BUS STOP SHELTERS AND SHADE IN THE SUBURBS:

AN ANALYSIS OF FACTORS AFFECTING BUS SHELTER PLACEMENT

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THESIS: BUS STOP SHELTERS AND SHADE IN THE SUBURBS: FACTORS AFFECTING BUS SHELTER PLACEMENT

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ABSTRACT

As climate change leads to increasing temperatures, driving less and using public transit is offered as one solution to reduce emissions and slow climate change. Yet increasing temperatures also put public transit users at risk for heat-related illnesses, particularly transit-reliant populations. This analysis explores how bus shelters can be a climate mitigation measure against extreme heat to protect transit riders. The study uses a multi-level logistic regression analysis considering variables both at the individual bus stop level variables and at the census tract level to assess how these variables impact the likelihood of shelter placement in southwestern San Bernardino County, an area prone to increasing extreme heat. Bus operations variables (ridership, service frequency, and transfers), environmental variables (building shade and tree canopy) as well as demographic variables (census tract data) were assessed for their impact on shelter placement. The regression results find that demographics do not impact the likelihood of shelter placement, while environmental and bus operations have mixed impacts on the likelihood of shelter placement. Policy recommendations for including demographics and bus stop variables such as service frequency and transfers in the criteria for shelter placement are suggested to ensure a more equitable distribution of shelters, particularly for transit-reliant populations, to protect these riders from heat-related illnesses. In this way, increased transit usage can be a vehicle for reducing emissions without putting transit riders at greater risk from extreme heat.

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CHAPTER 1:

INTRODUCTION

Climate change poses an ever-increasing risk to communities around the globe, but each community faces unique challenges from increased disasters based on its context. Whether stronger hurricanes and sea level rise along the Gulf coast or increased risk for fires due to drought in the Southwest, these disasters are growing in intensity due to rising global temperatures. For dry warmer regions such as southern California, extreme heat and the growing number of high heat days per year pose the biggest sustained risk. As global temperatures continue to rise, extreme heat events become more frequent, and high heat index conditions increase, often exceeding dangerous thresholds (Dahl, 2019). The US average temperature has increased by 1.3°F – 1.9°F since 1895 with the largest increase occurring after 1970 (Walsh et al., 2014). A 2020 report on Extreme Heat and Public Health from the Southern California Associations of Governments (SCAG) notes that extreme heat days per year are expected to more than double across the region after 2085 (p. 3). The cost of these extreme heat days is incredibly high. According to the National Weather Service, heat is the leading cause of weather-related deaths in the United States, and in 2023, it was more than all other weather fatalities combined, including flood, hurricane, tornado, and rip currents (NOAA, 2023). In particular, heat disproportionately impacts marginalized groups (Karner et al., 2015; Larsen, 2015). The need to address and mitigate heat-related illness and deaths is vital, especially given that many heat-related deaths are preventable through outreach and intervention.

Concurrent with calls for building resiliency against extreme heat, there are efforts to tackle the source of climate change – greenhouse gas (GHG) emissions. Global temperatures have been rising as a result of rising heat trapping emissions from anthropogenic activities such as fuel combustion from motor vehicles, heat and power generation, and industrial facilities (WHO, 2020). Transportation is one of the leading contributors to GHG emissions accounting for 28% of all GHG emissions in the US (Environmental Protection Agency, 2024). Increasing public transportation usage has been one tactic to not only address congestion, but to also reduce emissions from the transportation sector. With fewer people driving cars, the reduction in emissions will help slow climate change. However, this proposal is set for a collision course with the realities of extreme heat. Those who are transit-dependent are most at risk for heat-related illnesses as they access public transportation (Karner et al., 2015). If increased public transit use can help reduce GHG emissions, how can this be achieved without putting any new or current rider at increased risk for heat-related illnesses? This study will seek to address one component of this conflict between extreme heat and increased public transit use – bus shelters.

Taking the bus on the outset seems like a great step towards greater sustainability until one is waiting for the bus in 105°F heat. As Figure 1 shows, bus shelters and shade structures can significantly reduce a person's heat burden by as much as 20-40°C (68-104°F) when they are shaded versus being in direct sunlight (Turner et al., 2023). Recently, several studies have begun to assess the impact of shade at bus stops, particularly bus shelters (Dzyuban et al., 2022; Lanza et. al., 2021, 2025; Reginald 2024). Shelters, when designed well with airflow, provide protection from the most intense heat with tree canopy

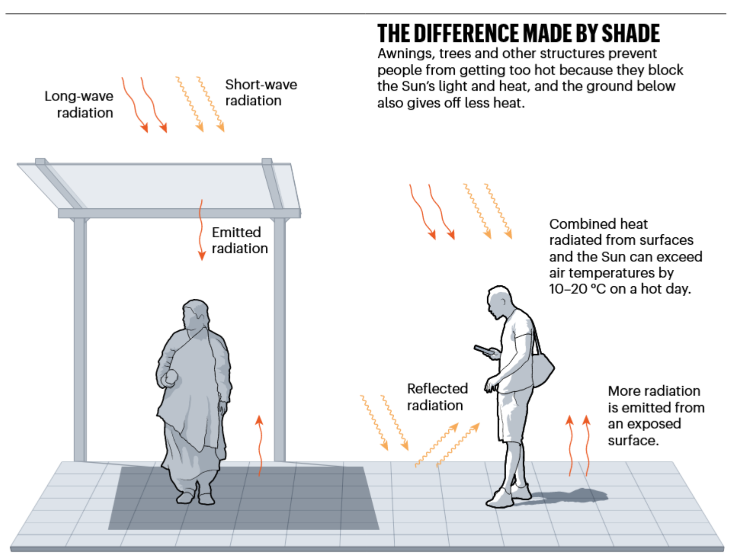


Figure 1: The Difference Made by Shade (Turner et al. 2023, p. 696)

providing an even greater cooling effect at bus stops. Many of these studies have looked at larger cities such as Houston, Los Angeles, Phoenix, and Austin. Additionally, other studies have looked at bus shelter distribution more generally in larger metropolises such as Salt Lake City, San Francisco, and Los Angeles (Miao et al., 2019; Moran, 2022; Yoon, 2023). However, few studies have looked at suburban regions with mid-size transit agencies. Yet in suburban areas, where automobile dependence is basically assumed, and transit service is often not as frequent, those who use the bus are often more exposed to heat and the risks associated with high temperatures. Additionally, mid-size transit agencies do not have as much funding and staffing compared to large metropolitan agencies, thus effective use of the resources available for shelters and their placement is key for the areas they serve.

To fill this research gap, this study will focus on San Bernardino County. With an increasing population in neighboring Los Angeles, continued growth and the need for public transportation will spill over into communities such as cities in San Bernardino County. As infill development increases density to meet this population growth, and state investment in transit seeks to reduce GHG emissions, it is clear transit will continue to be a key mode of transportation, particularly for those who cannot afford a private vehicle. Beyond the needs due to growth, the climate is not getting any cooler, particularly in inland regions such as San Bernardino County. The 2020 report on Extreme Heat and Public Health from SCAG notes that, with climate change, San Bernardino County is expected to have 131 days above 90º F by mid-century (2035 - 2064) with increasing average temperatures throughout the century (p. 15). Preparing for increased extreme heat through shade implementation is a wise and proactive method of climate mitigation measures especially at bus stops.

Despite this reality, shade and other environmental factors are understudied as a factor for where to place bus shelters. Ridership is often the primary criteria for determining shelter placement (Robertson, 2022). While this is a crucial factor, this study will analyze a variety of variables to understand their influence on shelter placement with a lens towards how agencies and local jurisdictions will need to consider environmental factors to mitigate the effect of extreme heat on bus riders. This research will specifically study the effect of shade, demographic and bus service factors in bus shelter placement in southwestern San Bernardino County. The study will primarily be quantitative, employing a multi-level logistic regression analysis, considering both bus stop level variables and variables at the census tract level to assess how these variables impact the likelihood of shelter placement. The unit of analysis is individual bus stops in the service area of Omnitrans, the local transit agency. The analysis explores how bus operations, environmental, and demographic factors affect the likelihood of a bus shelter being present at a stop.

The purpose of this study is to provide an understanding of factors that affect bus shelter placement and offer a framework for where to put shelters for those who rely most on transit, thereby mitigating the risks that come with rising temperatures due to climate change. Building on the research of recent studies, this study does not compartmentalize one factor over the others, but looks at bus service, environmental, and demographic factors together to push for a more wholistic strategy and planning protocols for bus shelter placement. Transit-reliant populations are in the minority in suburban communities, and often, due to less frequent bus service, they have much longer travel times. From city staff and transit agencies that oversee shelter implementation to concerned community members and transit riders, this research is meant to offer insight that can help address the disproportionate heat burden transit dependent populations face in their mobility needs and help communities be more climate resilient in extreme heat. The goal of this study is to help cities and transit agencies plan for extreme heat mitigation for vulnerable communities through bus shelters and other shade options using data to guide decisions. Ultimately, this research stems both from a place of highlighting the needs of a marginalized community that can be easily overlooked as well as preparation for the realities of a changing climate.

This thesis is organized into six chapters. A literature review of previous research on the topic of shelters, extreme heat and social equity follows this introduction. The methodology chapter then details the steps of the analysis with an overview of the results in the following chapter. A discussion of the significant findings comprises the subsequent chapter. Finally, the conclusion chapter brings together the findings of the study offering transit agencies and suburban cities policy recommendations for how to consider shelter placement in light of climate change and extreme heat.

CHAPTER 2:

LITERATURE REVIEW

Much research has been done on climate change including the increasing risk associated with extreme heat, and mitigation measures to build climate resilience. Similarly, several studies have analyzed the impacts of amenities on transit ridership. But it is only in recent years that studies have begun to explore the intersection of these two arenas. This is not only in academic circles, but even in popular media, there is growing concern that transit dependent populations are particularly vulnerable to heat-related illnesses. A three-episode podcast series from Houston Public Media explored the impact of heat on bus riders in Houston from both a social and environmental perspective (Ernst & Watkins, 2023). The following review of the literature explores the research that has been done on the individual components of this study as well as research at the intersection of heat, bus rider demographics, and bus shelters. Finally, a brief summary of how this study builds upon previous research and analysis while integrating the various components with a new perspective concludes this section.

Shade in Urban Spaces

For many years now, research has pointed to the realities of climate change reflected in increasing average temperatures (when compared to historic records), the number of extreme weather events, and sea level rise among other factors (Walsh et al., 2014). With particular relevance to this study, prolonged extreme heat and droughts has been unprecedented since regular temperature recording began in 1895 (p. 20). In Phoenix in 2024, the city recorded 113 consecutive days with a temperature over 100°F, shattering the previous record of 76 days (Salgado, 2024). Cities are being forced to consider how to mitigate the effects of extreme heat and the urban heat island effect particularly through their infrastructure, otherwise cities will become unlivable and unsustainable (Larsen, 2015). According to the National Weather Service, heat is the leading cause of weather-related deaths in the United States, even though many of these heat-related deaths are preventable through outreach and intervention (NOAA, 2023). And in particular heat disproportionately impacts marginalized groups (Larsen, 2015).

As the realities of a warming world push organizations and agencies to respond to growing extreme heat, shade particularly in urban areas becomes a vital mitigation to the risk of heat-related illnesses. Turner, Middel, and Vanos (2023) in their article emphasize that a person experiences a significantly increased heat burden (up to 20-40°C) in direct sunlight as opposed to shade (p. 695). In response to this growing need, Turner et. al. call for cities and governments to think broadly about shade as a key element of city infrastructure. Similarly, Bloch calls cities to conceptualize shade itself as a "public good" similar to water or other resources (2019). More comprehensive planning, assessment, and implementation are vital to provide the shade that cities need.

Both Turner et al. (2023) and Bloch (2019) note that "shade deserts" often exist in lower-income neighborhoods and disproportionately affect people of color. This is usually due to a lack of tree canopy, but the authors call for a broader assessment of shade beyond tree canopy to include building shade, awnings and other created infrastructure to promote shade. Bloch notes several examples where bureaucratic hurdles and regulations prevent the implementation of shade in communities of color. Better assessment of heat burden in these communities is needed to accurately see which areas are most vulnerable to heat. Cities and governments must also work to lower barriers in its implementation of shade as agencies consider the need for this resource in terms of housing, transportation, education centers, and public spaces.

Transit Ridership

GHG emissions contribute to increasing global temperatures and climate change. The Environmental Protection Agency report that transportation accounts for about 28 percent of total U.S. greenhouse gas emissions, making it the largest contributor of U.S. GHG emissions (2024). And between 1990 and 2022, GHG emissions in the transportation sector increased more in absolute terms than any other sector. In response to this, encouraging more people to use public transportation or other active transportation (i.e. biking or walking) and fewer single-occupancy vehicles has been a key policy initiative. This is a major shift from planning practices over the past several decades which have focused on the automobile and infrastructure for cars. Yet, the impact of this change is still to be seen with only 3.5% of workers commuting to work via public transportation across the US, and only 0.9% in San Bernardino County (US Census, 2023).

