6%)	32 (66.7)	68 (41%)	695 (43.8%)	6,097 (51.3%)	4,353 (54.5%)	11,245 (51.9%)
	PM-peak	1,391 (14.1%)	2,026 (17.1%)	8 (16.7%)	17 (10.2%)	455 (28.7%)	1,798 (15.1%)	1,139 (14.3%)	3,418 (15.8%)
Pearson Chi-Square (Asymptotic Significance)		41.448 p= <0.001***		659.940, p= <0.001***					
Trip distance segments	Q1_25percentil	2,846 (28.9%)	2,719 (23%)	9 (18.8%)	0 (0%)	11 (0.7%)	3,042 (25.6%)	2,503 (31.4%)	5,566 (25.7%)
	Q2_50percentil e	1,852 (18.8%)	3,168 (26.8%)	3 (6.3%)	19 (11.4%)	42 (2.6%)	3,137 (26.4%)	1,819 (22.8%)	5,020 (23.2%)
	Q3_75percentil e	2,661 (27%)	2,879 (24.4%)	20 (41.7%)	57 (34.3%)	631 (39.8%)	2,911 (24.5%)	1,921 (24.1%)	5,540 (25.6%)
	Q4_100percent ile	2,494 (25.3%)	3,054 (25.8%)	16 (33.3%)	90 (54.2%)	903 (56.9%)	2,802 (23.6%)	1,737 (21.8%)	5,548 (25.6%)
Pearson Chi-Square (Asymptotic Significance)		236.419 p= <0.001***		1761.771, p= 0.000***					
Total (row percentage)		9,853 (45.5%)	11,820 (54.5%)	48 (0.2%)	166 (0.8%)	1,587 (7.3%)	11,892 (54.9%)	7,980 (36.8%)	21,673 (100%)
The percentage for the column is shown in parentheses. Parentheses in the last column show row percentage among genders or age groups, e.g., the DRT passengers include 45.5% male and 54.5% female.									

of seven binary logit models - one for each trip purpose. An odds ratio greater than 1 implies that a trip with a specific value for the independent variable is more inclined towards a specific trip purpose in comparison to the reference group for that independent variable. In contrast, an odds ratio of less than 1 indicates that the trip is less inclined towards a specific trip purpose compared to the reference group of that independent variable. The parentheses depict the reference group for each independent variable. The reference group for each model, with a specific trip purpose as the dependent variable, includes all the other six trip purposes. The Omnibus Tests of Model Coefficients is statistically significant ($p < 0.01$), indicating that the predictors as a set meaningfully improve the model's ability to predict the outcome variable at a 99% confidence interval.

The results indicated that women were significantly more likely to make Home-Healthcare DRT trips, Home-Home DRT trips, and Home-Leisure DRT trips while men were significantly more likely to make Home-Service DRT trips and Home-Work DRT trips.

Differences by age were also evident in DRT trip purposes. All else being equal, passengers in childhood (under 12 years old) and the elderly (more than 65 years old) had respectively 3.896 times and 3.959 times the odds of making Home-Healthcare DRT trips compared to those aged 30 to 64 years old. The odds ratios for the age variable in the Home-Work model were less than 1, suggesting that other age groups were less likely to make Home-Work DRT trips than adults aged between 30 to 64 years old.

The logit models also revealed some interesting findings for DRT trip start time and trip distance. Compared to trips at midday, DRT trips that occurred in the early morning were more likely to be Home-Healthcare trips and less likely to be Home-Work trips. Regarding DRT trips during the AM peak, there was a 99% confidence interval that they were 5.199 times and 2.998 times more likely to be Home-School trips and Home-Work trips respectively, compared to trips occurring at midday. This outcome aligns with the widely accepted notion that both school and work commuting are more likely to occur during the AM peak periods.

Trip length (segmented into four groups) also showed some significant differences. The odds ratio values below 1 implied that Home-Healthcare and Home-Service trips were more likely to have a short trip distance (fall below the first quantile of all DRT trip distances). The Home-

Table 10 Binary logit odds ratio results of trip purposes for home-based DRT trips

	Home- Healthcare	Home- Home	Home- Leisure	Home- Other	Home- School	Home- Services	Home- Work
Gender (Ref: Male)							
Female	1.174***	22.221***	2.805***	0.786***	0.909	0.717*	0.569***
Age (Ref: Adulthood)							
Childhood	3.895***	0	2.106	0.138	6.923***	0	0
Adolescence	0.436***	0	0	0.475**	69.542***	0.702	0.017***
Young Adulthood	0.134***	0.048***	0.576***	1.422***	12.223***	1.853**	0.861*
Older Adulthood	3.958***	0.043***	0.608***	0.736***	0.045***	0.373***	0.445***
Time segment (Ref: Midday)							
Early-Morning	4.220***	0	0	0	0	0	0.584***
AM-peak	0.177***	0.641***	0.607***	1.526***	5.199***	1.195	2.998***
PM-peak	0.797***	0.864	0.380***	2.552***	1.020	0.020***	1.144**
Distance segment (Ref: Q1_25 percentile)							
Q2_50 percentile	0.446***	0.027***	4.567***	1.396**	2.819***	0.235***	1.668***
Q3_75 percentile	0.449***	3.127***	4.330***	6.671***	0.926	0.578**	0.685***
Q4_100 percentile	0.581***	0.247***	1.166	2.978***	2.386***	0.765	1.337***
Intercept	1.145***	0.006***	0.017***	0.035***	0.015***	0.028***	0.519***
-2 Log Likelihood	23163.569	3869.157	7741.961	12170.83	6382.703	2285.081	23988.396
Omnibus test Chi-Square	6652.697***	1990.900***	1005.703***	1635.515***	3354.007***	199.802***	2629.436***
Overall accuracy (%)	72.5%	97%	94.9%	90.3%	94.1%	99%	72.5%
Observations: 21,673							
* $p < 0.05$, significant at 0.05 level; ** $p < 0.01$, significant at 0.01 level; *** $p < 0.001$, significant at 0.001 level Reference group: all other trip purposes. Results show the odds ratio.							

Leisure model had the odds ratios of the median-short distance and the median-long distance (4.567 and 4.331, respectively) being significantly greater than 1. This suggests that Home-Leisure trips were more likely to be median length. Trips with median-long distance exhibited a higher likelihood of being Home-Home round trips. The Home-School and Home-Work models both displayed odds ratios significantly greater than 1 for the median-short distance category (2.82 for the Home-School model and 1.668 for the Home-Work model) and long distance category (2.386 for the Home-School model and 1.338 for the Home-Work model). The results indicate that school DRT trips and work-related DRT trips are more likely to be either of median short or long distance.

