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Analyzing gender and age differences in travel patterns and accessibility for demand response transit in small urban areas: A case study of Tennessee

Jing Guo
School of Traffic and Transportation Engineering
Changsha University of Science and Technology
jingguo97@outlook.com

Sabyasachee Mishra
Department of Civil Engineering
University of Memphis
smishra3@memphis.edu

Candace Brakewood
(corresponding author)
Department of Civil and Environmental Engineering
University of Tennessee, Knoxville
cbrakewo@utk.edu

Abstract: Demand Response Transit (DRT) services (e.g., dial-a-ride) play a crucial part in supporting transportation systems in small urban and more rural areas. 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 from Tennessee. 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 demographic groups, particularly women and the elderly. 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 destination 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.

Keywords: Demand Response Transit, gender, age, travel patterns, DRT accessibility, essential destination deserts

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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

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populated urban areas. However, dispersed travel demand in small urban and more 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). Previous studies have highlighted a significant distinction between DRT systems serving the general public and those serving specific population segments, such as seniors and persons with disabilities (Ellis & McCollom, 2009; National Academies of Sciences et al., 2008). Since the enactment of the Americans with Disabilities Act (ADA) in 1990, considerable attention has been directed towards ADA complementary paratransit service, which is a specific type of DRT available to individuals with disabilities (National Academies of Sciences et al., 2008). DRT systems catering to the general public are prevalent in small to medium-sized communities (LaMondia & Bhat, 2010; National Academies of Sciences et al., 2008); however, there exists a notable research gap concerning the needs and experiences of the general public utilizing DRT services. To address this gap, this study presents a case study of the Morristown DRT, which serves the general public.

Prior studies have primarily concentrated on the operational evaluation of DRT, focusing on elements such as vehicle numbers, scheduling, and fleet distribution (Davenport et al., 2005; Sandlin & Anderson, 2004). However, it is crucial to note that DRT operations alone offer only a partial view (LaMondia & Bhat, 2010). Previous research underscores the importance of considering user travel needs to conduct a comprehensive assessment of DRT system effectiveness (LaMondia & Bhat, 2010). The literature also highlights accessibility as an important metric for assessing user-level performance in DRT (LaMondia & Bhat, 2010). Measuring accessibility for various population groups and travel purposes can offer decision-makers insights to identify areas of concern for DRT service improvement or specific populations requiring targeted interventions (LaMondia & Bhat, 2010).

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 (Crossland et al., 2023; Guo et al., 2021; Hightower et al., 2024; Jain et al., 2017; Shah et al., 2023; 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.

Therefore, this paper aims to contribute to the literature by examining travel patterns and accessibility of DRT in a small urban area across demographic groups with a specific focus on the elderly and females who use DRT for diverse trip purposes such as healthcare and leisure. The utilization of Morristown, TN as a case study is particularly relevant due to its alignment with the characteristics commonly observed in smaller-sized communities, including widespread service facilities, limited public transit options, and a prevalence of low-income groups.

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.

2 Literature review and research objectives

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.

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.

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). Trip chaining typically involves making multiple-stop trips for family or household errands and may contribute to their higher overall usage of public transit compared to men (Fan, 2017; Gendered Inovations, 2015). 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).

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 trip purpose, prior studies revealed that the elderly make more non-work trips, including shopping, family visiting, social, recreational, 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 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 focusing specifically on the DRT travel patterns of women and the elderly.

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.

2.2.1 Transit accessibility

Over the past decade, there has been a significant increase in research focused on transit accessibility, particularly for fixed-route transit systems. Transit accessibility generally refers to the ease of accessing destinations from a specific place via public transit. However, prior studies quantify transit accessibility differently based on their specific scope and focus. Some studies focus on the initial stage of the trip, measuring transit accessibility in terms of proximity to transit facilities like bus stops (Manout et al., 2018). While proximity is important, it alone does not fully capture the scale and ease of access to regional activities (Welch, 2013). Most commonly, transit accessibility is defined as the ease with which individuals can reach desired destinations using public transit from a specific location, considering the entire trip including all trip stages (Alam et al., 2010; Wessel & Farber, 2019). Under this broader definition, prior studies have measured transit accessibility with various contextual considerations (Bok & Kwon, 2016). For example, (Wessel & Farber, 2019) define accessibility as the ease of reaching destinations distributed in space, primarily focusing on travel time. (El-Geneidy et al., 2016b) emphasize travel time and fare for job accessibility. (Owen & Murphy, 2020) discuss the ability of people to reach the destinations they must visit to meet their living needs (e.g., grocery stores, healthcare facilities), while (Stewart, 2017) considers the potential to reach destinations based on the built environment and individual attributes, reflecting broader transport and land-use systems. These varying definitions highlight the multifaceted nature of transit accessibility and its importance in urban planning and policy development.

Previous studies have predominantly relied on two types of metrics for measuring accessibility: opportunity-based and cost-based (Cui & Levinson, 2020). An opportunity-based measure calculates the number of opportunities that can be reached within a specified travel cost (often represented by travel time of distance). In contrast, cost-based methods measure the travel cost (commonly presented as travel time or distance) associated with accessing a fixed number of opportunities. The cost-based measure is frequently employed in previous studies to assess accessibility to specific services and facilities, such as schools (Guo & Brakewood, 2024), healthcare facilities (Ghorbanzadeh et al., 2020; Rosero-Bixby, 2004), food stores (Farber et al., 2014; Sharkey et al., 2009), and recreational facilities like parks (Xu et al., 2017). Higher (or lower) accessibility is often represented by lower (or higher) values of travel time or travel distance (Mavoa et al., 2012).

Different approaches exist in the literature to implement accessibility measures. An important difference lies between studies based on potential accessibility versus actual accessibility (Niedzielski & Boschmann, 2014). Calculating potential accessibility requires making assumptions about travel behavior, such as travel time 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 directly by the observed travel distance or travel time from actual trip data (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 a cost-based measure and actual travel distance from DRT trip data ensures the repeatability of the methodology across DRT systems in other small urban and more rural areas.

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).

Transit demand is usually defined as 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, 2023; Jeddi Yeganeh et al., 2018). In this study, DRT demand analysis will include total DRT demand, female DRT demand, and 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 females 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) 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). Most recently, one prior study referred to areas characterized by restricted access to destinations with services essential to daily life as "*essential destination deserts*" (Guo & Brakewood, 2024). However, these studies have primarily focused on urban areas with well-established fixed-route transit networks. Therefore, the following analysis in a small urban area contributes to the literature by examining *essential destination deserts* in a less populated community 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). The quadrant classification method is relatively simple to construct, as it categorizes regions into four distinct categories based on demand and accessibility thresholds. This simplicity allows for a clear visual representation that can be effective in producing meaningful outcomes by enabling policymakers to quickly identify and prioritize areas of concern, facilitating targeted interventions. 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.