For transit agencies, ridership becomes the metric to assess usage rather than percent commuting to work as many passengers use transit for more than just getting to or coming from work. Transit ridership is "conceivably … the single most important dimension of transit system performance" (Kashfi et al, 2015, p. 3). Transit ridership is impacted by a variety of factors with the most significant being frequency of service, service span, and access or coverage. Litman (2008) argues that increased service reduces rider wait time and thus increases the demand for transit service. An analysis by Karunakaran et al. (2023) looked at various factors that influence ridership (bus commercial speed, service frequency, in-vehicle travel time, bus stop distance, and rainfall) and found that all variables have a statistically significant impact on ridership. But for both peak and off-peak hours, service frequency had the highest influence on ridership (p. 11). From these studies, one might assume that more bus service is the solution to greater transit ridership.

Transit Ridership and Bus Stop Amenities

However, there are other variables that impact transit ridership. Kashfi et. al. (2015) categorizes these as "Comfort and Convenience" variables, which include safety and cleanliness at bus stops, wait time, and customer service. It is not only the speed of service, but it is also the quality of service. Kim et al. (2020) studied the impact of improved bus stops around Salt Lake City and found that there was a statistically significant correlation between improving stops with increased ridership as well as decreased paratransit demand. The improvements included creating a concrete boarding area, connecting sidewalks, a shelter, bench, and a trash can. This study also notes that the improvements cannot be said to conclusively cause the increased ridership as riders may have switched from other stops to the improved ones. However, the authors do conclude that improved stops are popular whether they attract new riders or current ones. Another study on Salt Lake City's transit system found that bus stops with shelters have higher ridership than bus stops without shelters, specifically during extreme low and high temperatures and during heavy precipitation (Miao et al., 2019).

One other key aspect of comfort and convenience is waiting time particularly at bus stops. A study by Fan et al. (2016) compared riders' perceived wait time (through a survey) vs. observed wait time and assessed the impact of amenities on this difference. After controlling for actual wait times and other trip characteristics, Fan et. al. found that real-time information, shelters, and benches reduced the perceived wait time of riders, with all three amenities combined having the greatest impact on reducing riders' perceived wait time. In a few studies, wait time is a variable that is considered for impacting shelter placement (Law & Taylor, 2010; Reginald, 2024; Yoon, 2023) with the average wait time estimated as half of the headway. However, Law and Taylor (2010) expanded this with a unit called person-min wait-time, which is half the headway multiplied by ridership. This provides a broader picture of the impact of waiting at stops as it shows the average cumulative wait time of passengers using the stop. This study also found that the needs of transit passengers, particularly at stops with high person-min-wait-time, were a more peripheral consideration rather than placing shelters at locations with the greatest potential to generate advertising revenue.

Shelters are important not only for the shade and cover they provide, but also as the gateway for many to the transit system. They can be the first touchpoint for bus riders, giving a first impression of the transit system, thus their placement is crucial. Many cities and transit agencies often have criteria for where to place shelters, but these criteria may lack consistency and not actually impact shelter placement. Ridership is often cited as a crucial component, yet a study of Utah Transit Authority's system (Miao et. al, 2019) found that there was not a strong correlation between ridership and shelter placement (p. 130). A report from the nonprofit Ride New Orleans (Robertson, 2022) examined different cities as case studies for best practices around bus shelters. The top recommendation for transit agencies from this study was to have clear and logical rules and protocols for creating and managing bus stop shelters in addition to being transparent with providing data on shelters to the public (pp. 11-13). Additionally, Buchanan and Hovenkotter (2018) examined a few cities as case studies to develop best practices for improving bus stops. Developing guidelines that consider existing ridership patterns, rider demographics, conditions of stops, nearby walking environment and other data, including rider feedback, are key to developing clear protocols for shelter and amenity placement (p. 79).

Transit Stop Amenities and Social Equity

While the above studies analyze the relationship between transit stop amenities and ridership, one key component that is easily overlooked is shelter distribution. The inequitable distribution of shelters was studied as early as 2010 in Los Angeles (Law & Taylor, 2010). However, this study focused more on the tension between placing shelters based on revenue-generating advertising potential versus where they provide the most comfort for bus riders (those stops that have more riders who wait for a longer period of time). Since then and particularly in recent years, other studies have looked at how equitably distributed transit amenities are (Lanza & Durand, 2021; Miao et. al, 2019; Moran, 2022; Yoon, 2023) through an analysis of socioeconomic factors.

The factors that have regularly been considered in these studies have included race / ethnicity, age, income or poverty level, and vehicle ownership. These are characteristics that tend to be correlated with greater transit dependency. Both seniors (over 65) and youth (under 18) are less likely to use a personal vehicle for their transportation. LA Metro (Los Angeles County Metropolitan Transportation Authority) has developed an index using income, race/ethnicity, and household vehicle ownership, "to identify areas with high concentrations of historically disinvested and disenfranchised households and populations that are anticipated to most benefit from new mobility investments" (Yoon, 2023, p. 17). These variables then serve as equity measurements to see if the benefits of shelters, amenities, and services are being shared across a region's various socio-economic groups.

The locations of the studies present different perspectives on the distribution of shelters and the impacts to various socioeconomic groups. In Yoon's study of Los Angeles County, more than two-thirds of stops did not have shelters, and District 2 had the highest proportion of unsheltered riders in the County. These riders were more likely to be in neighborhoods with higher socioeconomic and transit-related need. Moran (2022) found that shelters were more likely to be found in census tracts with a higher percentage of white residents, but income did not show a difference in the likelihood of shelter placement (p. 7). Miao et al. (2019) studied the distribution of shelters in Salt Lake City, Utah and found that shelters were more likely to be in areas with higher incomes, higher ratios of seniors, and lower percentages of white residents (p. 129). In Austin, Texas, Durand and Lanza (2021) found that an increase in the median age decreased the likelihood of a shelter by 4.2%, but race/ethnicity and poverty level did not have a significant association with the presence of a shelter (p. 8). Each of these studies highlight that differences in the distribution of shelters do exist, but the nature of these disparities and which demographics are negatively impacted seem to be reflective of the unique context studied. For example, in Utah, areas with white residents were less likely to have a shelter, but in San Francisco the opposite was true while in Austin, there was no impact from race/ethnicity. Thus, demographic characteristics are important to study and analyze for their unique context and the impact that has on transit amenities.

Transit Stop Amenities and Extreme Heat

As studies have compared the distribution of shelters along socio-economic categories, there has been growing relevance in also looking at environmental factors, particularly those related to extreme heat. Karner et al. (2015) used travel-activity and urban meteorological models to understand the impact of exposure to dangerously high outdoor air temperatures while walking or biking with a focus on low socio-economic groups. Because such groups disproportionately use non-motorized forms of transportation, they are more likely to be exposed to extreme heat. Karner acknowledges the challenge that this creates particularly as states like California push for more active transportation and public transit use. To reduce the harm and heat exposure of vulnerable groups, mitigation and planning are essential.

A study from Lee and First (2023) confirms Karner's results as heat vulnerable bus stops in the city of Knoxville, Tennessee were more likely to be in marginalized communities, and most stops lacked a shelter or trees. Another study from Lanza and Durand (2021) in Austin, Texas, mapped shelters and trees and researched their effect on ridership during the warm summer season. In contrast to other studies on amenities and ridership, their results showed that trees and shelters only minimally if at all affected this ridership loss. Lanza and Durand attribute this finding to the transit dependency of bus riders in their study (p. 10). When riders have no other option besides the bus, they must inevitably walk and wait in the heat.

Other studies have confirmed the importance of bus shelters as a mitigation strategy, but design and tree canopy play a role in the impact of shade. Dyzuban et al. (2022) surveyed bus riders and studied bus shelter design in Phoenix to determine the impact in lowering physiological equivalent temperature (PET), a measure of thermal comfort. They found that except for vegetated awnings (which were poorly maintained) all other shelter designs significantly reduced average PET. But overall, the PET even in the shade was still above what is comfortable with the majority of survey respondents saying they were hot or very hot. Additionally, respondents said that looking for shade was the primary way of coping with the heat while waiting at the bus stop. Similarly, Lanza et al. (2025) confirmed Dyzuban's findings, but did note that trees provided a greater cooling effect than bus shelters because of evapotranspiration. Lanza et al. found that design also played a role as translucent shelters that limited air flow with side and back walls created a greenhouse effect where inside the shelter was hotter than unshaded areas outside the shelter. Overall, these studies highlight that for the most part any shade is better than no shade in protecting against heat from direct sunlight given that the design of the shelter does not trap heat. Yet the impact of heat on vulnerable communities cannot be overstated as they are often more exposed to higher temperatures due to higher rates of non-motorized transportation. Without planning and mitigation through bus shelters or trees, vulnerable populations will be at even greater risk of heat-related illnesses as the climate warms.

Summary

As this literature review shows, there has been a growing body of research that explores the different components of extreme heat, transit ridership, transit amenities and their distribution. Recently, studies have begun to analyze the intersection of these components, but often one aspect is the focal point. Some studies prioritize the interplay and effects of amenities on ridership (Fan et al., 2016; Kashfi et al., 2015; Kim et al., 2020). Others focus on equity from a demographic perspective (Moran, 2022; Reginald, 2024; Yoon, 2023). Still others focus on the impact of shade on riders, but do not focus as much on the reasons for placement of a shelter at the stops studied (Dyzuban et. al., 2022; Lanza et. al., 2025, 2021; Lee & First, 2023). This study seeks to bring these elements together to address what transit agencies and city municipalities can do to respond to extreme heat from climate change and the risk it poses to transit-dependent populations, particularly in suburban communities. How can shelters be placed more effectively to mitigate the impact of extreme heat on bus riders?

Research has shown that shade is a key mitigation to extreme heat due to climate change, particularly given the high risk it poses to public health. Additionally, cities and agencies must consider the barriers to implementing shade so that individuals are not as exposed to heat, particularly as they access public transit. Bus shelters not only serve as a landmark and representation of the transit system but also serve a crucial link in a city’s urban shade infrastructure providing much needed protection, particularly for transit-dependent and vulnerable populations.

Due to climate change, many policies have begun to push for more public transit use to reduce GHG emissions from the transportation industry. Transit ridership is an important metric not only of public transit use, but also to assess the transit system's performance. Although frequency of service is often a primary determiner of ridership, passenger comfort and convenience particularly having amenities at stops can also impact ridership. Riders prefer stops with amenities, and it reduces their perceived wait time. However, agencies do not always have clear protocol for how shelters are placed, and the result is often an inequitable distribution of shelters with certain demographics having shelters while others are more exposed to the elements. The specifics of this inequity vary from region to region, but an analysis of a region's demographics is vital for having a clear picture of these realities. Finally, recent studies highlight the relief that shelters and trees provide from heat particularly for those who bike or walk to their locations, which tend to be lower socio-economic groups. In order to protect vulnerable populations even as policies push for higher transit usage, shade infrastructure at bus stops must be implemented in order to mitigate the impacts of extreme heat due to climate change.

This research will assess shelter distribution with an analysis of bus operation, environmental and demographic factors to see their effect on shelter placement in order to offer data to guide policies and strategies for how cities and transit agencies can implement shelters as important extreme heat mitigation measures to protect vulnerable populations. This analysis focuses on bus stops in San Bernardino County because suburban populations and mid-size transit agencies are rarely prioritized for this kind of research. One study from Lee and First (2023) did look at heat vulnerable bus stops in the more suburban city of Knoxville, Tennessee. Although this article considered the effect of trees and shelters, it did not focus on bus operation variables such as service frequency and transfer stops, and it did not offer a strategic framework to help cities and transit agencies prioritize shelters for communities vulnerable to extreme heat. With Lee and First as one of the few articles focused on suburban communities and shelter at bus stops, more research is needed. To see reductions in GHG emissions from transportation and slow climate change, it is these locations where the automobile has been dominant that must attract more transit riders. Understanding shelter placement and developing a strategy that helps mitigate the effects of extreme heat as people, particularly vulnerable populations, walk to the bus stop is vital for public health, increasing transit ridership, and greater sustainability in reducing GHG emissions.

CHAPTER 3:

METHODOLOGY

Study Area

The Inland Empire is generally known for two things: being hot and being on the way to Las Vegas, NV. These inland valley communities in San Bernardino County approximately 30 to 60 miles east of Los Angeles are primarily suburban, initially planned with a strong reliance on the automobile. Residents primarily live in detached single-family homes, and major arterials and freeways connect residents to jobs and activity centers. As the population of this area has grown, so has the need for public transportation. Particularly during the long summer months, drivers with air conditioning in their personal cars can be blissfully ignorant of the intense heat burden those who rely on public transit experience as they walk to the nearest bus stop for their mobility needs. Mitigations for the increasing heat due to climate change must be addressed to protect these transit-reliant riders.