4.6.2 Spatial analysis results for DRT demand, DRT accessibility, and essential destination deserts

The following sections present the results of the spatial analysis of DRT demand, the spatial distribution of DRT accessibility, and the classification of the spatial relationship between DRT demand and DRT accessibility to identify potential essential destination deserts.

4.6.2.1 Spatial distribution of DRT demand

This section analyzed the spatial distribution of total DRT demand and DRT demand specifically from two demographic groups: female and elderly. **Figure 24** shows the spatial patterns of total DRT trips, DRT trips taken by the elderly, and DRT trips by females. The orange shading indicates the count of DRT trips; lighter shades represent lower DRT demand levels and darker shades signify higher DRT demand levels. Black circles indicate areas with a higher level of demand from females or the elderly. Blue circles represent areas with a high DRT demand from those who are both female and elderly, green circles depict areas with a higher concentration of DRT trips made by male elderly riders, and red circles show areas characterized by a high density of DRT trips by non-elderly females.

To provide context and comparative insights, corresponding maps of the distribution of the total population, female population, and elderly population from 2020 Census data are presented in **Figure 25**. Notably, these maps revealed that areas with higher population density did not consistently correspond to higher DRT demand. Similarly, areas with higher population density among females and the elderly did not consistently have a higher DRT demand within these

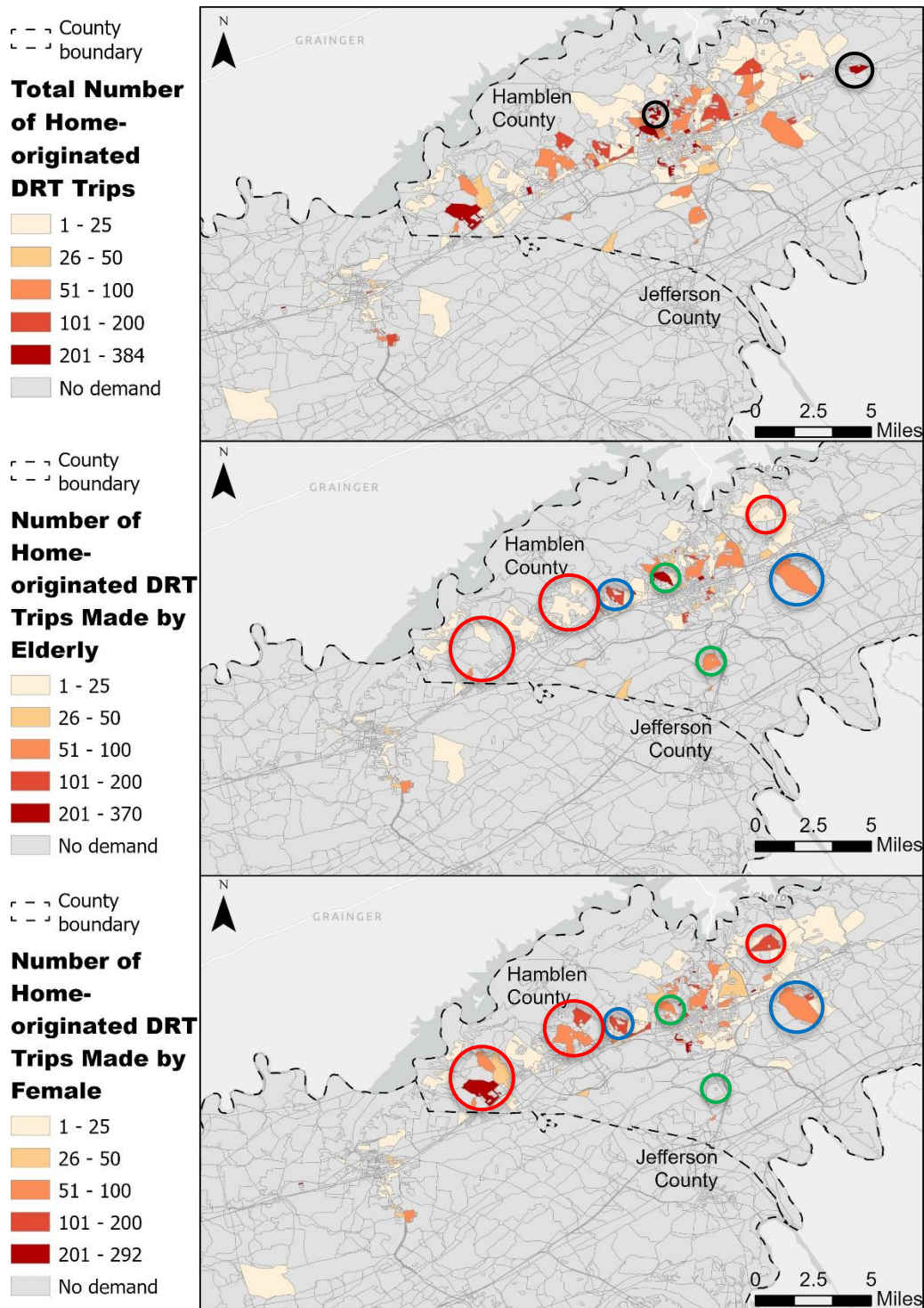


Figure 24 Spatial distribution of total DRT demand, elderly demand, and female demand represented by DRT trips