2.3 Research objectives

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

1. Identify differences in DRT trip purpose (defined by origin and destination land uses) and DRT trip distance by gender and age.
2. Analyze DRT demand distribution across demographic groups (particularly women and the elderly) and its correlation with the demographic composition using Census data.
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 small urban area in Tennessee, as discussed in the following sections.

3 Study area and data

3.1 Study area

The study area focused on the small urban 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, n.d). 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 (ACS) Data (U.S. Census Bureau, 2020b, 2020c).

According to the 2021 ACS data, 97.35% of Morristown households possess at least one car, and the average car ownership in Morristown stands at 2 cars per household (Data USA, 2021). Additionally, the ACS reports that in 2021, 86.2% of workers in Morristown drove to work, followed by 8.3% who carpooled (Data USA, 2021). These statistics underscore the automobile-dependent nature of Morristown. In addition, Morristown is a relatively small urban area 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. 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 with a call-based request system for rides. Furthermore, while the DRT service is available to the general public, it also adheres to ADA regulations, ensuring compliance with accessibility standards for individuals with disabilities. The cost for a one-way trip is $3, and trips crossing county lines incur an additional $3 fee.

Figure 1 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.

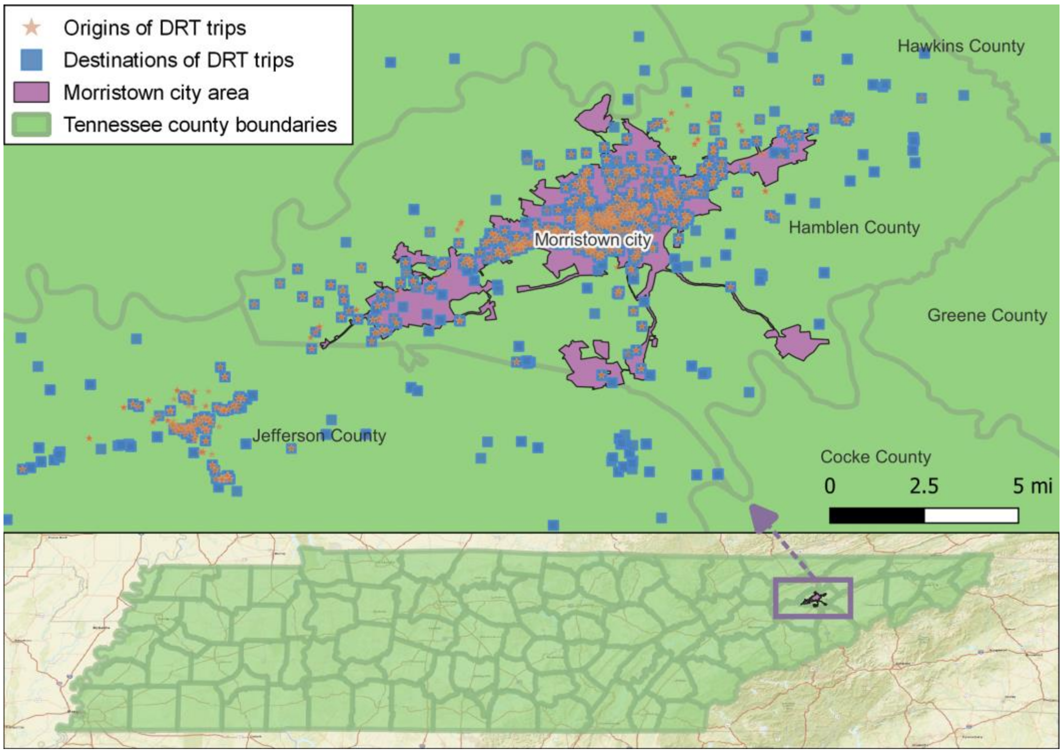


Figure 1. Study area and the origins and destinations of DRT trips in Morristown

3.2 DRT trip data and variables

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. Trip distance and trip start time were also recorded in the dataset discussed in the following paragraphs.

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. To ensure precision, a meticulous geocoding process was employed to reassign the coordinates by 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 1. The column count represents the number of trips made by gender, age groups, time segments, and distance segments, respectively.

Table 1. Variables creation and explanation

Category	Explanation	Trip Count (%)
Gender		
Male	Passengers identified themselves as male or female, NA or "prefer not to say" records were removed from analysis	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 5:00 a.m. to 6:59 a.m.	1,589 (7.01%)
AM peak	Trips start between 7:00 a.m. to 9:59 a.m.	5,736 (25.3%)
Midday	Trips start between 10:00 a.m. to 3:59 p.m.	11,783 (51.98%)
PM peak	Trips start between 4:00 p.m. to 6:59 p.m.	3,561 (15.71%)
Distance segments	Distance range: (0.08-89.42] miles	
Short distance	The trip distance falls within the first quartile (Q1) range (shortest distance to the median length of distance): [0.08-1.45] miles	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): [1.46-2.47] miles	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): [2.48-6.07] miles	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): [6.08-89.42] miles	5,668 (25%)

3.3 Identification of DRT trip purposes

Figure 2 shows a heatmap of the count and proportion of trips to/from varying origin and destination types in the initial DRT trip data. This visualization aids in understanding different types of origins and destinations before the identification of DRT trip purposes. 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 2 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.

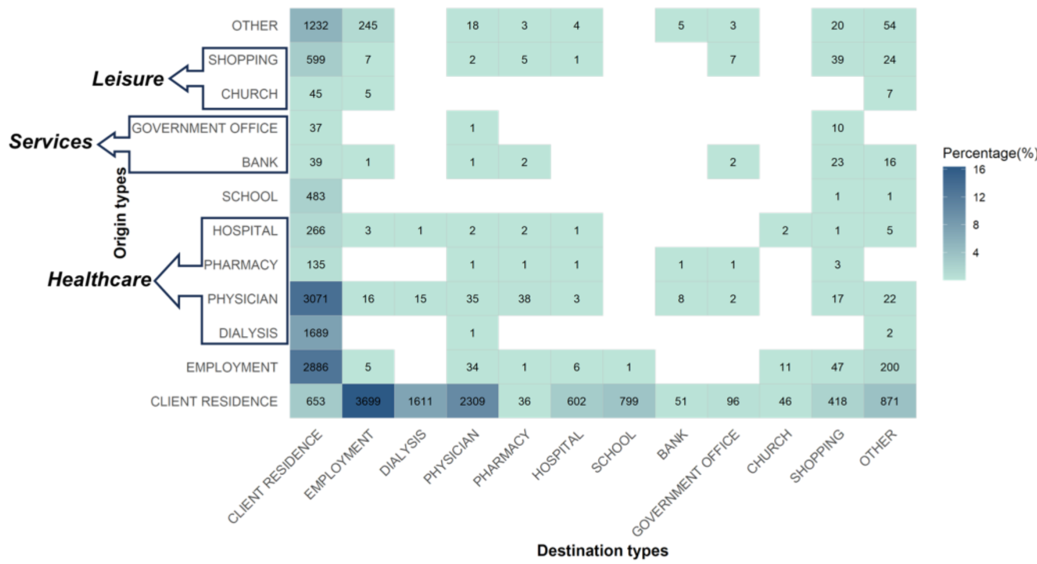


Figure 2. Heatmap for trips with different types of origins and destinations

Based on types of origins and destinations, DRT trips were categorized into various trip purposes. First, all trips were categorized into three distinct types: Home-Based Work (HBW) including 29.05% trips between home and work; Home-Based Other (HBO) including 66.56% trips with one end at home and the other end not related to work; and Non-Home-Based (NHB) including 4.39% 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 HBO category was the most common, with Home-Healthcare trips accounting for the highest count. 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 statistical analysis.