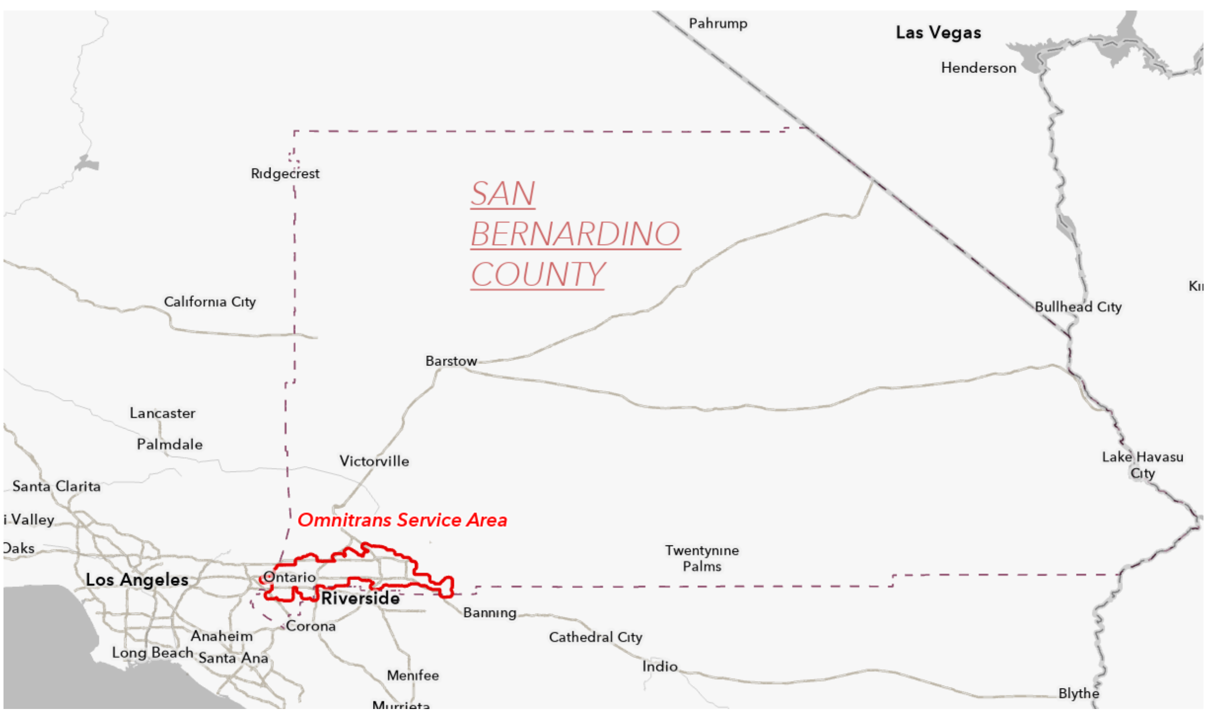
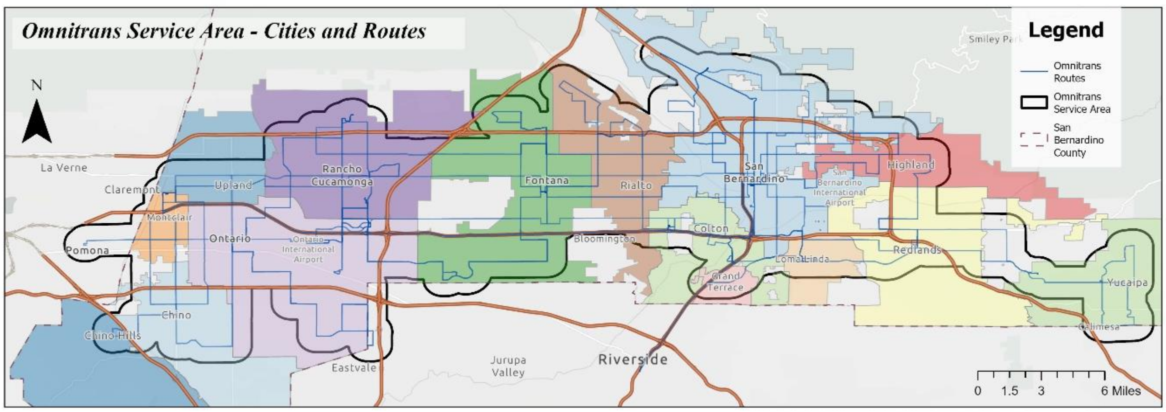


Figure 2: Omnitrans Service Area within San Bernardino County

The study area focuses on the service area of Omnitrans, the local transit agency, which is generally the southwestern portion of the county (Figure 2). This is the most populated region of the county stretching from Montclair in the west to Yucaipa in the east and along the San Gabriel mountains in the north to the Riverside County line in the south. As of March 2025, Omnitrans serves 2,286 bus stops in 15 different cities and unincorporated portions of the county. For its bus operations, Omnitrans runs 28 fixed bus routes, three micro-transit services, one bus rapid transit line, and paratransit service (Figure 3). This service area was chosen for the accessibility of the



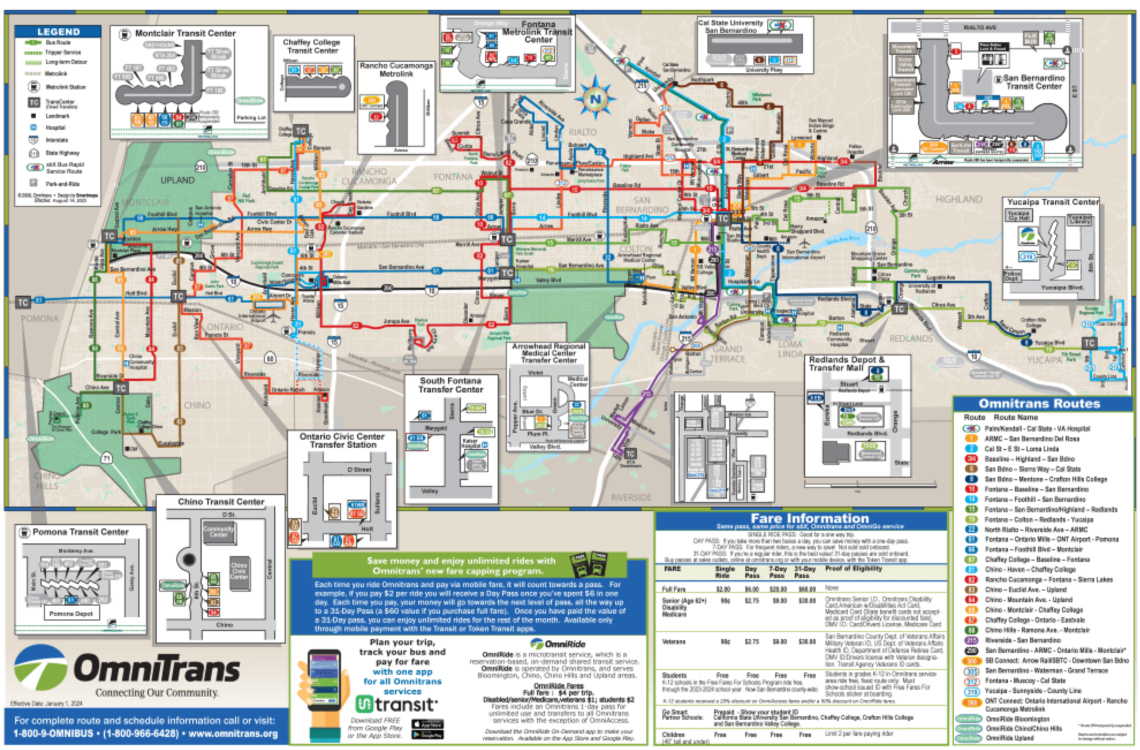


Figure 3: Omnitrans Service Area Map and Routes (Omnitrans, 2025)

data as well as to assess shelter data for a midsize transit agency. Other papers have looked at much larger transit agencies, such as Los Angeles Metro (Yoon, 2023), Houston METRO (Lanza et al., 2025), Valley Metro in Phoenix (Dzyuban et al., 2022) and Capital Metro in Austin (Lanza and Durand, 2021). The following table (Table 1) shows the annual ridership for 2024 for these agencies in comparison to Omnitrans. Southwestern San Bernardino County was chosen to understand factors affecting shelter placement for more suburban areas and mid-size transit agencies.

Agency	City	2024 (Jan – Dec) Annual Ridership
LA Metro	Los Angeles, CA	311,250,200
Houston METRO	Houston, TX	76,833,400
Valley Metro	Phoenix, AZ	38,600,000
Capital Metro	Austin, TX	26,967,700
Omnitrans	**San Bernardino, CA**	**7,231,100**

Table 1: Public Transportation 2024 Annual Ridership (APTA, 2025).

In terms of shelter placement, Omnitrans has a great deal of influence, similar to Metro Transit in the Minneapolis-St. Paul region (Buchanan & Hovenkotter, 2018). With 12 of its 16 Joint Powers Authority jurisdictions (Colton, Fontana, Highland, Grand Terrace, Loma Linda, Montclair, Ontario, Redlands, Rialto, San Bernardino City, Yucaipa, and unincorporated sections of San Bernardino County), Omnitrans has an established Passenger Amenity Program. This allows Omnitrans to install and maintain shelters and other amenities in the public right-of-way. Some cities still require a permit, but the approval and decision making for placing shelters rests primarily with Omnitrans. Cities provide input and make requests for amenities, but responsibility for these amenities is under Omnitrans' authority. This governing structure allows Omnitrans to assess the placement of shelters. In determining shelter placement, Omnitrans noted in a recent board meeting (March 5, 2025) that ridership and space for a shelter were the primary criteria as well as public feedback and requests for amenities.

Research Method

This study employs a quantitative method, specifically multi-level logistic regression modeling (MLRM), as the primary research method. The unit of analysis is individual bus stops in the jurisdiction of Omnitrans. This logistic regression was chosen since the dependent variable was defined with a binary categorization; 0 if the bus stop has no shelter and 1 if a shelter had been placed at the bus stop. As a logistic regression model, the odds of an event occurring (in this case a bus stop having a shelter) are analyzed with each of the independent variables (described in the following section) to see the impact of these variables on the likelihood of a shelter being present at a bus stop. In this way, the factors that impact shelter placement in a statistically significant way are identified in the logistic regression.

Furthermore, the MLRM was employed because of the hierarchical structure of the contributing factors. In other words, this study considers both specific bus stop information (Level 1 – individual variables) as well as larger census tract data (Level 2 – neighborhood variables). A multi-level model was the most appropriate given the context and structure of the data where bus stops were nested within census tracts. Some factors correspond to individual bus stops (particularly bus operations variables and a couple environmental variables). Other factors in this analysis correspond to neighborhood level (census tract demographics data and one environmental variable). Because bus stops within the same census tract would have the same neighborhood level data, a multi-level model was coupled with the binary logistic regression for the dependent variable for this analysis. Because of the nested data structure, standard regression violates the independence assumption and, as a result, underestimates the standard errors of the regression coefficients. For spatial analysis ArcGIS Pro is used, while SPSS is used for statistical analyses.

Variables

In reviewing the literature and other studies around bus shelters, various variables were considered, and those that were relevant to this analysis were categorized into three different groups: Bus Stop Operations, Physical Environment, and Demographics (Table 2). For this study,

Dependent Variable		Measurement	Level	Source
	Bus Shelter	Binary variable (1 = shelter present)	Level 1	2022 Master Bus Stop File
Independent Variables		**Measurement**	**Level**	**Source**
Bus Operations	Ridership	Average daily riders	Level 1	2022 Master Bus Stop File
	Service Frequency	Half the headway	Level 1	2022 Master Bus Stop File & Route information
	Transfer Stop (binary variable)	2+ routes intersect (1 = transfer stop)	Level 1	2022 Master Bus Stop File & System Map
	Transit Center (binary variable)	Multiple routes intersect (1 = transfer stop)	Level 1	2022 Master Bus Stop File
Physical Environment	Space for a Shelter (binary variable)	Area 8' x 20' or larger (1= enough space)	Level 1	2022 Master Bus Stop File
	Building Volume	In 25 m buffer, ft^3	Level 1	2021 SB County Bldg Footprint
	Bus Stop Tree Canopy	In 25 m buffer, ft^2	Level 1	2022 SBCTA Comprehensive Sidewalk Inventory
	Neighborhood Tree Canopy Cover	% of tract area	Level 2	Tree Equity Score (data collected from 2019-2023)
Demographics	Youth (under 18)	% of tract population	Level 2	ACS 2022 5-year estimate
	Senior (over 65)	% of tract population	Level 2	ACS 2022 5-year estimate
	White, non-Hispanic	% of tract population	Level 2	ACS 2022 5-year estimate
	Below Poverty Level	% of tract population	Level 2	ACS 2022 5-year estimate

due to constraints with data availability particularly for the building footprint and tree canopy, data from 2022 was used to ensure a consistent time frame for all the variables. While using data

Table 2: Summary of study variables

from 2022 allowed for consistency in the study's time period, ridership was still recovering post-

COVID. Omnitrans had an annual ridership of almost 11 million pre-pandemic compared with just over 5 million in 2022 (Omnitrans, 2025), but consistency with the analysis time period took priority over the impact of the pandemic on ridership. Omnitrans maintains a database, titled the Master Bus Stop File, which contains information on all its bus stops including the latitude and longitude of the stop. A copy of this database from 2022 was used for the bus operations variables. The section below details each variable that was used in the analysis, its source, how it was measured, and the reason for its inclusion in this study.

Bus Stop Operations

1. **Ridership**: the total average daily riders who board or alight at a particular stop.
    a. This data was imported from Omnitrans' Master Bus Stop file and reflects fall 2022 ridership for all bus stops across Omnitrans' service area.
    b. This variable was selected because it was one of the criteria that Omnitrans' uses to determine shelter placement. The analysis would test to see the impact that ridership has on the likelihood of shelter placement.
2. **Service Frequency**: this is how frequent bus service arrives at a stop.
    a. This variable has served as a proxy for wait time in other studies, calculated as half of the headway or frequency of bus service at the stop (Law & Taylor, 2010; Yoon, 2023). However, this is merely a rough approximation as not all passengers arrive at the stop randomly with many passengers planning their trip. Yet, service frequency does provide useful information in terms of which stops riders are more likely to have a higher wait time because service frequency is every hour versus every 15 minutes. Headways for each route were used from Omnitrans' full-service plan, which was the frequency or service at pre-pandemic levels.

b. This variable was selected because shelters decreased perceived wait time (Fan et al., 2016) and for those stops where service is infrequent, a shelter would provide greater comfort and protection from the sun. As noted above, this was a variable analyzed in other studies (Law & Taylor, 2010; Yoon, 2023).