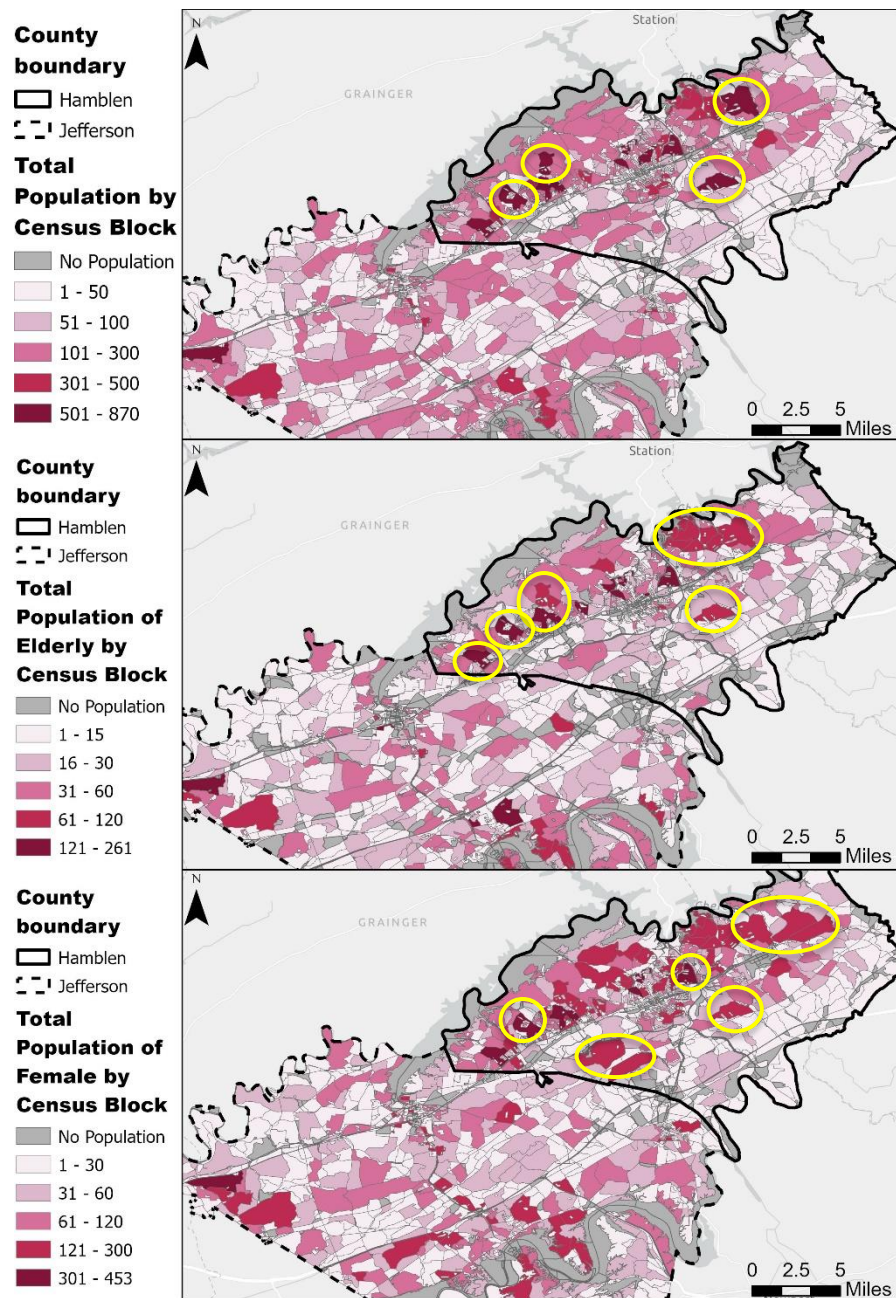


Figure 25 Spatial distribution of total population, elderly, and female from Census data

demographic groups. For instance, yellow circles in **Figure 25** have a high density of population distribution; however, these Census blocks in **Figure 24** were not shown as high DRT demand. This underscores the potential limitations of relying solely on Census data for transportation planning, as it may not always accurately reflect actual demand for some modes of travel such as DRT.

4.6.2.2 Spatial distribution of DRT accessibility

The second part analyzed the spatial distribution of DRT accessibility, as measured by the average DRT trip distance. **Figure 26** includes maps displaying the trip distances of total DRT trips and DRT trips made by females or the elderly. **Figure 27** visualizes the spatial distribution of DRT trip distance to access three essential purposes: home-healthcare (trip with destination land use of healthcare facilities), home-leisure (trip with destination land use of shopping stores and churches), and home-service (trip with destination land use of government offices and banks). These maps aimed to analyze DRT accessibility for different demographic groups (i.e., female and elderly) to essential destinations, with shorter distances indicating higher accessibility (shaded in darker green) and longer trip distances signifying lower accessibility (shaded in lighter green).

As suggested by **Figure 26** and **Figure 27**, the distribution of DRT accessibility, measured by the DRT trip distance, showed a scattered distribution. This contrasts with the more predictable accessibility trends of fixed-route transit, which typically decreases gradually from the urban center towards the city outskirts or away from fixed-route bus stops.

Figure 26 indicates that, overall, the spatial distribution of DRT trip distances in areas with both elderly and female DRT demand tends to be similar. For instance, the red symbol labeled number one highlights areas characterized by short trip distances for DRT trips made by the elderly and females, and the red symbol labeled number two highlights areas with longer trip distances for both groups. However, **Figure 26** also pinpoints a few areas where the spatial distributions of DRT trip distances differ between the elderly and females. This discrepancy is exemplified by the blue symbol labeled number three, which identified areas with shorter trip distances for females, contrasting with longer trip distances for the elderly.

To understand the spatial distribution of DRT accessibility to essential destinations, **Figure 27** illustrates the DRT trip distances for three specific trip purposes. This figure shows the locations