For further details on the classification process and criteria, readers are referred to (Guo, 2023) for additional information.

4 Method

This section describes the method used in this study. Figure 3 shows the conceptual framework. The analysis includes two demographic categories: gender and age, and two aspects of travel patterns: DRT trip purpose and DRT trip distance. The overall research objectives are to (1) identify gender and age differences in DRT travel patterns; (2) to explore the potential influence of demographic composition on the gender and age differences in DRT demand; and (3) to investigate spatial differences between DRT demand and DRT accessibility to identify potential *essential destination deserts*. Accordingly, the method was done in three parts.

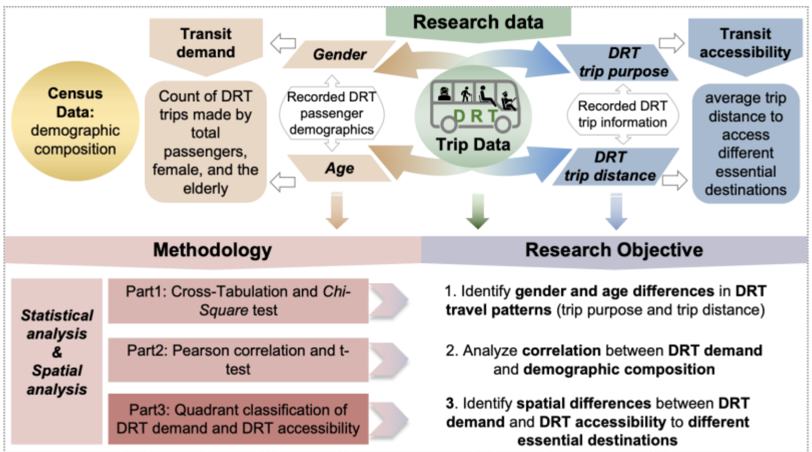


Figure 3. Conceptual framework

In the first part of the method, cross-tabulation analysis was employed to examine the differences in DRT use by gender and age for different DRT trip purposes. In addition to trip distance, trip departure time was also introduced as the control variable for the trip pattern 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.

The second part of the method focused on the DRT demand distribution across gender and age groups and its correlation with the demographic composition from 2020 Census data. First, the total DRT demand within each Census block was calculated by summing the total count of DRT trips originating from that block. In addition to the total DRT demand, the number of DRT trips made by different gender and age groups were calculated separately; for example, female demand was computed as the total count of DRT trips made by females, and elderly demand was determined as the total count of DRT trips made by the elderly. DRT demand was subsequently compared with 2020 Census data using a Pearson correlation analysis and also visualized geographically using maps. It is noted that only home-origin DRT trips were included in this part of the method, in order to accurately depict the demographic attributes of DRT riders within each Census block. 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.

In the third part of the method, a spatial analysis was conducted to identify differences between DRT demand and DRT accessibility, again using only home-origin DRT trips. First, DRT accessibility was measured 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 times (Antipova, 2020; Casas, 2007; Horner & Schleith, 2012; Páez et al., 2010). The DRT accessibility for each Census block was computed by averaging the travel distances of specific DRT trips originating from within that block.

The DRT accessibility analysis specifically focused on two different aspects: (1) access to essential destinations and (2) differences in accessibility between DRT user groups. To understand 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). Moreover, to understand differences in DRT accessibility among special user groups, separate calculations were performed for the average distance of DRT trips made by all users, female users, and elderly users. These demographic groups were selected for analysis due to their significant representation among DRT users in the study area. 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 based on two criteria: the DRT trip count and DRT trip distance, as illustrated in Figure 4. The x-axis represents trip distance values, where a higher value indicates lower DRT accessibility. Census blocks with an average DRT trip distance higher than the regional median were classified as low accessibility, indicating longer travel distances to reach destinations. These areas are represented by light pink and darker blue (in the first and fourth quadrants). Conversely, the red and light blue in the second and third quadrants represent Census blocks with higher DRT accessibility, as the average DRT trip distance to access trip destinations is lower than the regional median level. The y-axis represents the amount of DRT demand measured by the count of DRT trips in each Census block. Similarly, Census blocks were categorized into high demand (with trip counts higher than the regional median) in the first and second quadrants (shown in pink and red) and low demand (with trip counts lower than the regional median) in the third and fourth quadrants (shown in lighter and darker blue).

Based on this, Census blocks were classified into four categories based on the relationship between the level of DRT demand and accessibility. 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*.