3. **Transfer Stop**: this is a stop where a passenger would transfer from one route to another.
    a. This variable had a binary categorization; 0 being not a transfer stop, and 1 being a transfer stop. Transfer stops were determined from the Omnitrans system map as any point where two routes intersected. Where two routes overlapped, the first and last stop of overlap was included as a transfer stop. Transit centers were included in this variable. (See Appendix A for the list of transfer stops and corresponding routes.)
    b. This variable was included because transfer points are locations where passengers often wait longer. Although the most frequent bus headway was used in the service frequency variable, if a passenger was transferring from a more frequent route to a less frequent one, there would likely be a longer wait time. As noted above, a shelter would increase the passenger's comfort and protection from the sun during the longer wait. Only one study from the literature review considered transfers as a variable in its analysis of bus shelters (Miao et al., 2019)
4. **Transit Center**: a key transfer point where multiple bus routes overlap, often the start or end of a route.
    a. Similar to transfer stops, transit centers were a binary variable; 0 being not a transit center, and 1 being a transit center. Transit centers were designated facilities for transferring between routes and already established by Omnitrans.

Only transit centers in San Bernardino County were included (see Appendix A for the list of transit centers).

   b. This variable was included because transit centers often have many amenities given that many riders transfer at these locations, and they are designated transportation facilities. It was also included to compare with transfer stops outside of transit centers to see how each of these categories impacted the likelihood of shelter placement.

Physical Environment

1. **Space for a Shelter**: this variable notes if there is enough concrete space for a shelter.
   a. This is a binary variable noting if enough space was available for a shelter with 0 being not enough space, and 1 being enough space for a shelter. For Omnitrans shelters, the minimum size for a boarding area is 8 feet wide by 20 feet long for a 13-foot shelter. The boarding area length and width were pulled from Omnitrans' 2022 Master Bus Stop File. Any stop that measured 8 or more feet wide and 20 or more feet long for its boarding area was given a 1. All other stops were 0.
   b. This variable is important to analyze because it is one of the criteria that Omnitrans noted as a part of its shelter placement process. The analysis would test whether this variable impacts the likelihood of shelter placement or not.
2. **Building Volume** served as a stand in for building shade and was calculated based on building volume within a buffer around the bus stop.
   a. This variable was calculated using spatial analysis tools in ArcGIS. The process of calculation as well as the parameters of the variable (i.e. the 25-m buffer) are

detailed in the Analysis section below, but it is the sum of building volume within a 25-m buffer around the bus stop.

b. The data was sourced from San Bernardino County 2021 building footprint data and downloaded as a shapefile from the county's Open Data Portal. The shapefile contained a polygon layer for buildings in San Bernardino County as well as the building height.

c. This variable was included in the analysis as a stand in for building shade to explore the impact that building shade has on the likelihood of shelter placement. Areas with lower building shade (building volume) should have more priority since riders are more exposed to the sun. This variable was analyzed to study the relationship between building volume and the likelihood of shelter placement.

3. **Bus Stop Tree Canopy**: this is the square footage of tree canopy coverage within a 25-m buffer around the bus stop.

   a. This variable was calculated using spatial analysis tools in ArcGIS. The process of calculation as well as the parameters of the variable (i.e. the 25-m buffer) are detailed in the Analysis section below, but it is the sum of tree canopy square footage within a 25-m buffer around the bus stop.

   b. Tree Canopy data from March 2022 was collected from the San Bernardino County Transportation Authority's Comprehensive Pedestrian Sidewalk Inventory Plan II. For this project, SBCTA and its consultant Fehr & Peers used Ecopia AI to process large amounts of high-resolution geospatial imagery and convert these into vector maps for GIS (Ecopia, 2022). Tree canopy was one of the layers that was processed for this project. The tree canopy layer was downloaded and imported as a polygon layer into ArcGIS Pro.

c. This variable was important to measure because trees along with shelters can be a part of protecting transit-dependent riders from extreme heat and its associated health risks (Dyzuban et. al., 2022; Lanza et. al., 2025). In order to provide the most shade for the most needed areas, locations with lower tree canopy square footage would be prioritized for shelters. The examination of this variable looks at the likelihood of a shelter being placed in relation to the amount of tree canopy present within the buffer.

4. **Neighborhood Tree Canopy Coverage**: The percentage of tree canopy coverage in the census tract.

   a. This variable data was sourced from treeequityscore.org by city and unincorporated regions of San Bernardino County within Omnitrans' service area. Tree Equity Score provided a percentage of tree canopy coverage by block group using high-resolution images processed from Google Environmental Insights. The tree canopy coverage percentage is the percent of the total block group's that is covered by a tree's shade. Using an Excel pivot table, the average tree canopy coverage of block groups within a census tract was used to calculate the overall percentage of tree canopy coverage by census tract. This data was then imported and joined to the census tract layer for San Bernardino County.

   b. This variable was important to include in the analysis to provide an environmental variable at the neighborhood level. Research has shown that lower-income and minority neighborhoods tend to have fewer trees (Kolosna and Spurlock, 2018;

Watkins and Gerrish, 2018), though the magnitude of such disparities depends on local contexts. To provide the most benefit, shelters should be placed in census tracts with less tree canopy coverage as this is correlated with vulnerable populations and could protect transit-dependent riders. For this reason, the variable was included in the analysis.

Demographics variables:

Demographic data was collected from U.S. Census using the 2022 five-year estimates from the American Community Survey (ACS) tables at the tract level. For the report from Yoon (2023) on bus shelter equity in Los Angeles County, her demographic factors used an index from Metro (the Los Angeles County transit provider) based on percentile measurements for income, race/ethnicity, and vehicle ownership (p. 17). Lanza and Durand (2021) in their analysis of bus shelters in Austin, Texas considered the following demographic categories: race/ethnicity, poverty level, workers who take the bus to work, and median age. (p.5). These demographic categories are correlated with more transit dependency. Based on these articles and others discussed in the Literature Review, variables for poverty level, race, and age were chosen. Commuting by public transit was a variable that was considered, but in the analysis, ridership more accurately captured the impact on the likelihood of a shelter being present.

1. **Youth**: the percentage of the census tract population which is under 18 years old
    a. This variable was sourced from the American Community Survey 2022 five-year estimates from Census.gov. Table B17001 (Age and Poverty) provided the total youths in San Bernardino County by census tract. This value divided by the total population was analyzed for the percentage of the population under 18.
2. **Senior**: the percentage of the census tract population over 65 years old

    a. This variable was sourced from the American Community Survey 2022 five-year estimates from Census.gov. Table B17001 (Age and Poverty) provided the total seniors in San Bernardino County by census tract. This value divided by the total population was analyzed for the percentage of the population over 65.

3. **White** (non-Hispanic): the percentage of the census tract population that identified as non-Hispanic whites.
    a. This variable was sourced from the American Community Survey 2022 five-year estimates from Census.gov. Table B03002 (Race by Hispanic or not) provided the total number of people who identified as white, non-Hispanic in San Bernardino County by census tract. This value divided by the total population was analyzed for the percentage of the population that identified as white, non-Hispanic.
4. **Poverty Level**: the percentage of the tract population whose income in the past 12 months was below the federal poverty line.
    a. This variable was sourced from the American Community Survey 2022 five-year estimates from Census.gov. Table B17001 (Age and Poverty) provided the total number of people whose income over the last 12 months was under the federal poverty level in San Bernardino County by census tract. This value divided by the total population was analyzed for the percentage of the population under the federal poverty level.

Data Mapping

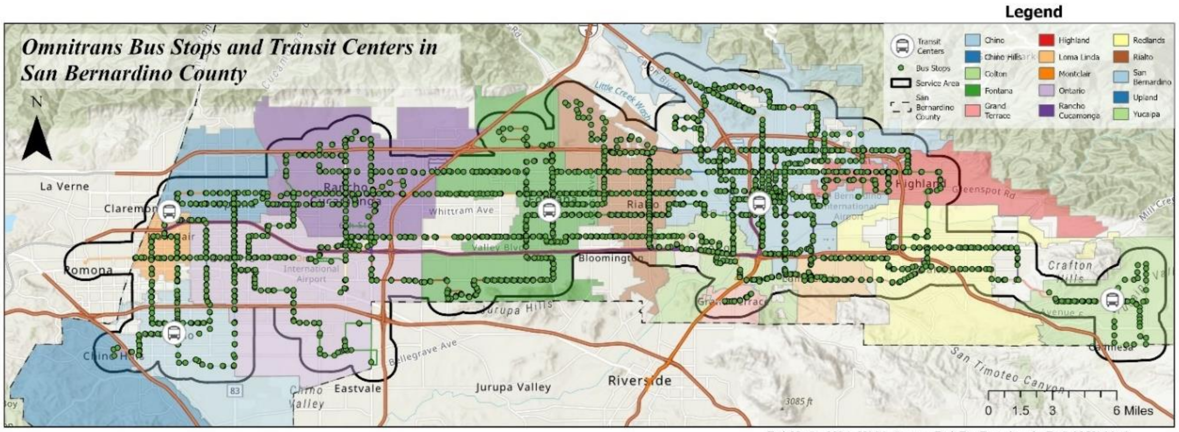


Figure 4: Bus Stops and Transit Centers in study area.

Esri, NASA, NGA, USGS, Sources: Esri, TomTom, Garmin, FAO, NOAA, USGS, © OpenStreetMap contributors, and the GIS User Community

The Master Bus Stop File data was cleaned and organized in Excel. The file was imported into ArcGIS Pro along with transit centers, cities in Omnitrans' service area, and Omnitrans routes. Each bus stop's latitude and longitude from the Master Bus Stop File was used to geocode the bus stops in ArcGIS Pro. Figure 4 shows the distribution of bus stops across Omnitrans' service area while Figure 5 shows the locations of transfer stops and transit centers.

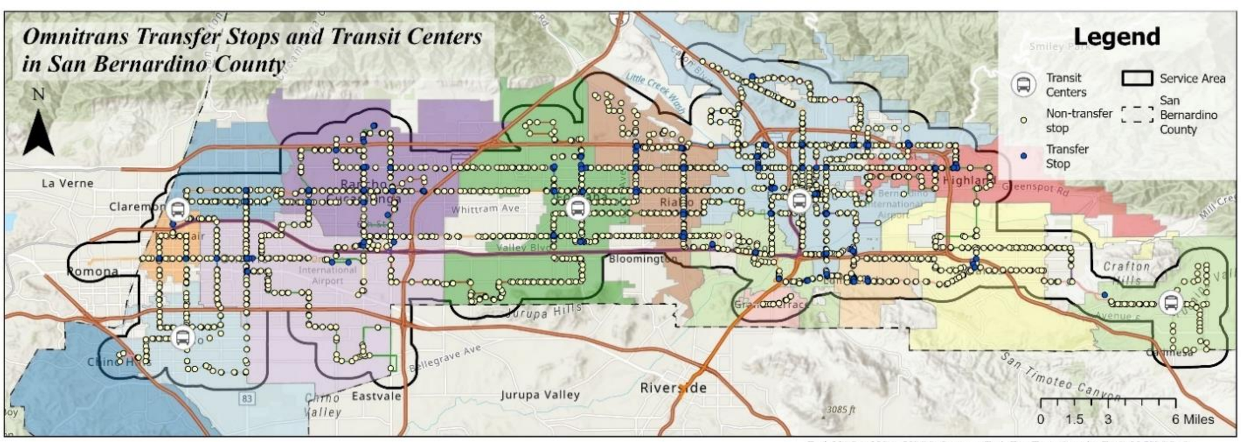


Figure 5: Transfer stops and transit centers in the study area.

Esri, NASA, NGA, USGS, Sources: Esri, TomTom, Garmin, FAO, NOAA, USGS, © OpenStreetMap contributors, and the GIS User Community

	Shelter	No Shelter	Total
Total	575	1685	2260 stops
Transfer Stop	110	124	234 transfer stops outside of transit centers
Transit Centers	41	1	42 unique locations in 5 transit centers.

Table 3: Breakdown of Count Variables by Shelter and No Shelter

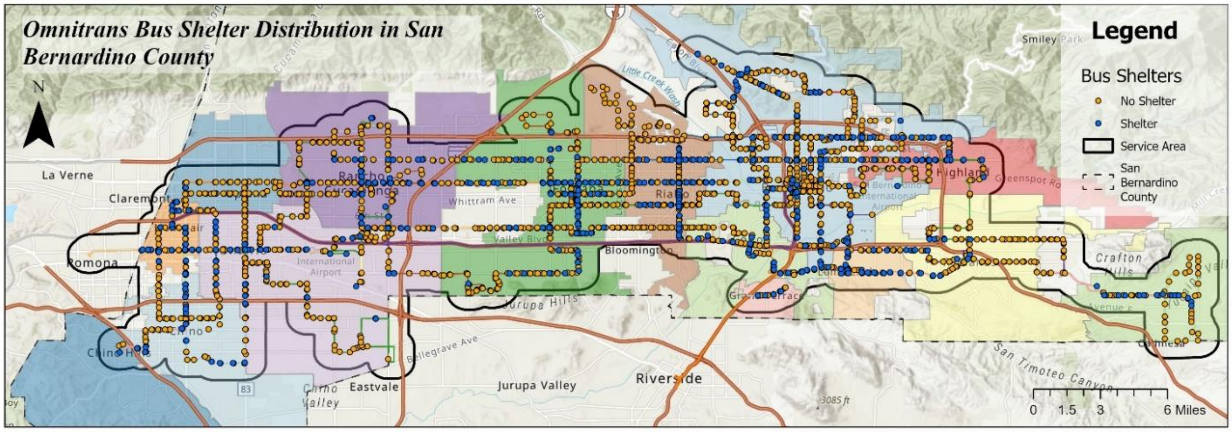


Figure 6: Distribution of bus shelters in study area.