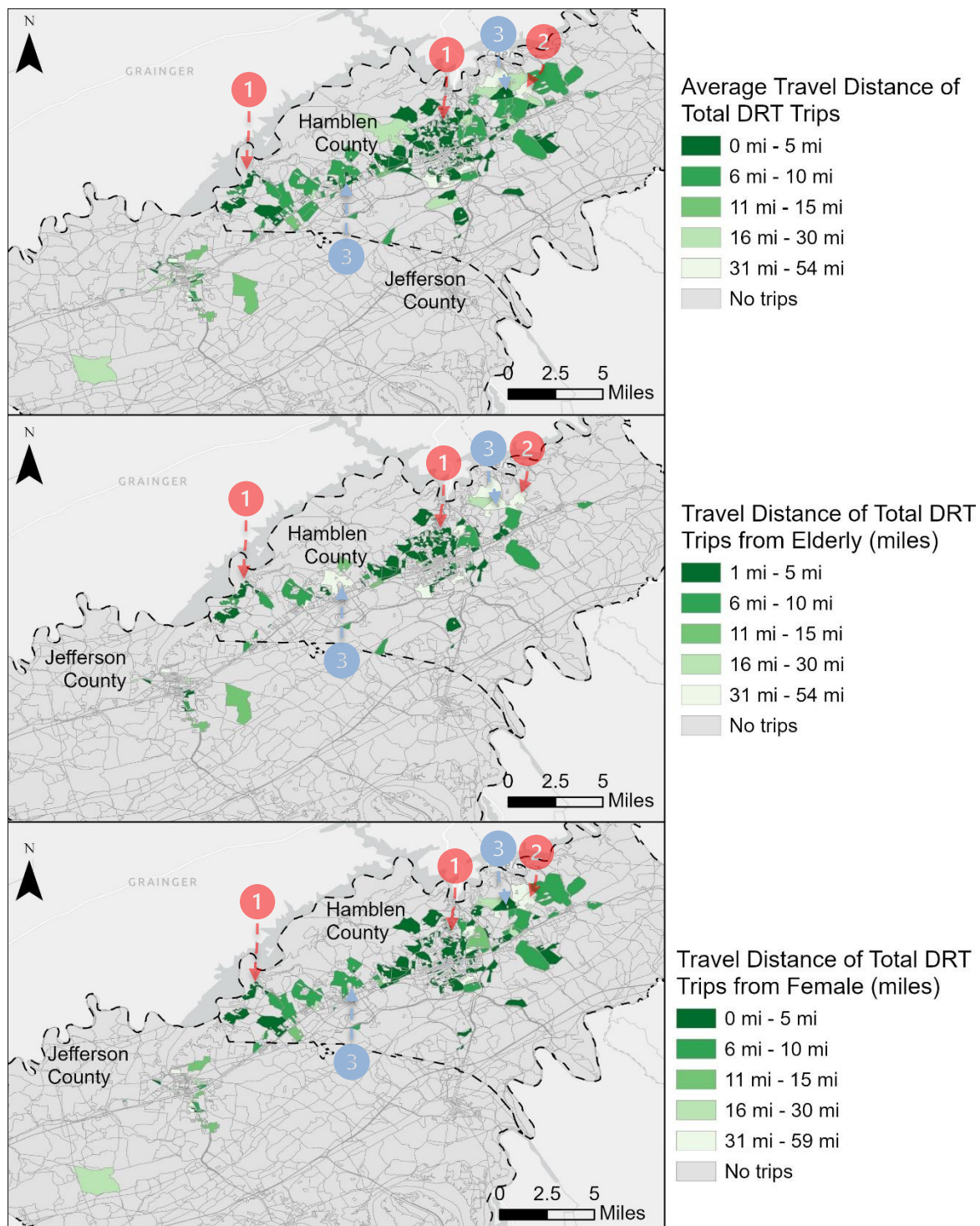


Figure 26 Spatial distribution of DRT trip distances of total trips, trips made by elderly, and trips made by female

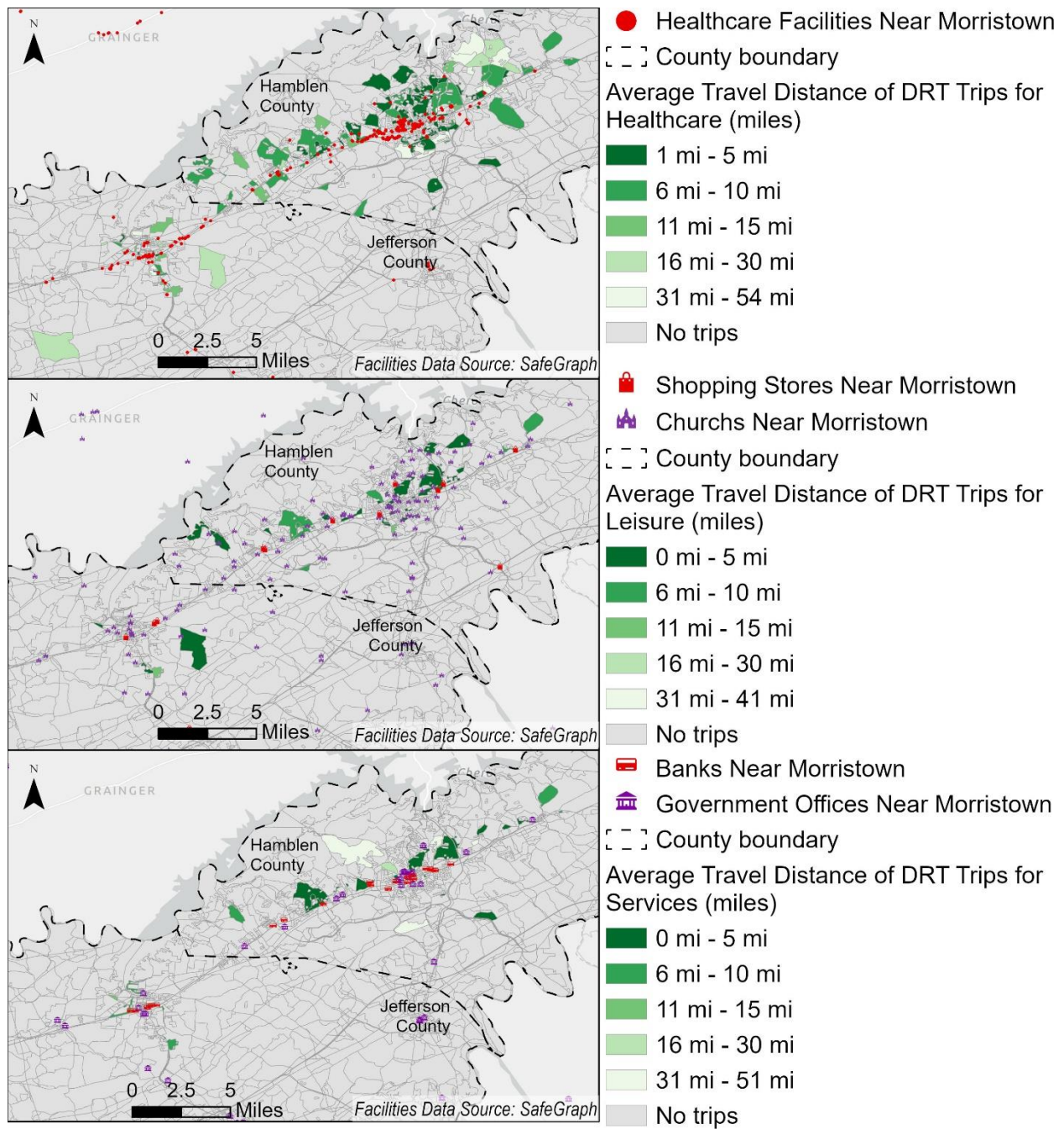


Figure 27 Spatial distribution of DRT trip distance to access three essential destinations

of nearby essential destination facilities using the SafeGraph dataset within the ArcGIS tool. In general, DRT trips with different purposes showed varying spatial patterns of trip distances. Nonetheless, DRT trips to essential destinations typically displayed shorter trip distances in residential areas closer to facilities. For instance, individuals residing near Census blocks with a notable concentration of healthcare facilities tend to have shorter DRT trips, implying a potential preference for nearby healthcare facilities. Similarly, DRT passengers showed a potential trend of accessing nearby shopping stores, churches, banks, and government service locations. Leisure trips were largely concentrated within the 0-15 mile range, with no recorded trip distances falling between 16-30 miles.

To delve deeper into the identification of potential areas of concern where there was notable DRT demand (measured by the number of DRT trips) but limited DRT accessibility (assessed by DRT trip distance), the spatial relationship between DRT demand and DRT accessibility will be analyzed in the subsequent section.