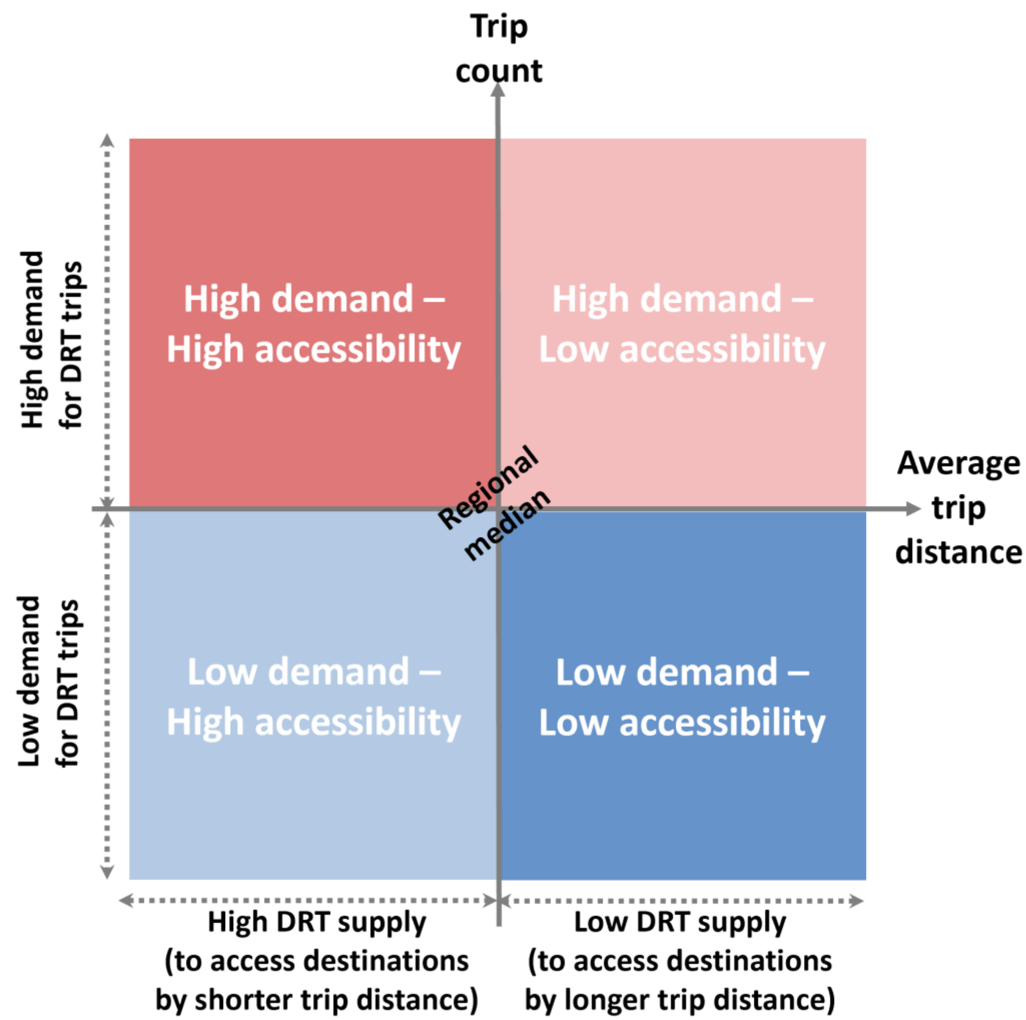


Figure 4. Classification of the number of DRT trips and DRT trip distance

5 Results

5.1 Gender and age differences in DRT travel patterns

Table 2 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%). It is worth noting that female residents (52%) slightly outnumber male residents (48%) in Morristown, as indicated by the 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 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. However, the elderly constitute only 17% of the total population in Morristown 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 showed 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 quantile of all DRT trips. In contrast, younger adults tended to take longer trips where more than half of them exceeded the third quartile.

Table 2. 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-Service	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<0.001****					
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	Short distance	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%)
	Median-short distance	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%)
	Median-long distance	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%)
	Long distance	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<0.001****					
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.

5.2 DRT demand and its correlation with Census data across gender and age groups

This section includes two parts of the result: 1) the correlation between DRT demand and Census data across gender and age groups, and 2) the spatial distribution of total DRT demand and DRT demand specifically from two demographic groups: female and elderly. The focus on these two demographic groups is justified by their relatively high correlation coefficients and their substantial proportion of DRT trips in the study area.

5.2.1 Pearson correlation analysis

Table 3 shows the correlation analysis results. Notably, the Pearson correlation coefficients provide a quantitative measure of the strength and direction of relationships between DRT demand and Census demographic composition across gender and age groups, and the associated t-test values and p-values offer insights into their statistical significance. The results reveal statistically significant positive correlations between DRT demand and demographic composition across all gender and age groups of children, adults, and the elderly, at a significance level of 0.05. Notably, some degree of correlation was observed between total DRT demand and total population (with a coefficient of 0.282), between female demand and female population (with a coefficient of 0.239), and between the elderly demand and the elderly population (with a correlation coefficient was at 0.386).

However, it is important to note that even the highest correlation observed, represented by the Pearson correlation coefficient between elderly DRT demand and the elderly population, stands at only 0.386, indicating a relatively weak correlation. While demographic factors do play a role, their impact appears to be relatively weak. Thus, relying solely on Census data may not provide sufficient insight for accurately understanding DRT demand in the transportation planning process.

Table 3. Pearson correlation analysis of DRT trip demand and Census data by Census block

Variables		**Correlation with significance levels**		
DRT trip demand	***Census demographic***	***Pearson correlation coefficient***	***t-test value***	***p-value***
Total trips	Total population	0.282	4.736	<0.001***
Female trips	Female population	0.239	3.957	<0.001***
Male trips	Male population	0.160	2.600	0.0099**
Children trips	Children population	0.195	3.195	0.0016**
Adolescent trips	Adolescent population	0.040	0.640	0.523
Young adult trips	Young adult population	0.050	0.809	0.420
Adult trips	Adult population	0.174	2.846	0.0048**
Elderly trips	Elderly population	0.386	6.731	<0.001***