Esri, CGIAR, USGS, Sources: Esri, TomTom, Garmin, FAO, NOAA, USGS, © OpenStreetMap contributors, and the GIS User Community

For the analysis, a total of 2260 stops in San Bernardino County from the 2022 Master Bus Stop file were included. The presence of a shelter at a bus stop was coded in a binary format (0 = no shelter; 1 = shelter), and the binary code was used as the dependent variable. Of the total stops, 575 (25.4%) had a shelter (Figure 6). Of the 234 transfer stops (excluding transit centers), 124 of them (53%) did not have a shelter. See Table 3 for a breakdown of total stops, transfer stops, and transit centers with and without shelters.

Spatial Analysis for Tree Canopy and Building Volume

Once all the data was input into ArcGIS Pro, the following spatial analysis was conducted to measure the bus stop tree canopy and building volume variables. A Euclidean buffer of 25

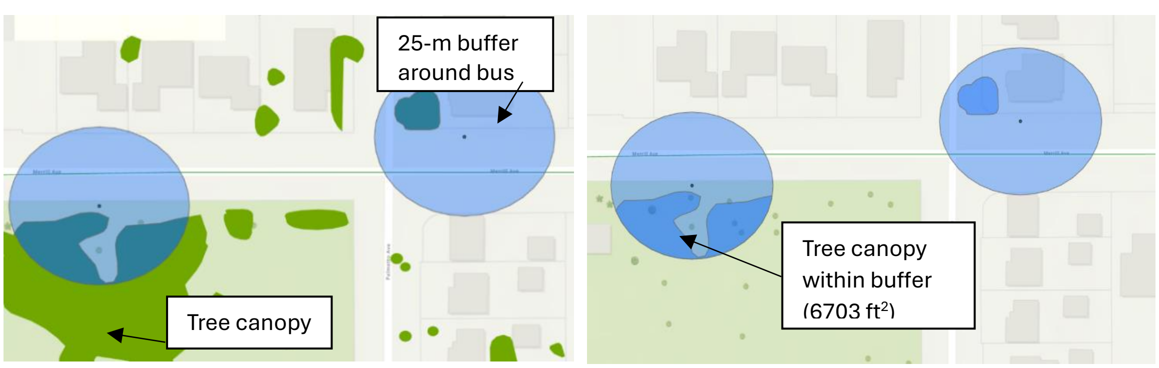


Figure 7: A 25-m buffer around bus stops was used for the intersect of tree canopy within the buffer (Left). The area of the intersect was extracted and then used to calculate for the tree canopy square footage variable.

meters was created around each bus stop. This distance was based on Lanza and Durand's study (2021) and Reginald (2024) which used tree canopy within a 25-meter and 75-foot (approximately 23 meters) buffer respectively. Lanza and Durand note that this is the equivalent to a 20-second walk and "a reasonable distance from the bus stop to seek shade without missing the next bus" (p. 5). This reasoning would also apply to the building shade calculation.

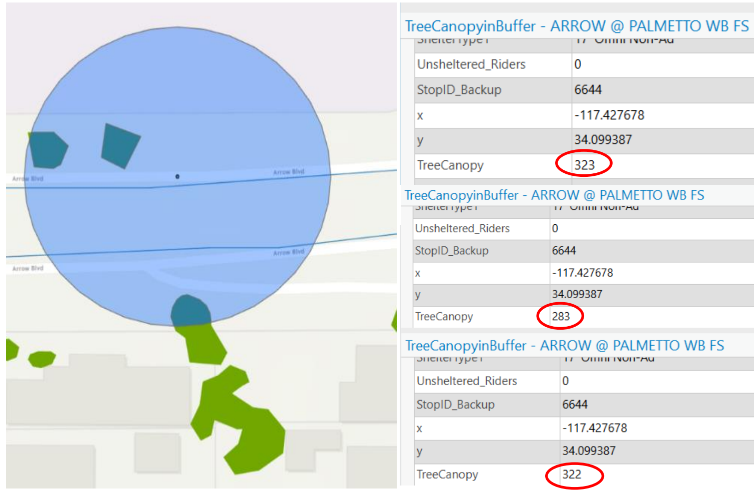


Figure 8: When multiple trees had canopies in one buffer, the square footage was summed to provide the total canopy square footage per bus stop.

For the Level 1 tree canopy variable, an overlap of the tree canopy layer and the 25-m buffer were identified (Figure 7). The area of tree canopy within the buffer was calculated using an ArcGIS Pro tool which captures the overlapped areas of the layers. When a bus stop had multiple tree canopy areas within one buffer, those tree canopy areas with the same bus stop ID were consolidated and the tree canopy square footage added together (Figure 8). This yielded a value of tree canopy square footage by bus stop which was joined to the Master Bus Stop File data.

Similarly, for the building volume, an overlap of the building footprint layer and buffer layer were used to find the building footprint within 25 m around a bus

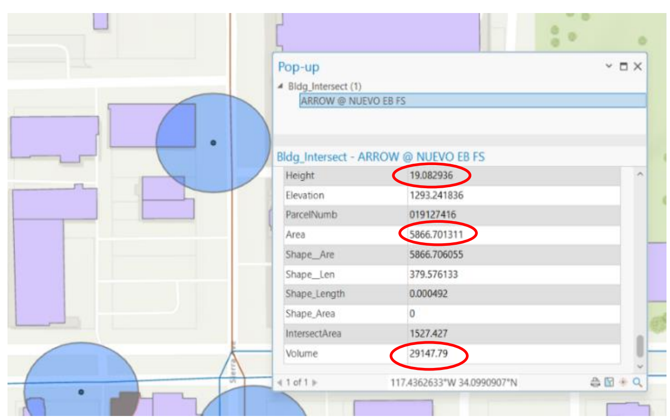


Figure 9: One calculation of the building volume from the San Bernardino County 2021 Building Footprint data and the intersect with the 25 m buffer.

stop. Using ArcGIS Pro tools, the area within the buffer was calculated and then this was multiplied by the building height which was in the original San Bernardino County Building Footprint dataset (Figure 9). Sometimes, a bus stop would have multiple buildings within one buffer. Similar to the tree canopy square footage, the building volumes were consolidated by bus stop ID and the sum of the volumes was used for the final calculation. This yielded a total value of building volume by bus stop which was joined to the Master Bus Stop File data.

After these calculations, the demographics data and tree canopy coverage by tract was mapped using a table join between the census tract layer for San Bernardino County and the demographics data. The census tract dataset and master bus stop file with the added tree canopy square footage and building volume were combined into a master data set to have both Level 1 (bus stop level) and Level 2 (census tract level) data in one table. Because the demographics data was focused on San Bernardino County, the few bus stops in Riverside and Los Angeles Counties were removed from the final dataset. Upon checking and cleaning the data, a total of 2260 bus stops in 267 different census tracts were included in the final dataset. The data was then analyzed in SPSS using a multi-level logistic regression model.

CHAPTER 4:

RESULTS

Table 4 details the descriptive statistics for each of the variables. Ridership, Building Volume, and Tree Canopy around the bus stop showed strong right skew with many stops having 0 for these variables. The other variables showed a more normal distribution for their data with some outliers. (See the histogram plots and SPSS outputs for each variable in Appendix B.) When comparing the means for variables between stops with and without shelters, it is clear that ridership and building volume show a clear difference in their mean values. This probably indicates the contributions of the variables to the binary classification of the dependent variable, the existence of shelters or not.

					Shelters (Dep. Var. = 1)		No Shelters (Dep. Var. = 0)	
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Ridership	18.2	46.08	0	696.9	41.86	82.21	10.07	16.94
Service Freq (min)	19.2	9.41	6.25	67.50	16.5	9.3	20.2	9.3
Building Volume (ft^3)	6810.75	9223.37	0	371,882.06	4513.53	19,894.16	7594.67	29,033.08
Tree Canopy at stop (ft^2)	1606.47	1883.06	0	13,933	1443.87	1822.11	1661.95	1900.758
Tree Canopy Cover	9.93%	3.24%	1.66%	19.87%	9.76%	2.92%	9.99%	3.35%
Youth (under 18)	24.24%	5.59%	0%	41.60%				
Senior (over 65)	11.34%	6.50%	0%	37.10%				
White, non-Hispanic	17.84%	13.15%	0%	64.81%				
Below Poverty Level	15.27%	10.08%	0.20%	52.06%				

Table 4: Descriptive Statistics of Continuous Variables in Analysis.

**Note: Dep. Var. = dependent variable; Std. Dev. = standard deviation*

From the Omnitrans ridership data, the county has a total of 16,962 unsheltered riders with the most riders in the city of San Bernardino (5186) and Ontario (2355). In terms of service frequency, riders at stops with a shelter had an average half of a headway of 16.5 minutes while riders at a stop without a shelter had an average of 20.2 minutes. Riders at a transfer stop without a shelter had a service frequency average of 30 minutes (half the headway), indicating that most of these transfer stops were locations on 60-min frequency.

For the multi-level binary logistic regression, various models were tested. A mixed effects model with a random intercept (Mixed Effects Model) was chosen. The Null Model yielded a very high AIC value (10,323) and 76.5% correct for the confusion matrix. When compared with the Mixed Effects Model, this model had a lower AIC value (1,846) and more accurate confusion matrix value (81.2%). Thus, the fixed effects model was selected for this analysis because of its lower AIC value, indicating a better fit of the model to the data. (Table 5.) For the Mixed Effects Model, the classification table showing the confusion matrix percent correct is shown in Table 6. The coefficients table and their significance are shown below in Table 7.

	Null Model	Mixed Effects Model
AIC Value	10,323	1,846
Confusion Matrix (Percent Correct)	76.5%	81.2%

Table 5: Comparison of Null and Mixed Effects Models

		Predicted Shelter	**Predicted** no shelter
Observed – shelter	Count	234	341
	% within Observed	40.7%	59.3%
Observed – no shelter	Count	83	1602
	% within Observed	4.9%	95.1%
Overall Percent Correct = 81.2%			

Table 6: Classification table showing percent correctly predicted by model

From the analysis, five variables were statistically significant: ridership, transit centers, space for a shelter, and building volume at the bus level and tree canopy coverage at the tract level with a 95% confidence level. Service frequency, transfer stops, and tree canopy square footage around the bus stop did not show a statistically significant correlation with the confidence level. Also, none of the demographics variables at the neighborhood level were statistically significant.

	Variable	Coefficient	Std. Error	Exp (Coefficient)	Significance
	Intercept	-2.591	0.5558	0.075	0.000
Bus Operations	Ridership	0.025	0.0042	1.025	0.000
	Service Frequency	-0.015	0.0087	0.985	0.082
	Transfer Stop	0.406	0.2281	1.500	0.075
	Transit Center	3.079	1.2707	21.731	0.015
Physical Environment	Space for a Shelter	2.392	0.1688	10.932	0.000
	Building Volume	-8.461E-06	3.6380E-06	1.000	0.020
	Tree Canopy at stop	5.419E-05	3.8918E-05	1.000	0.164
	Tree Canopy Cover	-5.307	2.5194	0.005	0.035
Demographics	Youth (under 18)	1.493	1.5795	4.449	0.345
	Senior (over 65)	0.904	1.5229	2.469	0.553
	White, non-Hispanic	-0.056	0.6723	0.946	0.934
	Below Poverty Level	-1.388	0.9129	0.250	0.129

Table 7: Coefficients Table.

Of the variables that were significant, ridership, transit centers, and space for a shelter had a positive correlation. This means that stops with higher ridership, at a transit center, or with space for a shelter, are more likely to have a shelter present. Building volume and tree canopy cover showed a negative correlation. This means that stops with larger building volume (more building shade) and more tree canopy cover at the tract level are less likely to have a shelter present. For the full outputs from SPSS, see Appendix B.

CHAPTER 5:

DISCUSSION

The results above highlight what variables have an impact on the likelihood of shelter presence and which ones do not. The significance of the results goes beyond confirming Omnitrans' criteria for shelter placement. They point to gaps in assessments for shelter locations and how to build on current criteria to work towards a more equitable distribution of shelters in San Bernardino County.

The most prominent fact is that none of the Level 2 demographics variables were statistically significant. Neighborhood level characteristics which could lead to greater transit dependency are not considered in the placement of shelters. It may be argued that ridership serves as a proxy variable for the demographics since greater transit dependency should be reflected in higher transit ridership. However, higher ridership tends to be concentrated on the most frequent routes. Thus, areas where service is less frequent may still have characteristics of greater transit dependency, but these stops will be overlooked because the ridership is lower.