4.6.2.3 Essential destination deserts: gaps in the spatial relationship between DRT demand and DRT accessibility

Census blocks were then classified based on the regional median value of DRT trips. Those with DRT trip counts equal to or below the regional median were categorized as “low demand”, while those with counts above the regional median were labeled as “high demand”. Similarly, blocks were classified as “high accessibility” or “low accessibility” depending on whether their average trip distance fell above or below the median average trip distance among all areas. Consequently, the study blocks were divided into four categories using quadrant classification and spatially visualized in **Figure 28** and **Figure 29**. These categories include “high demand-high accessibility” represented in red, “high demand-low accessibility” in pink, “low demand-high accessibility” in blue, and “low demand-low accessibility” depicted in indigo. The objective of this section is to identify the “high demand-low accessibility” areas where DRT users had limited accessibility (long travel distances) to access essential destinations, which were then categorized as potential *essential destination deserts*.

Figure 28 provides a visualization of the relationship between DRT accessibility and various DRT demand groups. Notably, certain areas have been identified as potential essential

destination deserts for both the elderly and females, denoted by green circles in **Figure 28**. It was evident that there were distinct spatial variations between essential destination deserts for the elderly and for females. For instance, yellow circles show potential areas of concern for non-elderly females. These areas are identified as pink (“high demand-low accessibility”) on the bottom map but appear as indigo (“low demand-low accessibility”) in the middle map. This is due to the low demand from the elderly, even though DRT accessibility is limited. On the other hand, a purple circle highlights a Census block that is colored indigo on the middle map but appears in red on the bottom map. This signifies that this specific Census block exhibits high demand from females who also have higher accessibility levels. However, in this area, there is low demand from the elderly, who similarly experience long travel distances to access their destinations.

Moving beyond DRT accessibility for specific demographic groups, **Figure 29** delved into the spatial analysis of DRT accessibility to access three essential destinations (based on destination lane use) for total DRT demand. In **Figure 29**, Census blocks marked in pink indicate areas characterized by high DRT demand but limited accessibility for accessing healthcare facilities, shopping stores, churches, bank services, and government services.

As **Figure 29** illustrates, Census blocks highlighted by green circles were classified as “high demand-low accessibility” (pink areas) for healthcare and leisure trips while they were classified as “high demand-high accessibility” (red areas) for services-seeking trips. This suggests that in these areas, despite having a high demand for all three essential destinations, they only have higher levels of accessibility for service destinations (i.e., government services and banks). However, the accessibility to healthcare and leisure destinations was lower than the regional median. Two Census blocks are highlighted in **Figure 29** with a yellow and purple circle, respectively. These blocks had relatively high DRT accessibility to both healthcare and leisure destinations. However, due to the blocks having higher demand solely for healthcare trips, they were categorized as healthcare deserts and classified as “low demand-low accessibility” for leisure trips. The block encircled by a yellow circle displayed a low accessibility to banks and government services, whereas the block encircled by a purple circle had a higher accessibility to these destinations, even though both blocks had demand for these trips lower than the regional median.

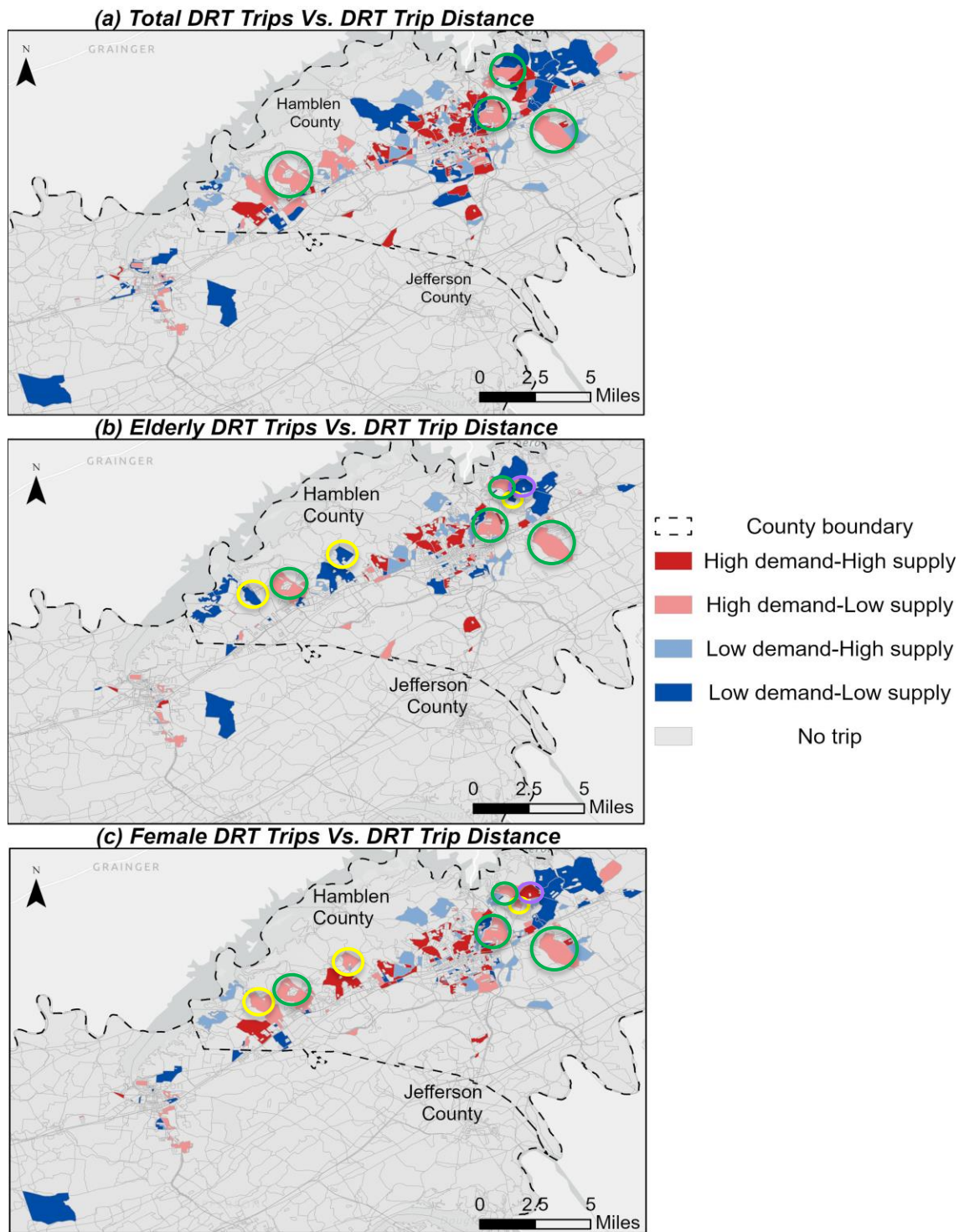
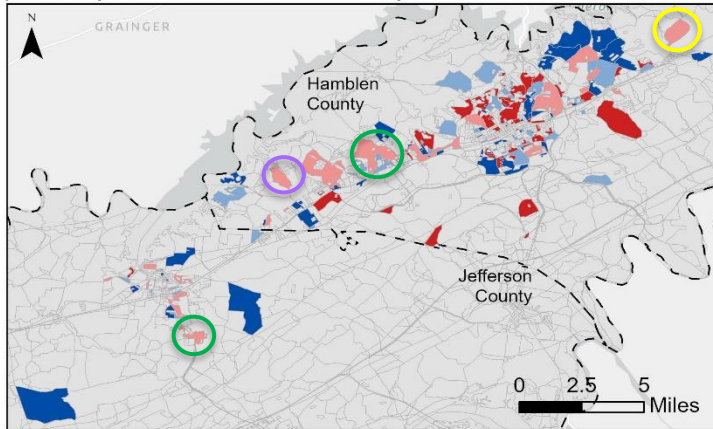
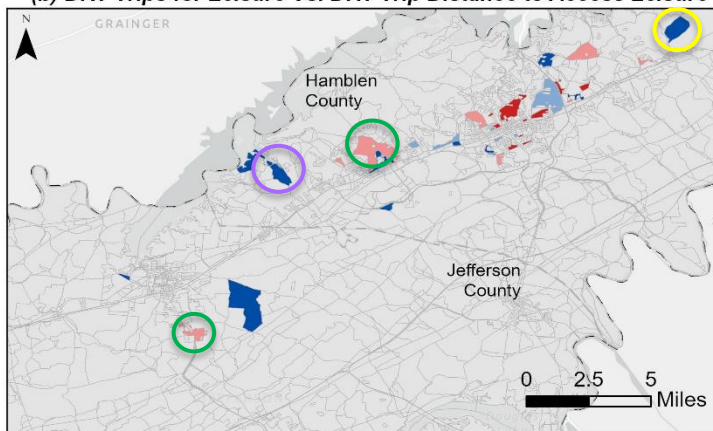