** p<0.05, significant at 0.05 level; ** p<0.01, significant at 0.01 level; *** p<0.001, significant at 0.001 level*

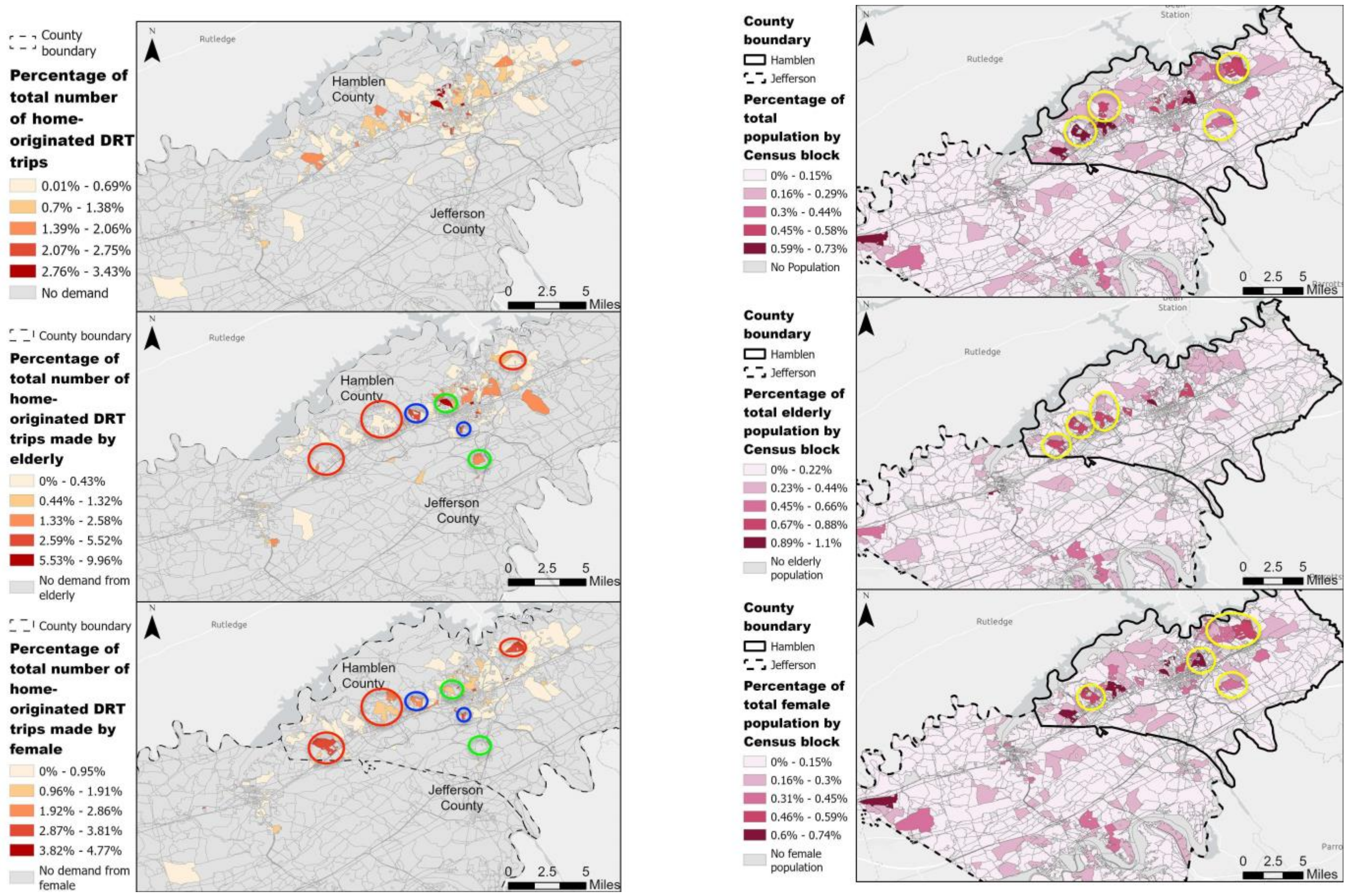
5.2.2 Spatial distribution of DRT demand

The following part presents the spatial distribution of total DRT demand and DRT demand specifically from two demographic groups (female and elderly) and the spatial distribution of the total population, female population, and elderly population within the study area. Notably, the map presents normalized values, specifically percentages of the total, to ensure comparability across variables.

The objectives of this part are twofold: first, to understand the spatial distribution of DRT demand from women and the elderly, which is crucial for subsequent analysis involving essential destination classification; and second, to visually depict the relationship between DRT demand and Census demographic composition through spatial visualization. Despite the weak correlation, comparing the spatial distribution of DRT demand with Census demographic composition for female and elderly groups can help provide insights into potential spatial disparities.

Figure 5 (a) shows the spatial patterns of total DRT trips, DRT trips taken by the elderly, and DRT trips made by females, presented as percentages of the total. The orange shading reflects the percentage of DRT trips, with lighter shades indicating lower demand levels and darker shades indicating higher demand levels. These maps reveal distinct spatial distribution trends among total DRT demand, female DRT demand, and elderly DRT demand. For instance, areas highlighted by green circles exhibit a higher concentration of DRT trips by elderly riders but lower demand from females. Conversely, regions marked by red circles demonstrate a high density of DRT trips by non-elderly females. Additionally, there are a few small areas where both female and elderly riders have high DRT demand, as indicated by blue circles.

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 5 (b). It is crucial to acknowledge that Census data has many noteworthy differences from the DRT dataset. Nevertheless, Census data provides an important point of comparison because it is the most recent and accessible dataset within the study area. Many transit agencies and planning organizations rely on Census data for planning analyses and decision-making. Consequently, the inclusion of Census data serves a dual purpose: providing demographic context for the study area and evaluating the applicability of Census data to inform DRT planning. 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 demographic groups. For instance, yellow circles in Figure 5 (b) have a high population density; however, these Census blocks in Figure 5 (a) were not shown as high DRT demand. This underscored the 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.



(a) Spatial distribution of total DRT demand, elderly DRT demand, and female DRT demand

(b) Spatial distribution of total population, elderly population, and female population

Figure 5. Spatial distribution of DRT trips demand (a) and Census data (b)

5.3 Spatial analysis results for DRT accessibility and essential destination deserts

The following sections present the results of 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*.

5.3.1 Spatial distribution of DRT accessibility

The next part of the method analyzed the spatial distribution of DRT accessibility, as measured by the average DRT trip distance. Figure 6 includes maps displaying the trip distances of total DRT trips and DRT trips made by females or the elderly. Figure 7 visualizes the spatial distribution of DRT trip distance for three essential purposes: home-healthcare (trips with destination land use of healthcare facilities), home-leisure (trips with destination land use of shopping stores and churches), and home-service (trips 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 6 and Figure 7, 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, as suggested in the literature, which typically decreases gradually from the urban center towards the city outskirts or away from fixed-route bus stops (Guo & Brakewood, 2024; Xu et al., 2015).

Figure 6 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 highlight areas with longer trip distances for both groups. However, Figure 6 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 7 illustrates the DRT trip distances for three specific trip purposes. The locations of nearby essential destination facilities in the figure were obtained from the SafeGraph dataset through ArcGIS Marketplace and Business Analyst tool. SafeGraph provides point-of-interest (POI) dataset that includes place name and location for over five million places. 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 miles 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 is analyzed in the subsequent section.