As Karner et al. (2015) points out minority and low-income populations are disproportionately exposed to increasing risk for health-related illnesses because they are more likely to use non-motorized transportation. When demographic factors would point to greater transit dependency, but lower ridership leads to deprioritizing these stops for a shelter, an issue of environmental justice arises. These passengers are exposed to greater risk, and thus, transit agencies and local jurisdictions must consider mitigation measures to protect riders for extreme heat exposure. A key policy change that could lead to a more equitable distribution of shelters would be to consider the demographic characteristics of a neighborhood in shelter placement.

These can help identify gaps where selection of shelter placement by ridership alone would miss and ensure that these riders are protected from increased heat exposure at bus stops.

The second major finding from this analysis is that key bus operations variables are statistically significant except transfer stops outside of transit centers and service frequency. For transit agencies, many of the variables such as tree canopy, building volume, and demographics are not in the direct control of transit agencies. But variables such as service frequency, transfer stops, and to some degree ridership (Karunakaran et al., 2023; Litman, 2008) are within the transit agency's control. For these variables, the transit agency can have a direct influence on prioritizing stops based on its operations, thus protecting riders with longer wait times, especially at transfer points, from increased exposure to extreme heat.

In this model, a transfer stop does not impact the likelihood of a shelter being present, but a transit center does. This highlights a gap in the shelter placement model. Riders who transfer outside of transit centers may experience longer wait times due to their buses' schedules and differences in route frequency. For example, if a rider transfers from a 15-minute frequency route to a 30-minute frequency route, there is potential for up to 30 minutes, and a lack of shelter can make this wait seem even longer (Fan et. al. 2016). It does make sense from the results that transit centers would have more shelters as they are specifically transit facilities, making shelter implementation a key priority. However, stops that are transfer points outside of transit centers present a key opportunity for agencies to meet the needs of riders, sheltering them from extreme heat during this wait between transfers. Fan et al. (2016) also notes that waiting at a transfer stop is viewed more negatively by riders than waiting than the initial wait at a start of a trip (p. 4). A shelter at transfer stops can make the wait more comfortable for riders, particularly helping during high heat days. This is a key consideration for transit agencies to implement in their shelter placement. For cities where the jurisdiction oversees shelter placement, this can be a key area of collaboration with the transit agency to protect riders as they transfer. When ridership and spacing take the priority as criteria for determining shelter placement, riders who need to transfer outside of transit centers can end up being overlooked in the process.

Similar to transfer stops, service frequency is not a variable that impacts the likelihood of shelter placement in a statistically significant way. The results indicate that stops with less frequent service are underestimated in shelter placement, regardless of ridership. An analysis by Karunakaran, et. al (2023) looked at various factors that influence ridership (bus commercial speed, service frequency, in-vehicle travel time, bus stop distance, and rainfall) and found that all variables have a statistically significant impact on ridership. But for both peak and off-peak hours, service frequency had the highest influence on ridership (p. 11). In line with this study, Omnitrans routes with lower frequency overall tend to have lower ridership. When ridership is the key criteria for shelter placement, stops along these low frequency routes are less likely to be prioritized for a shelter. However, the needs of riders who use these stops would benefit greatly from a shelter since their wait time may be much longer.

While placing shelters based on ridership may be most cost-effective with a lower cost per capita, service frequency provides an important consideration for shelter placement due to the risk of increased exposure. One policy implementation could be similar to how transit agencies consider service – coverage versus efficiency, where a percentage of routes are coverage routes meant to spread out service, while efficiency is a percentage of routes that are productive carrying many passengers per hour. Similarly, a percentage of shelters could be placed based primarily on service frequency while the remaining percentage of shelters could be placed primarily on ridership. Additionally, considering a transfer stop variable in shelter placement is key. Few studies that analyzed shelter distribution looked at transfer stops as a variable, and thus more research on the impact of transfers on passenger wait time could provide more clarity on the correlation between transfer stops and wait time. And including this variable in shelter placement could provide protection for riders who must wait as they transfer from one route to another.

Finally, when looking at the results for the environmental variables, it is clear that space for a shelter is statistically significant. This aligns with Omnitrans' stated criteria and practical applicability. However, it is important to note the other environmental variables that are statistically significant. Building volume and census tract tree canopy cover were found to be significant, but both were negatively correlated with the likelihood of a shelter being present. This means that the more buildings that exist within the 25 m buffer the less likelihood there is of a shelter being present. And the more tree canopy cover percentage for a census tract, the less likely a shelter would be present at stops in the tract. This finding suggests that Omnitrans' shelter placement takes consideration of the shade cast by buildings adjacent to the bus stop. Riders at the bus stops with more building shade may be able to avoid heat and direct sunlight without a shelter. Similarly, it is reasonable to assume that riders who make their first- and last-mile trips in neighborhoods with abundant trees are less exposed to extreme heat. Thus, taking consideration of physical environment adjacent to bus stops and in neighborhood can be an efficient strategy to allocate limited resources.

Yet with these variables, it would be helpful to conduct further research, particularly since Omnitrans did not specify building shade nor tree canopy cover in the process of shelter placement. The building volume data does not provide exact shadow areas at bus stops. The building volume variable is a proxy variable for building shade. For more accurate data, it would be important to analyze the areas shaded by buildings. I attempted to compute the shade cast by the buildings on a summer afternoon using the ArcGIS Pro's Sun Shadow Volume geoprocessing tool. However, the results from these attempts were not accurately generated despite several iterations using the 2021 San Bernardino Building Footprint data and the Sun Shadow Volume tool. As a result, the Building Volume variable was used as a proxy, but further research could develop a methodology that more accurately measures building and tree shade to assess the impact and correlation between building shade and shelter placement.

For the tree canopy variables, it is important to note that the Level 1 square footage variable in the 25 m buffer is not significant, but the level 2 tree canopy variable is statistically significant. This discrepancy points to the need for more research as the impact of tree canopy on shelter placement is not consistent at the different levels of analysis (bus stop level and census tract level). However, the results do indicate a negative correlation between tree canopy cover at the tract level and the likelihood of shelter placement. This generally aligns with prior research which has shown that lower-income and minority neighborhoods tend to have fewer trees (Kolosna and Spurlock, 2018; Watkins and Gerrish, 2018) though the magnitude of this disparity depends on the local context. These same demographic characteristics are associated with greater transit-dependency. More research would be needed to see the correlation between these characteristics with high ridership stops that are more likely to have shelters. This result for tree canopy cover at the tract level is an important consideration particularly when shelters are a limited resource. Putting shelters where tree canopy is lower means that more exposed stops have shade and can help mitigate riders' risk of heat-related illnesses, particularly during summer months. Considering more of the local context for tree canopy around bus stops would help to ensure that shelters are placed where they are most needed.

Overall, this analysis and the results confirm the realities of Omnitrans' shelter placement criteria but also point to important other factors at play. First, Omnitrans' shelter placement is primarily based on the operation factors, especially ridership, but places where riders do experience greater exposure (transfer points outside of transit centers and stops with less frequent service) are not prioritized. Second, aside from the variable of space for a shelter, there is an inconsistent relationship between physical environment factors and shelter placement. Although the results do indicate shelters are being placed in areas with lower tree canopy at the tract level and less building volume, it will be important to develop consistent criteria that incorporate surrounding conditions when making shelter placement decisions. This can have a significant impact on a rider's heat exposure. Finally, a lack of consideration for factors connected with vulnerable populations highlights another gap in the current shelter placement criteria. Having a clear understanding of the socio-economic characteristics of riders at each stop can help transit agencies and jurisdictions make more-informed shelter placement decisions. Overall, a wider consideration beyond ridership and space could ensure that shelters are not only meeting the needs of current bus passengers but also being used as a resiliency effort to prepare for extreme heat due to climate change.

CHAPTER 6:

CONCLUSION

While this analysis provides important data on the distribution of shelters and the factors that impact their placement in a suburban region, this thesis is also meant to provide more practical input and larger frameworks for mid-size transit agencies, local jurisdictions, and community members concerned about extreme heat. First and foremost, this paper offers a framework shift by comprehensively analyzing the supply and demand sides of shelter placement, particularly from the perspective of climate resilient infrastructure as they provide key relief from heat (Dzyuban et al., 2022; Lanza et al., 2025). This is particularly important for transit-reliant communities which are often at greater risk of heat-related illnesses (Karner et al., 2025). While this analysis confirms Omnitrans' main criteria for shelter placement (ridership and space for a shelter), this paper also points to considering other factors (i.e. demographics associated with transit-reliant populations, service frequency, and other shade present around a stop) to have a more wholistic framework that guides shelter placement. Particularly for transit agencies, considering other criteria that are within their purvey such as service frequency and transfer stops could ensure that the protection shelters provide extend to riders who may be overlooked. These passengers face greater risk as they have more exposure to heat at unsheltered bus stops.

This study also highlights the ways demographic factors can be overlooked when implementing shelters. Yet, adding this variable to criteria during shelter placement can ensure that vulnerable communities are protected as they access bus routes rather than just places with high ridership. This study used a multi-level analysis, but transit agencies and local jurisdictions do not have to use such intense statistical analyses. Transit agencies like LA Metro (Yoon, 2023) have created their own index that integrates the different socio-economic categories. Other options include using the CalEnviroScreen score or Healthy Places Index which integrates both socio-economic variables as well as pollution and health burden variables. One limitation in this study for the demographics analysis was the use of census tracts. Because tracts are relatively larger geographically, they can blur more of the localized impacts. Future analysis, particularly if data is directly included from the Census Bureau rather than indexes, would be to use a smaller geographical unit such as census block group as the unit of the neighborhood . This would allow for more focus geographically and provide a clearer picture of the impacts of demographics on bus stop amenities. For mid-size transit agencies, using either block group data or scores/percentiles to assess where to place shelters, the key recommendation is to ensure that marginalized populations are not overlooked in the midst of shelter placement, particularly as these groups are more at risk to heat exposure (Karner et al., 2025).

One limitation of this study is public input. Because this was a quantitative study that used Omnitrans' Master Bus Stop File, this analysis did not incorporate public feedback or opinions on bus shelter locations. However, best practices and case studies around shelter placement (Buchanan & Hovenkotter, 2018; Robertson, 2022) stress the importance of community engagement and public feedback. This kind of qualitative analysis could provide a more thorough picture of riders' experience at stops and how their input impacts shelter placement from an Omnitrans staff perspective. For future analysis of shelter distribution as well as for local tracking of an agency's bus shelters, including a public feedback variable is vital. Surveys of bus riders could also highlight a concern or need that is not captured from quantitative data. This coupled with the other variables mentioned above can provide valuable guidance for where to place shelters.

Overall, creating a framework for shelter placement that incorporates bus operations, environmental factors, and demographic data along with public input can help ensure that shelters protect riders from exposure to extreme heat. Additional variables that could be included would be population density and land use density or diversity to see how these also impact shelter placement. Locations with greater population density or areas with higher land use diversity would be places with the potential for increased transit ridership, and thus focusing shelter placement in these areas can protect riders from extreme heat.

With a framework that includes these various variables, weighting these variables can help agencies identify key criteria in shelter placement. Assigning scores based on data for these variables can be used as part of a suitability analysis to guide agencies for where to prioritize shelters. In this way, agencies can work to address extreme heat due to climate change through bus shelters and work towards placing these shelters in locations where riders and vulnerable communities need them most.

This paper has built on the research of many other studies, particularly recent ones that have begun to explore shelters as a mitigation for extreme heat. Further research could expand on the best implementation of shade. This analysis strictly focused on bus shelters, but as Lanza et al. (2025) points out, trees can provide an even greater cooling effect on a hot day. Additionally, space for a shelter particularly to meet compliance with the Americans with Disabilities Act (ADA) is a key factor in shelter placement. For areas where the space is too small for a traditional shelter, research on alternative designs as well as using trees for shade could add to the discussion on how to prepare for extreme heat in the context of transit. A study from 1991 (McPherson and Biedenbender) looked at the cost-effectiveness of trees versus bus shelters.

Given the more recent impacts of climate change, an updated study could benefit transit agencies and local jurisdictions in the most cost effective ways to implement shade at a bus stop.

Further research around vandalism and maintenance costs would add to the conversation around bus shelter placement. Although rarely explicit, bus shelter placement is also impacted by vandalism. Some stops have shelters removed due to riders or community members breaking plexiglass for ad panels or sometimes outright theft of amenities such as lights. Additionally, city staff may request a shelter to be removed because of complaints from residents. This kind of public input is more difficult to measure quantitatively, yet similar to requests for amenities mentioned above, this can be a key factor in shelter placement. For transit agencies and local jurisdictions, vandalism is an important variable to consider particularly given that this does increase the cost of maintenance and can be a deterrent to placing a shelter where it could provide relief from the heat. Finding a way to quantify the impact of vandalism is one challenge and then integrating it as a variable for analysis is another challenge. However, adding this variable to a study like this on the distribution of shelters could provide key insights for agencies in their placement of shelters. It could also coincide with consideration of other shade implementation such as planting trees.