Figure 28 Spatial distribution of relationship between different DRT demand types and DRT trip distance

(a) DRT Trips for Healthcare Vs. DRT Trip Distance to Access Healthcare



(b) DRT Trips for Leisure Vs. DRT Trip Distance to Access Leisure



(c) DRT Trips for Services Vs. DRT Trip Distance to Access Services

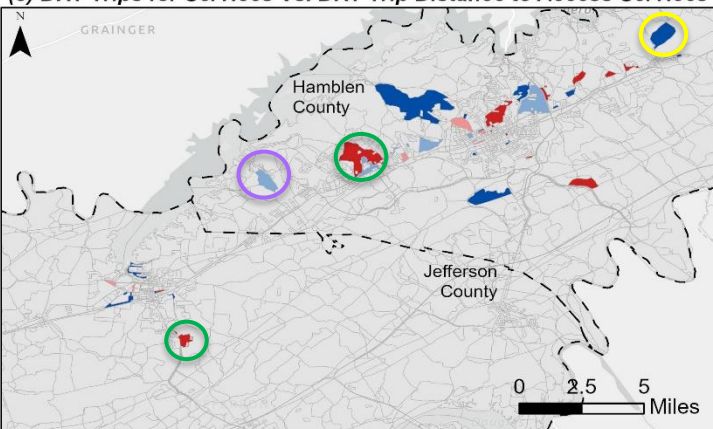


Figure 29 Spatial distribution of relationship between DRT demand and DRT trip distance to access different essential destinations

4.7 Discussion and conclusions

This paper statistically analyzed gender and age differences in the travel patterns of DRT, focusing on trip purpose and trip distance, and spatially analyzed the relationship between DRT demand and DRT accessibility to identify potential *essential destination deserts* in a rural setting. A case study was conducted for the DRT system in Morristown, TN, which is representative of rural towns in the United States. This study contributed to the exploration of the under-researched areas of DRT trip patterns and spatial analysis employing real world trip data (not surveys). Furthermore, this study enriched existing knowledge on the difference in travel patterns among different gender and age groups, adding new sights to public transportation analysis in rural areas. This study also contributed to the literature by proposing a methodological framework for assessing DRT travel patterns and accessibility, which has been excluded from most of the prior literature on accessibility.

The first part of this study examined the gender and age differences in DRT trip patterns by employing cross-tabulation analysis and binary logit regression models. The results suggest that females made more DRT trips than males across all trip purposes, except for the Home-Work purpose where men recorded more trips. This finding is reasonable since there are more females than males in the population of Morrison, TN. This finding was consistent with previous studies that women tended to make more fixed-route transit trips, often involving multiple purposes and skewed more towards non-work-related travel (McGuckin & Fucci, 2018; Metro Los Angeles, 2019). Given that females were the majority of DRT passengers, they were chosen as one of the DRT demand groups for the subsequent spatial analysis.

Regarding trip time and distance segments, it was found that both genders predominantly utilized DRT services during midday, contrasting with studies on other transportation modes that show women were more likely to use fixed-route transit services during midday (Metro Los Angeles, 2019), and the general expectation of higher travel demand during AM or PM peak times (Downs, 2000; Wang et al., 2022). Contrary to prior findings that women tended to travel shorter distances (Fan, 2017; Hanson & Johnston, 1985; Metro Los Angeles, 2019), there were not many notable statistical differences in trip distance by gender in this DRT dataset.

It is noted that about 36.8% of the total DRT trips were made by the elderly (over 65 years). This result revealed an important need for DRT from the elderly in the study areas, considering that the elderly population constituted only 17% of the total population according to Census data (U.S. Census Bureau, 2020a). The elderly made about 67% of DRT trips for Home-Healthcare purposes and about 20% of DRT trips for Home-Work purposes. Adults between 30 and 64 years utilized DRT for approximately 37% of Home-Work trips and around 35% of Home-Healthcare trips. These results generally align with earlier research suggesting that the elderly are more inclined to use DRT compared to younger adults predominantly for healthcare-related purposes (LaMondia & Bhat, 2010; Mattson, 2017; Nguyen-Hoang & Yeung, 2010; Sultana et al., 2018). The occurrence of work-related trips among the elderly also provided some substantiation to previous findings that suggested a rise in work-based trips among the elderly, potentially driven by the recent trend of postponing retirement (Collia et al., 2003; Horner et al., 2015; Srinivasan et al., 2006). Another observation in the context of DRT in Morristown aligning with past findings is that the elderly tended to travel shorter distances (Giuliano et al., 2003; Jamal & Newbold, 2020; Mattson, 2012; Yang et al., 2018).