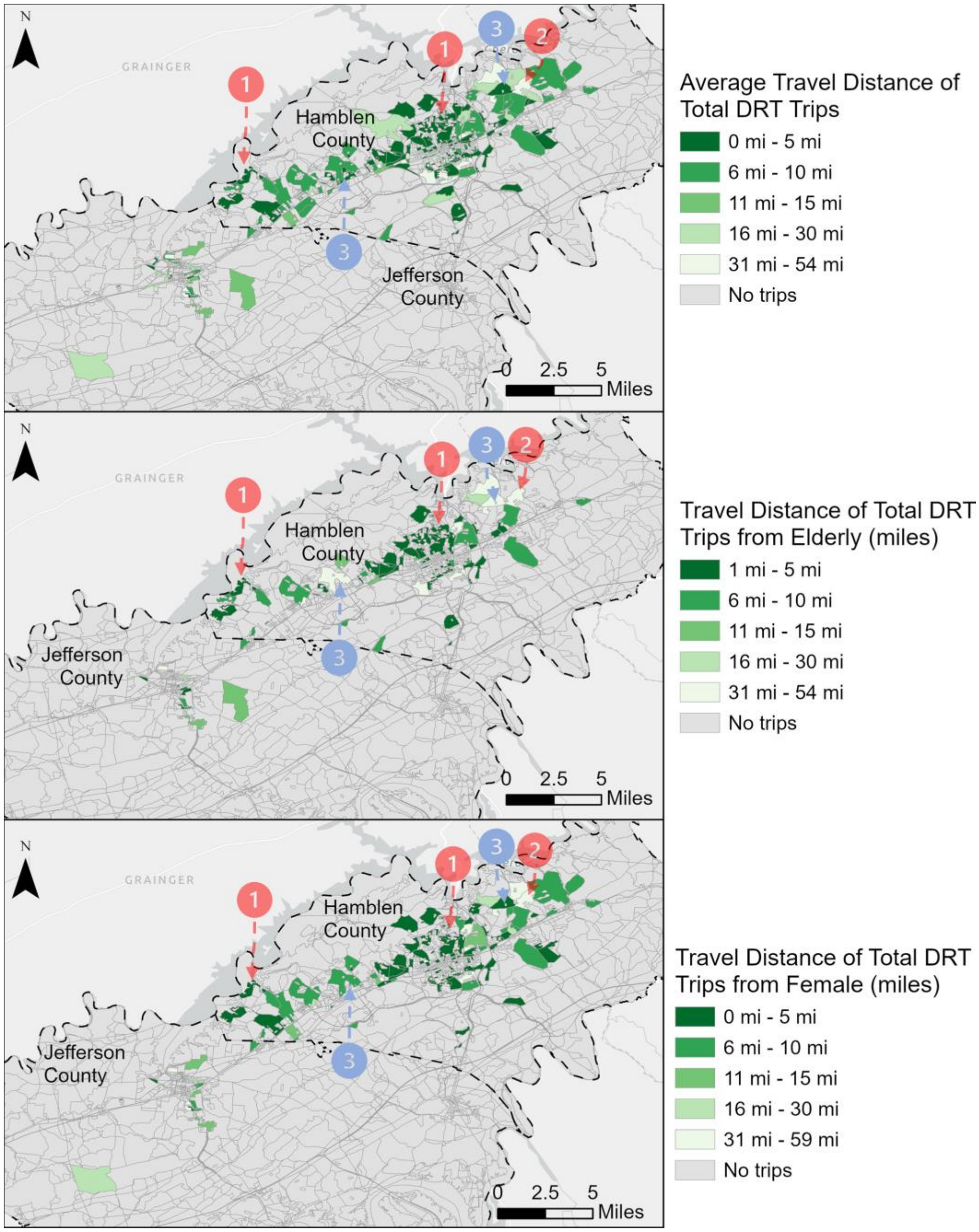


Figure 6. Spatial distribution of DRT trip distances of total trips, trips made by elderly, and trips made by female

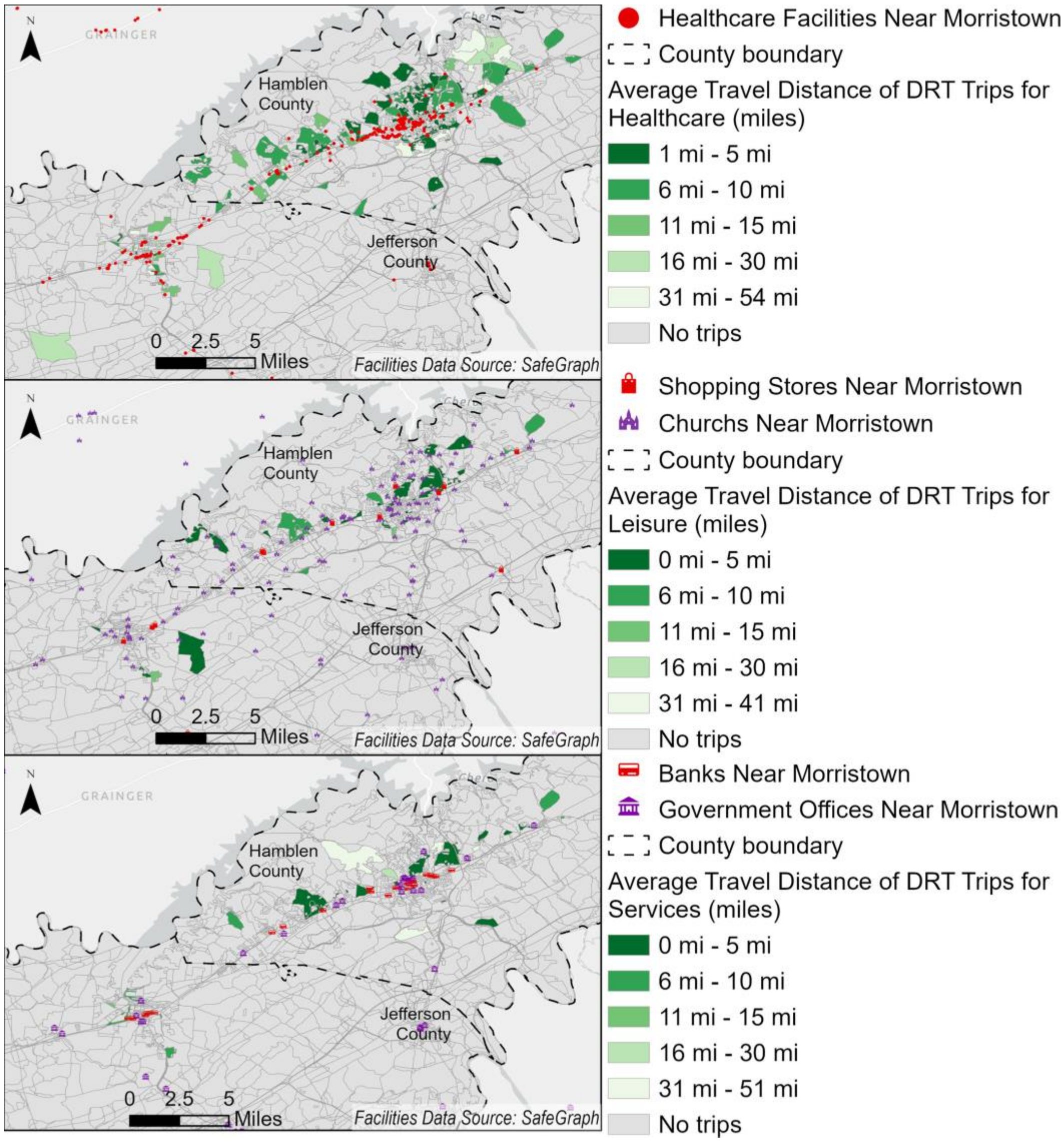


Figure 7. Spatial distribution of DRT trip distance to access three essential destinations

5.3.2 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 8 and Figure 9. These categories include “high demand-high accessibility” shown 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*. A summary of these four categories was also visualized in a bar chart, shown in Figure 10, illustrating DRT demand from various groups and the average accessibility within each group.