Finally, jurisdictions, transit agencies, and community members should also consider much larger visions of what a shelter could be. While this study looked at standard steel bus shelters in southwestern San Bernardino County, other cities around the world have implemented various improvements to upgrade bus shelters. In Dubai, the Road and Transport Authority is building 762 bus stops that include an air-conditioned area, shaded outdoor seating, as well as advertising and bus service information seen in Figure 10 (Nandkeolyar, 2023). With high summer temperatures well above 100, Dubai presents one option where bus stops are not minimal coverage but provide significant protection and comfort in extreme heat. In Madrid, a bus shelter uses evaporative cooling as hot air passes through a wet panel which is then directed towards those seated on the bench (Figure 10). This system can "lower the ambient air temperature by as much as 9°C (16°F)" (Morrisey, 2024). Additionally, the stop is powered by solar energy and harvests rainwater that is

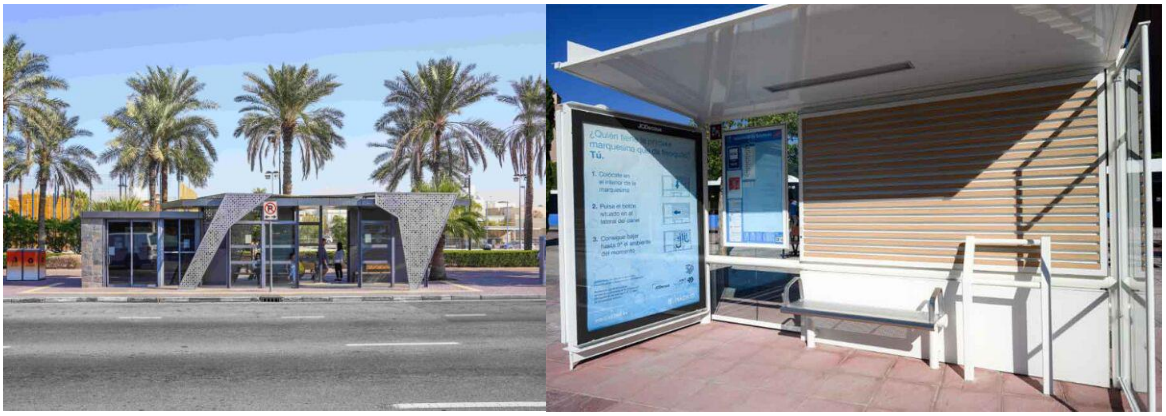


Figure 10: An air-conditioned bus stop in Dubai (Nandkeolyar, 2023). An evaporative cooling bus shelter in Madrid (Morrisey, 2024).

stored in a tank. Other cities have been exploring green roofs at bus shelters and other techniques to use evapotranspiration for cooling. Although these kinds of amenities require various considerations, particularly around cost, it is these kinds of innovations and creativity which can transform the often bleak news about climate change into a source of inspiration for the potential of bus stops. They inspire a vision for what shelters could be versus just maintaining the status quo.

This study seeks to respond and engage the growing tension between encouraging more transit use to reduce GHG emissions and the heat burden on transit riders (particularly transit-dependent riders) as they access transit. Shelters are a key link in protecting riders and mitigating the impacts of extreme heat and its associated risks. In this era of climate change, shade is a precious resource, and transit agencies and local jurisdictions must assess their implementation of shade not only as a factor impacting customer comfort and convenience, but a key element of climate resiliency. A wholistic framework and clear criteria that integrate bus service factors, environmental considerations and socio-economic realities can provide a strategy for how agencies prioritize shelter placement. This is vital to ensure that shelters are equitably distributed and providing shade where it is needed most.

This understanding and framing of shelters is only one component of addressing the conflict between increased transit usage and increasing temperatures due to climate change. This strategy is one of several that transit agencies, as well as local and regional governments, can use to protect transit-dependent populations. Bus shelters will not solve all issues related to extreme heat at bus stops. But they can serve a key link in the chain for mitigating the impacts of heat-related illnesses. Agencies must continue to adapt and plan for shade implementation initiatives to protect riders and respond to our warming climate.

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APPENDICES:

APPENDIX A: Transit Centers and Transfer Stops

Transit Centers	Routes	Address
Chino	83, 84, 85, 88, Omniride	13242 6th St, Chino, CA 91710
Fontana	10, 14, 15, 19, 61, 66, 67, 82, 312	16777 Orange Way, Fontana, CA 92335
Montclair	66, 84, 85, 88, Omniride	5060 Richton St, Montclair, CA 91763
San Bernardino	1, 2, 3, 4, 6, 8, 10, 14, 15, 215, 300, 305	599 W Rialto Ave, San Bernardino, CA 92410
Yucaipa	19, 319	34272 Yucaipa Blvd, Yucaipa, CA 92399

Routes	Key Transfer Points
3, 4, 312	16th & Medical Center
1, 6, 15	3rd & Sierra Way
3, 4, 14	5th & Mt. Vernon
67, 87	Archibald & 19th
81, 85	Arrow & Haven
85, 87	Arrow & Vineyard
1, 19, 22, 290	Arrowhead Regional Medical Center
2, 19, 202	Barton & Anderson/Barton & Benton
3, 4, 15	Baseline & Boulder
10, 67	Baseline & Citrus
67, 81	Baseline & Haven
67, 85	Baseline & Miliken
10, 22	Baseline & Riverside
3, 4, 6	Baseline & Sierra Way
2, 6, 202, 312	Cal-State San Bernardino
67, 81, 85, 87	Chaffey College
61, 82	Citrus & San Bernardino
8, 15	Colton & Orange St
8, 19	Crafton Hills
82 , 380	Cucamonga Metrolink
2, 3, 4, 202	E St & Highland
83, 85	Euclid & Arrow
83, 61, 87	Euclid & Holt
83, 87	Euclid & Mission
10, 66	Foothill & Citrus
66, 82	Foothill & Day Creek
66, 83	Foothill & Euclid
66, 81	Foothill & Haven
14, 312	Foothill & Linden
66, 82, 85	Foothill & Miliken
14, 22	Foothill & Riverside

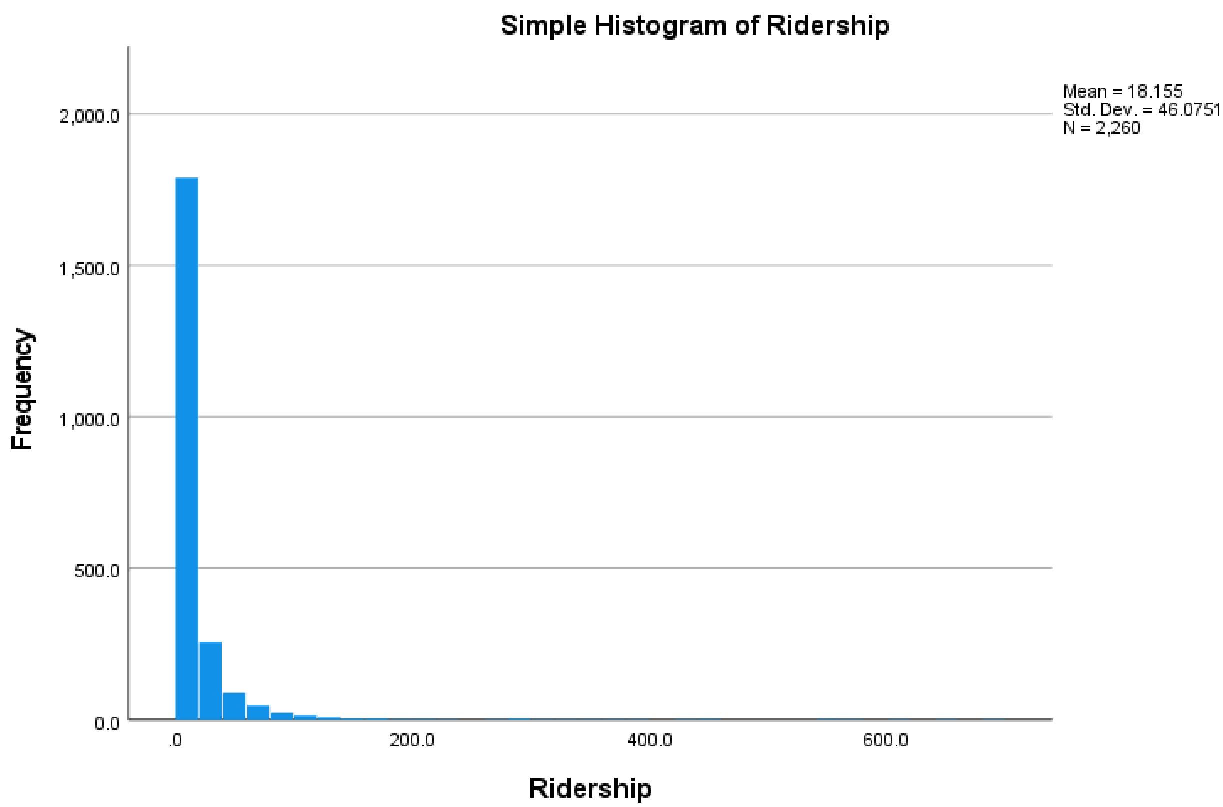
14, 67, 82	Foothill & Sierra
66, 87	Foothill & Vineyard
61, 380	Haven & Inland Empire
1, 3, 4	Highland & Del Rosa Ave
3, 4, 6	Highland & Golden
1, 3, 4	Highland & Victoria
3, 4, 312	Highland & Western
61, 85	Holt & Central
61, 84	Holt & Mountain
61,88	Holt & Ramona
67, 81, 87	Lemon & Haven/Alta Vista
10, 312	Linden & Baseline
19, 61	Marygold & Sierra
10, 3, 4	Medical Center & Baseline
15, 22	Merrill & Riverside
1, 15	Mill & Mt. Vernon
8, 305	Mill & Waterman
19, 215	Mt Vernon & Centerpointe
61, 380	Ontario Airport
61, 81, 82, 290	Ontario Mills
3, 4, 15	Palm & Baseline
8, 15	Redlands Depot
8, 9, 15	Redlands Mall
22, 312	Renaissance & Linden
22, 312	Riverside & Easton
19, 22	San Bernardino & Riverside
85, 88	San Jose & Monte Vista
10, 67, 82	Sierra & Baseline
2, 8, 202	Tippecanoe & Hospitality
1, 19	Valley & La Cadena
67, 82	Walnut & Sierra
19, 305	Washington Mohave & Washintgon Barton
1, 3, 4	Waterman & Baseline
2, 305	Waterman & Hospitality
19, 305	Waterman & Washington/Barton