The second part of this study conducted spatial analysis of DRT demand, DRT accessibility, and “essential destination” deserts. The spatial distribution of DRT demand revealed that the same areas can show differing spatial distribution patterns between the demand from females and the elderly. Additionally, the DRT demand levels represented by the historical DRT trip data did not consistently correspond to the population density from Census data, suggesting DRT trip analysis is important to provide a more precise representation of demand. The spatial distribution of DRT accessibility, as indicated by DRT trip distances, showed a scattered distribution, unlike fixed-route transit, which typically exhibits a gradual decrease in accessibility from the urban center or bus stops towards the city outskirts. However, DRT accessibility to essential destinations is typically spatially related to the location of facilities. Specifically, DRT trips to essential destinations typically displayed shorter trip distances in residential areas closer to destination facilities.

The last part of the spatial analysis classified study areas into four categories based on the relationship between DRT trip demand and DRT accessibility to destinations and identified

potential areas of concern as “essential destination deserts” due to their higher demand for DRT trips and more limited DRT accessibility to access specific essential destinations. The results reveal distinct spatial variations between essential destination deserts for the elderly and those for females. The classification results also illustrated certain areas displaying varying spatial relationships between DRT demand and DRT accessibility when accessing different essential destinations (i.e., healthcare, leisure, and service destinations). The identification of these potential areas of concern is critical to ensure equitable DRT accessibility to essential destinations for females and the elderly in future transportation planning and the development of facilities.

4.8 Limitations and future research

Some potential limitations and areas for future research emerged from this analysis. First, the study was based on data from Morristown, TN, and the generalizability of the findings may be limited to similar rural areas due to the unique demographic and geographic characteristics of this area. Hence, future research should consider broadening the geographical scope to encompass multiple rural regions in a comparative analysis. Second, this research was limited to age and gender due to the availability of this demographic information in the dataset. For a broader analysis of DRT usage purposes, it would be valuable to investigate other demographic factors, such as disability status, income level, and car ownership; this could be done in future research using Census data or by collecting survey data. Another area for future research is to consider a gravity model approach to assessing DRT accessibility; specifically, this study focused on travel time as a metric but did not consider the attractiveness of the destination. Previous studies have shown that destination attractiveness increases with size and decreases with distance, travel time, or cost (Papa & Coppola, 2012). Therefore, future research could use gravity-based models to assess DRT accessibility. Additionally, this study excluded the Non-Home-Based (NHB) category due to a limited number of observations; future research should consider including this category, as more comprehensive data may reveal intriguing findings. Last, most of the data used in this study was collected before the COVID-19 pandemic; future research can extend the study timeline to post-pandemic periods to assess the impact of COVID-19 on DRT.

CHAPTER 5. CONCLUSIONS

This chapter discusses the key findings and contributions of this dissertation, as well as areas for future research.

5.1 Summary and comparison of the key findings

This section presents a summary and comparison of the results of the three studies presented in this dissertation. This dissertation evaluated transit equity by analyzing transit supply to access job opportunities and essential services for different segments of the population that may rely on transit. Each study in this dissertation employed statistical and spatial analysis methods through case studies in the state of Tennessee. **Table 11** shows a comparison of the three studies.

Chapter 2 evaluated transit equity of existing affordable housing units in three major cities in the state of Tennessee, and proposed easy-to-implement modifications to local bus service to increase transit accessibility levels of an affordable housing location that were identified as underserved locations. First, this chapter measured job accessibility via fixed-route transit, utilizing GTFS data and employing a cumulative opportunity measure. Next, this study statistically evaluated the transit equity of affordable housing programs at the city level using Lorenz curves and Gini coefficients. The results revealed that the level of transit equity for affordable housing units differs across housing programs and cities. Then, this chapter identified specific affordable housing locations as underserved locations by proposing a simple inequity index. In the next step, an example of a bus service modification was evaluated for one underserved affordable housing location with a high inequity index to demonstrate the applicability of the method. The substantial increase in accessible jobs if bus service were modified highlights the potential effectiveness of implementing short-term transit service changes to improve the accessibility of existing affordable housing locations. The proposed method is practical and can be used by transit agencies to identify underserved affordable housing locations and better coordinate affordable housing and transit services.

Chapter 3 evaluated transit equity across multiple essential service categories for three transit-dependent groups (i.e., those in poverty, minority populations, and car-limited populations) in Nashville, TN. First, this chapter measured accessibility to essential services (food store, healthcare, childcare, school, and park) via fixed-route transit, utilizing GTFS data and employing

a travel time measure. Next, Theil's index was used to statistically evaluate transit equity. The results of the Theil index suggest that transit accessibility to healthcare had the greatest level of inequity and that parks were more evenly distributed throughout the city than the other essential service categories. This generally aligns with the pattern observed in the distribution of healthcare facilities and parks in Nashville. Most healthcare facilities are privately provided and concentrated in the central city, whereas parks, being predominantly public facilities, have a more balanced distribution throughout the city. This result may also be attributed to the greater availability of land for parks on the outskirts of the city compared to the densely developed downtown area. Next, bi-LISA spatial clustering was employed to identify areas characterized by higher levels of transit-dependent demand and limited transit access to essential services. The clustering results revealed variations in the distribution of underserved areas for the different transit-dependent demand groups. Last, underserved areas were identified as "essential services deserts" that have overall high transit-dependent demand but low transit supply. The identification of transit deserts to essential services is important for transit agencies and local planning departments to prioritize their resources and target interventions to improve transit access to essential services for specific populations.

Chapter 4 investigated gender and age difference in DRT travel patterns and DRT accessibility using the real-world DRT trip data from the rural city of Morristown, TN. First, statistical analysis including cross-tabulation analysis and logit regression analysis identified gender and age difference in DRT travel patterns. The results suggest that females made more DRT trips than males across all trip purposes, except for the Home-Work purpose where men recorded more trips. This finding is reasonable since there are larger female population compared to the male population in Morrison City. The age analysis revealed 36.8% of the total DRT trips were made by the elderly (over 65 years), primarily for Home-Healthcare trips (67%), and that the elderly made shorter DRT trips. This result revealed a significant DRT need from the elderly in the study area, considering that the elderly population constituted only 17% of the total population according to Census data (U.S. Census Bureau, 2020a). In the spatial analysis, DRT accessibility was measured using the actual DRT trip data and employing a measure of travel distance. The spatial distribution of DRT accessibility showed a scattered distribution, unlike fixed-route transit,

which typically exhibits a gradual decrease in accessibility from the urban center towards the city outskirts. However, DRT trips to essential services typically displayed shorter trip distances in residential areas closer to service facilities. Next, the study areas were classified into four categories based on the relationship between DRT trip demand and DRT accessibility to destinations; this spatial analysis was done to identify potential areas of concern, or “essential destination deserts,” with higher demand for DRT trips and more limited DRT accessibility to access specific essential destinations. The results reveal distinct spatial variations between essential destination deserts for the elderly and those for females. The classification results also revealed variations in DRT demand and DRT accessibility when accessing different essential destinations (i.e., healthcare, leisure, and government service and bank destinations). The identification of these potential areas of concern is critical to ensure equitable accessibility to DRT services for females and the elderly in future transportation planning and the development of service facilities.