Figure 8 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 8. 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. The count of blocks in each category is summarized in Figure 10, and the chart reveals that there is a larger proportion of high demand-low accessibility clusters (indicated by the pink bar) for females compared to the elderly.

Moving beyond DRT accessibility for specific demographic groups, Figure 9 delved into the spatial analysis of DRT accessibility to access three essential destinations (based on destination lane use) for total DRT demand. In Figure 9, 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 9 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 9 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. By examining the count of Census blocks in each category (Figure 10), it becomes apparent that there is a larger number of high demand-low accessibility blocks in the healthcare category.

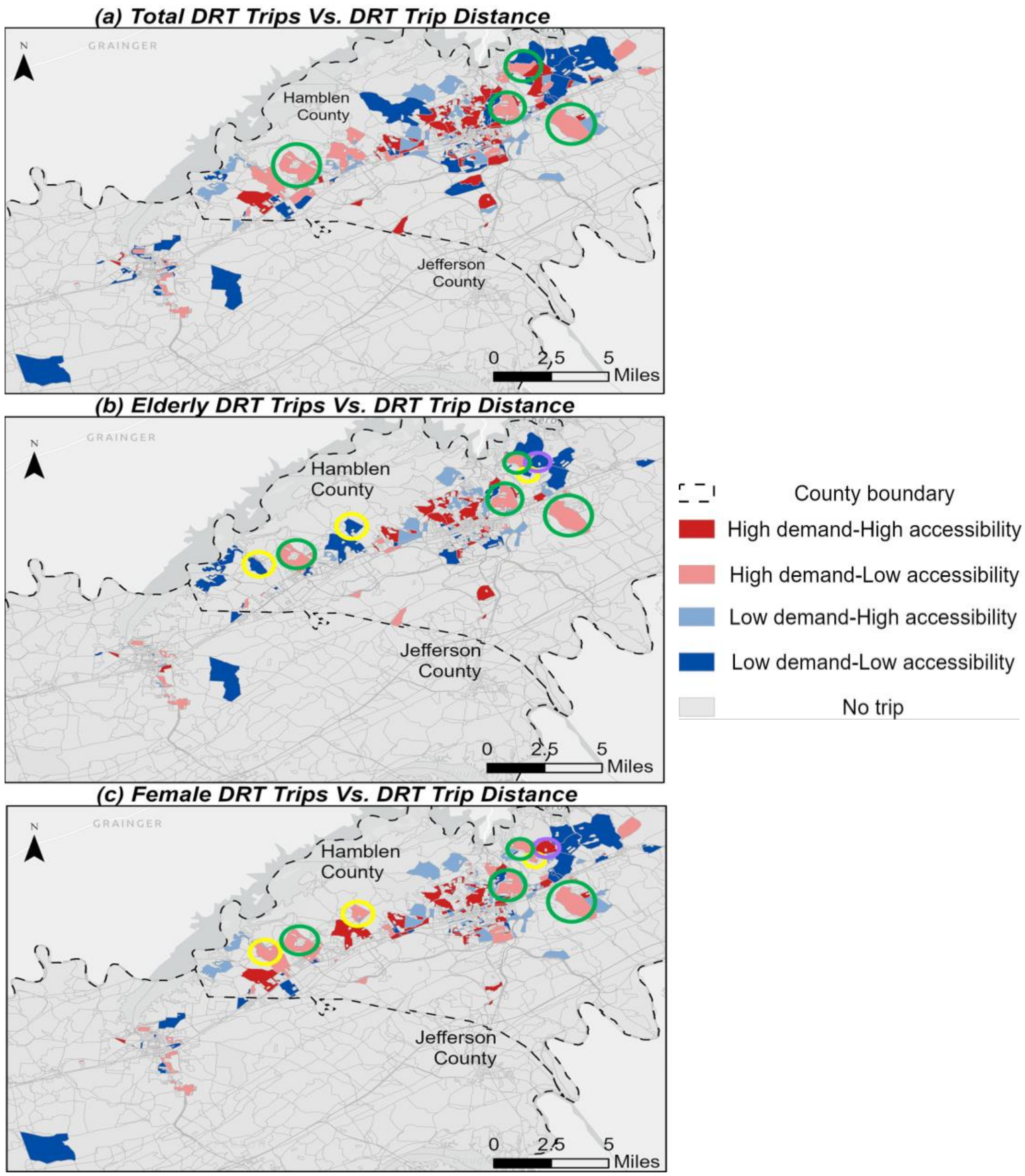


Figure 8. Spatial distribution of the relationship between different DRT demand types and DRT trip distance