Table 11 Comparison of case study findings

		Chapter 2	Chapter 3	Chapter 4
Context & potential transit demand	Study area	Nashville, Memphis, Chattanooga, TN	Nashville, TN	Morristown, TN
	Subject of investigation	Affordable housing locations	Poverty population, minority population, car-limited population	Total DRT users, female DRT users, elderly DRT users
	Unit of analysis	Housing location level	Census block group	Individual level (DRT trip record)
Transit accessibility	Transit system	Urban transit: fixed-route transit	Urban transit: fixed-route transit	Rural transit: demand response transit (DRT)
	Transit data	GTFS	GTFS	DRT trip data
	Type approach	Potential accessibility	Potential accessibility	Actual accessibility
	Measurement	Cumulative opportunities: number of jobs	Travel cost: travel time	Travel cost: travel distance
Transit equity	Statistical analysis	Gini coefficient	Theil's index	Cross-tabulation and Chi-Square test, logit regression analysis
	Spatial analysis	Inequity index	LISA clustering	Quadrant classification
Key Findings		1. Transit equity of affordable housing units can vary across different housing programs or different cities 2. Short-term transit service changes can improve the transit accessibility of existing affordable housing locations with limited transit access	1. Transit equity level from most equitable to least equitable essential services: park, food stores, childcare, school, healthcare 2. Essential service deserts with different transit demand and essential service were identified.	1. Females make more DRT trips than males 2. Females have higher DRT demand for healthcare, home visits, and leisure trips, while males dominate in work-related DRT demand. 3. Despite comprising only 17% of the population, the elderly display notable DRT demand, primarily for healthcare and shorter trips. 4. Essential destination deserts with varying DRT demand and trip destinations were identified.

5.2 Contributions

This dissertation presents several methodological contributions in the evaluation of transit equity and accessibility.

First, this dissertation introduced an inequity index to identify inequity levels for affordable housing locations. This inequity index contributed to its easy applicability in practice, providing a straightforward method to conduct location-level equity analysis. Second, this dissertation enhanced the evaluation of transit accessibility to multiple essential services by proposing a spatiotemporal transit supply index that considers the temporal variation in transit accessibility to different essential services facilities. Third, this dissertation also contributed to transit equity analysis by proposing spatial disparities and correlation analysis among underserved areas concerning various essential services. Fourth, the utilization of real-world DRT trip data from Morristown, Tennessee represented another significant methodological contribution, filling gaps in the existing literature on DRT travel patterns and accessibility assessment. Last, this study enriched the existing literature by focusing on low-density, automobile-oriented cities, suburban areas, and rural areas, which are typically underrepresented in the transit literature.

This dissertation also contributed to method transferability by relying primarily on open datasets, which includes GTFS data, Census data, geospatial affordable housing locations from HUD, and public geospatial location data of essential service facilities from federal or local departments. This makes the proposed methods widely applicable to other regions of the United States with fixed route transit service. The use of DRT trip data ensured the repeatability of the methodology across the DRT system in rural areas, where similar-format trip data is commonly available.

Overall, the analysis results have important real-world implications for transit planners and policymakers. The methods proposed in all three chapters helped identify areas of concern with limited transit accessibility, providing insights that can assist in resource allocation and decision-making in transit planning. The identification of these areas can help to ensure equitable access to transit services, helping people to reach job opportunities and essential services needed in their everyday lives.

5.3 Areas for future research

There are several areas for future research that emerged from this dissertation, including: 1) expanding the applicability to other areas in the United States and beyond; 2) broadening the inclusion of transit demand groups; 3) developing a comprehensive transit accessibility metric; and 4) analyze the transit accessibility of mixed travel modes incorporating fixed-route transit and DRT.

First, the applicability of the method proposed in this study may be limited to the certain areas in United States because housing policies, transit planning practices, and the availability of data vary significantly between different states in the USA and between countries. Thus, future research should consider extending the analysis to other contexts.

Second, this dissertation considered the following potential transit demand groups: 1) residents living in affordable housing units; 2) those in poverty, minority, and car-limited populations, as documented in Census data; and 3) female and elderly passengers recorded in DRT trips. Future research could enhance equity analysis by including more groups who may need transit services to fulfill their transportation needs, such as individuals with disabilities.

Third, in both Chapter 2 and Chapter 3, the assessment of transit accessibility involved certain assumptions about travel behavior, such as assuming individuals access jobs within a 1-hour threshold or choose to access the nearest essential service location. However, it is possible that people might make different choices based on alternative criteria, such as commuting more than one hour or selecting a facility farther away for specific preferences. Therefore, future research could evaluate these travel behavior assumptions by collecting travel survey data or trip data.

Last, this dissertation assessed fixed-route transit and DRT systems separately. A potential future research direction could consider both fixed-route transit and DRT to examine transit accessibility together. Such an approach would provide insights into transit accessibility at the intersection of these two modes, further enriching accessibility analysis by considering multiple transit services. This approach may also provide insights into the accessibility of inter-city transit trips.

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VITA

Jing Guo was born in Hunan, China, to the parents of Zhibing Guo and Fengjiao Gong. She received her bachelor's degree in Transportation Engineering at Changsha University of Science and Technology in 2019. Afterward, she went to The University of Tennessee, Knoxville to pursue her Ph.D. in Transportation Engineering in the Department of Civil and Environmental Engineering and Master of Science in Statistics. She works as a Graduate Research and Teaching Assistant under the supervision of Dr. Candace Brakewood. Her research mainly focuses on transit planning and transit equity analysis, aiming to evaluate and improve transit accessibility for disadvantaged people who significantly need public transportation in their daily life. She also has research experience in geospatial and statistical data analysis and ride-sharing usage investigation.

During her Ph.D. studies, Jing received many notable scholarships and awards, such as: 1) 2023 Fran Hooper Scholarship presented by the American Public Transportation Foundation; 2) 2022 American Public Transportation Foundation Board Scholarship; 3) 2023 Tickle Graduate Fellowship awarded by the University of Tennessee Tickle College of Engineering; 4) 2023 Tennessee Section Institute of Transportation Engineer's William L. Moore, Jr. Scholarship; 5) First place in the 2023 Southern District of Institute of Transportation Engineer's Graduate Technical Paper competition; 6) Second place in the 2023 Tennessee Section Institute of Transportation Engineer's annual student paper competition. As a doctoral student, Jing also served as a reviewer for several academic journals and conferences.