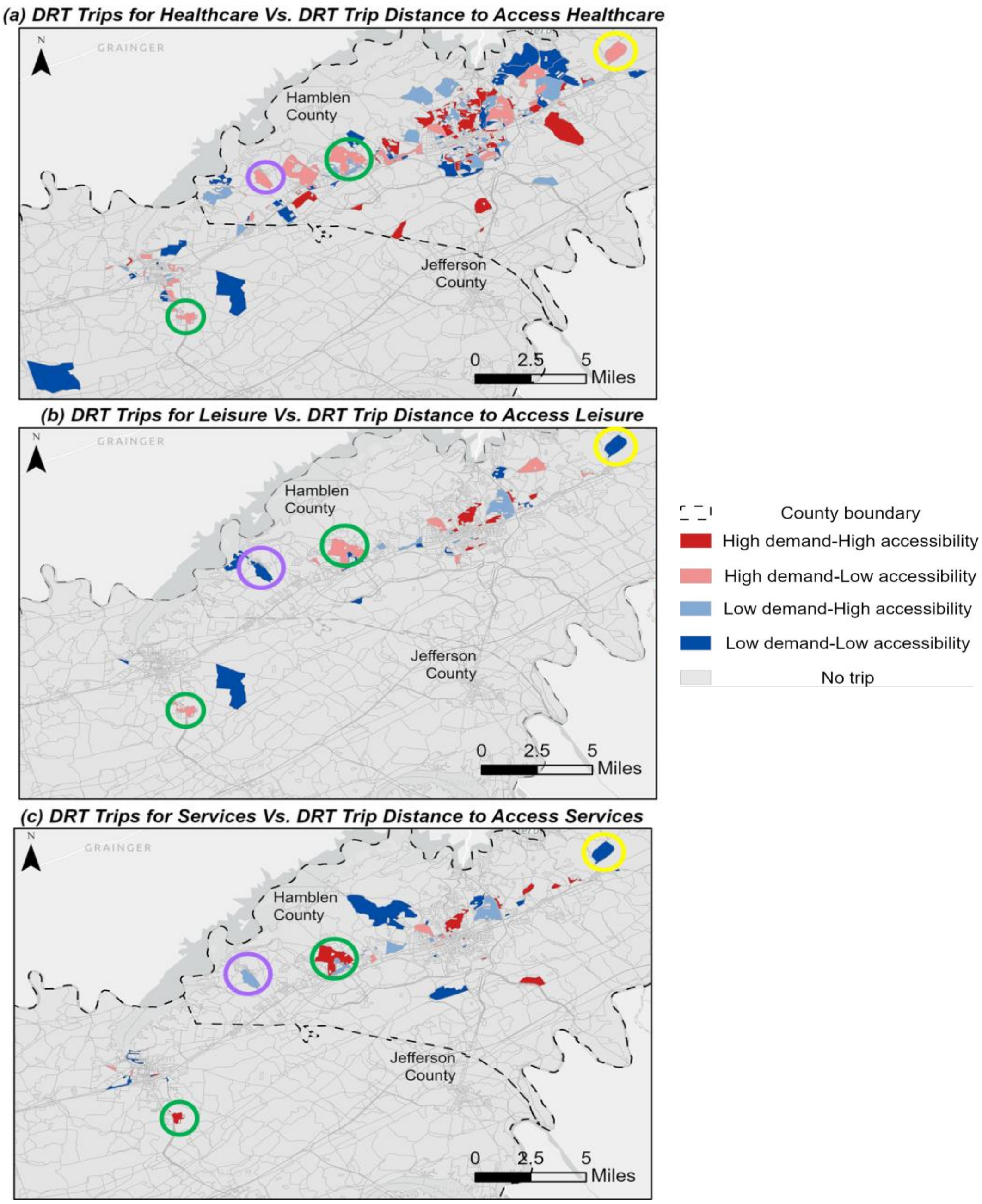


Figure 9. Spatial distribution of the relationship between DRT demand and DRT trip distance to access different essential destinations

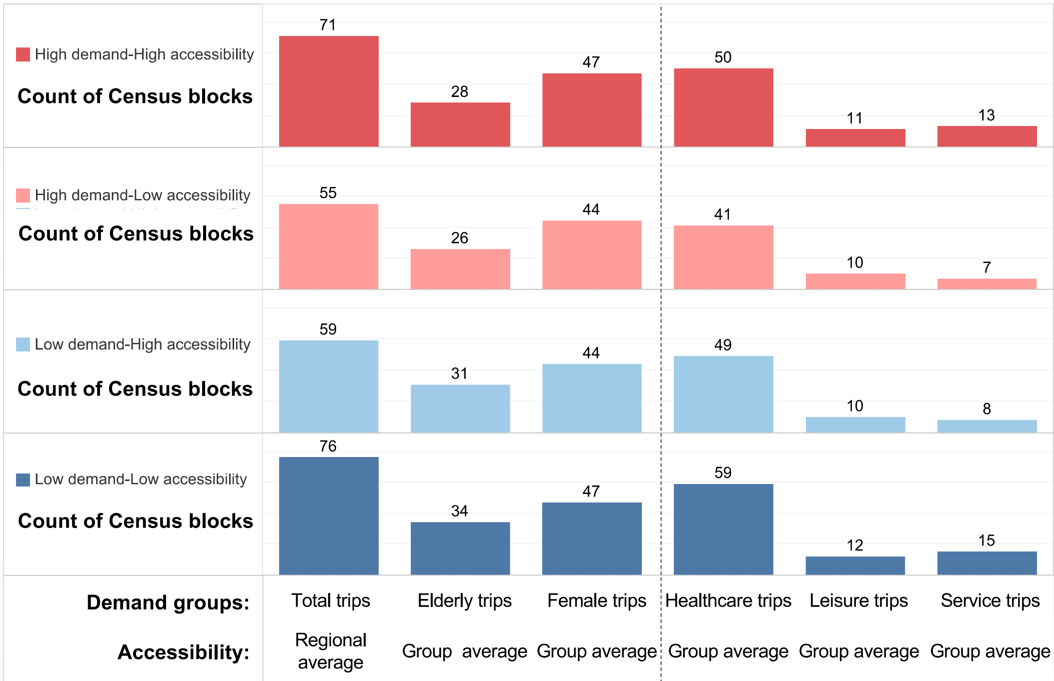


Figure 10. Bar chart summarizing the count of Census Blocks for four demand groups and accessibility level

6 Conclusions, discussions and future research

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 small urban setting. Additionally, the potential influence of demographic composition on gender and age difference in DRT demand was also examined using correlation analysis and spatial analysis. A case study was conducted for the DRT system in Morristown, TN, which is representative of small urban areas 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 small urban 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. 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 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 a correlation analysis for DRT demand and Census data across gender and age groups, with a specific focus on elderly and female demographic groups. Many transit agencies and planning organizations rely on Census data for planning analyses and decision-making. However, the relatively weak correlation result indicates that, while demographic factors do play a role, their impact on DRT demand appears to be somewhat weak. Thus, relying solely on Census data may not provide sufficient insight for accurately planning DRT systems.

The third part of this study conducted spatial analysis of DRT accessibility and *essential destination deserts*. 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. This analysis focused on the elderly and females and examined trip purposes related to healthcare, leisure, and service destinations. The results reveal distinct spatial variations between *essential destination deserts* for the elderly and those for females. Additionally, the classification results illustrated certain areas displaying varying spatial relationships between DRT demand and DRT accessibility for different essential destinations (i.e., healthcare, leisure, and service 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.

The findings from this study provide several important insights for transportation planning, policy, and development in Morristown to help ensure a more effective and inclusive transit system that meets the diverse needs of its residents. First, given the substantial proportion of DRT trips made by the elderly, particularly for healthcare-related purposes, enhancing DRT accessibility to healthcare facilities is an important future consideration. This can potentially be achieved by increasing the number of DRT vehicles that provide service to healthcare destinations and extending service hours to accommodate the needs of elderly passengers. Second, the relatively weak correlation between population demographics and DRT demand in Morristown suggests that relying solely on demographic data for DRT planning may be insufficient. A more comprehensive approach that includes analyzing trip purposes and spatial distribution patterns is necessary. Third, the approach provided in this study will provide transit agencies and decision-makers in Morristown a more accurate understanding of DRT demand and help identify underserved areas. Prioritizing these areas in future DRT planning is crucial for ensuring equitable access to services.

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 small urban areas due to the unique demographic and geographic characteristics of this area. Hence, future research should consider broadening the geographical scope to encompass multiple 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, in future research. Third, 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. Another limitation of this study was that the dataset contained unique trips but not a unique identifier (ID) for individual riders; future analyses of other datasets with rider IDs could study travel patterns over time for an individual. 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.

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Author contribution

The authors confirm their contribution to the paper as follows: Guo and Brakewood: study conception and design; Guo and Mishra: data collection; Guo: analysis and interpretation of results; Guo and Brakewood: draft manuscript preparation. All authors reviewed the results and approved the final version of the manuscript.

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