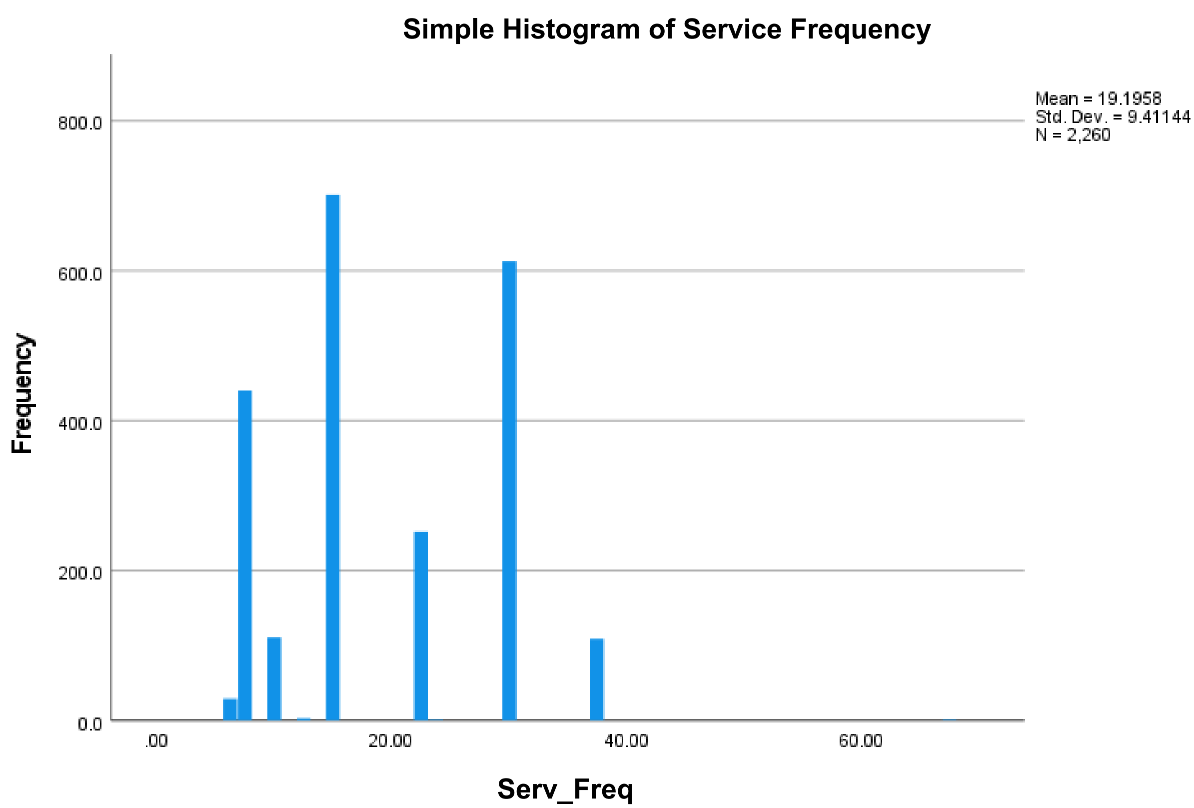
APPENDIX B: SPSS Outputs

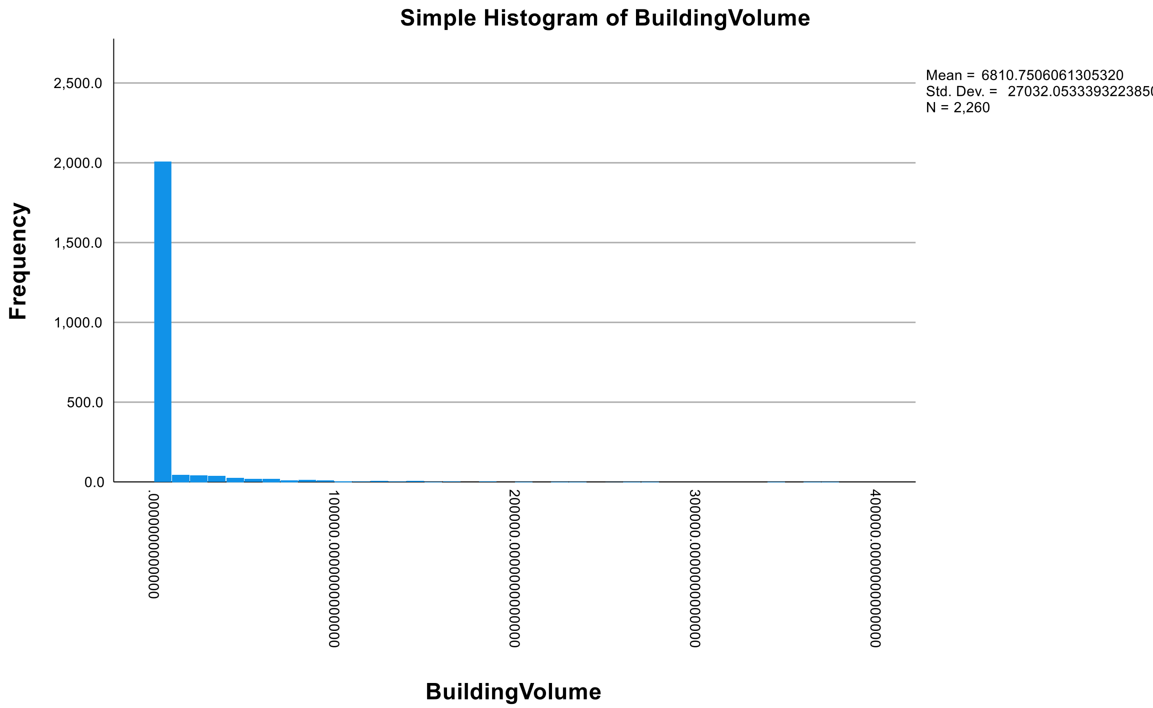
Descriptive Statistics & Multi-level Binary Logistic Regression

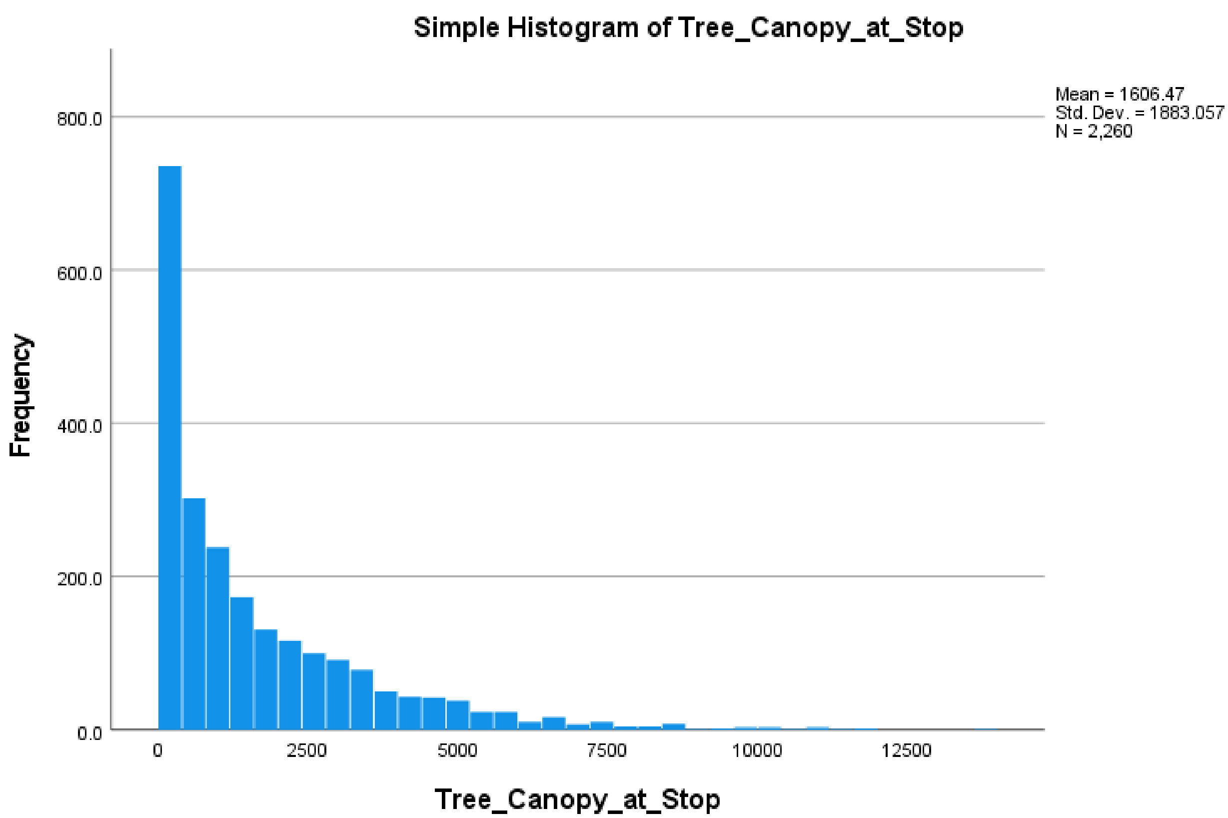
		Ridership	Serv_Freq	TransitCtr	TransferStop	Space_for Shelter	Building Volume	Tree_Can_at_Stop
Mean		18.155	19.1958	.02	.12	.48	6810.750	1606.47
Median		6.600	15.0000	.00	.00	.00	0	947.00
Std. Deviation		46.0751	9.41144	.135	.328	.500	9223.372	1883.057
Minimum		.0	6.25	0	0	0	0	0
Maximum		696.9	67.50	1	1	1	371882.1	13933
Sum		41029.8		42	276	1076		
Percentiles	25	2.600	10.0000				0	219.25
	50	6.600	15.0000				0	947.00
	75	16.575	30.0000				0	2395.00

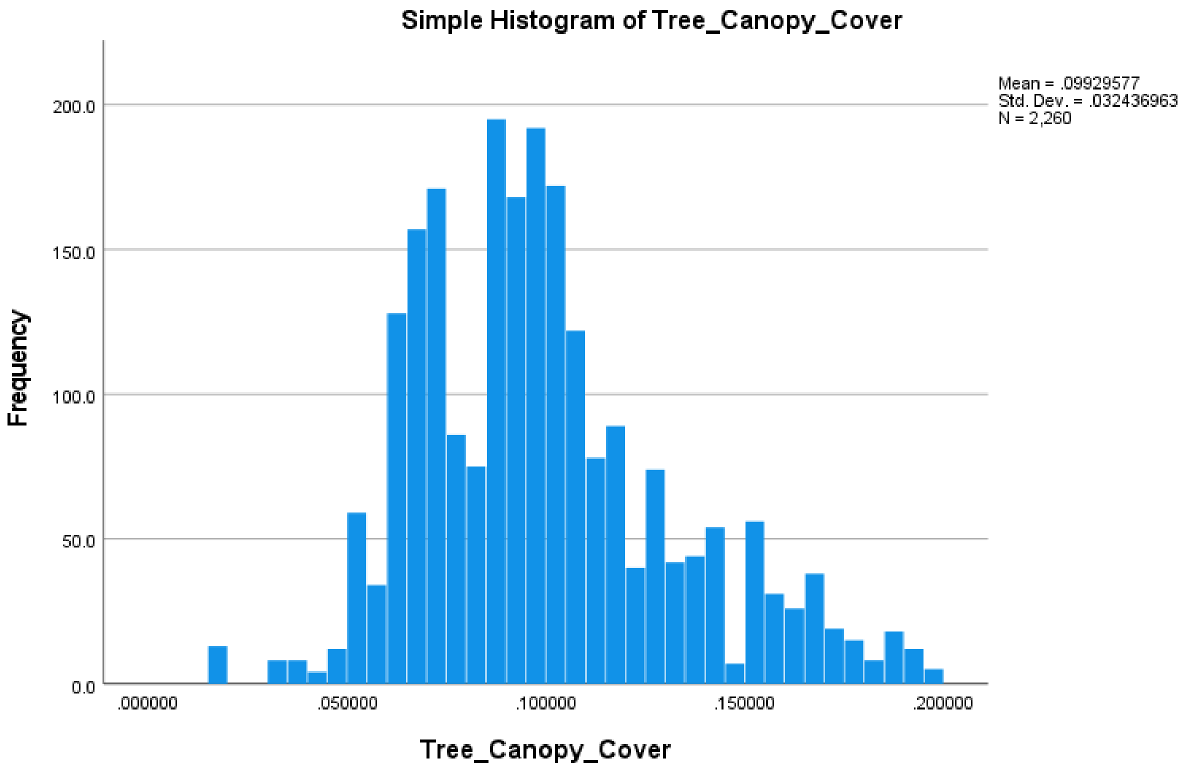
		Tree_Canopy_Cover	Youth_Under18	Senior_Over65	White_not_Hispanic	Below_Poverty_Level
Mean		.09929577	.24235661	.11338427	.17839158	.15268957
Median		.09555000	.24314000	.09773400	.15143400	.130308
Std. Deviation		.032436963	.055936221	.064996076	.131467294	.10081168
Minimum		.016600	.000000	.000000	.000000	.00200100
Maximum		.198700	.415800	.370977	.648085	.52061000
Sum						
Percentiles	25	.07290000	.21125425	.07500400	.080998	.087429
	50	.09555000	.24314000	.09773400	.151434	.130308
	75	.11560000	.28053900	.13214500	.240979	.194493

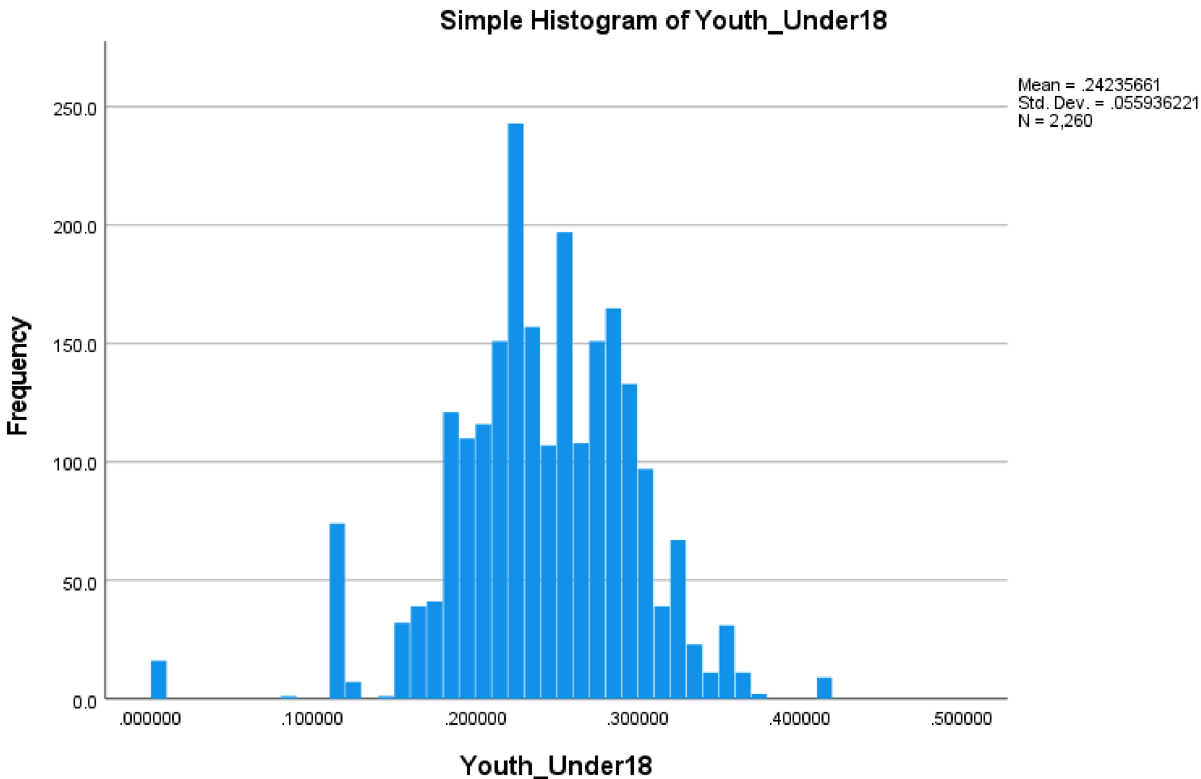

Simple Histogram of Ridership
Mean = 18.155
Std. Dev. = 46.0751
N = 2,260
2,000.0
1,500.0
1,000.0
500.0
0.0
Frequency
.0
200.0
400.0
600.0
Ridership


Simple Histogram of Service Frequency
Mean = 19.1958
Std. Dev. = 9.41144
N = 2,260
800.0
600.0
400.0
200.0
0.0
Frequency
.00
20.00
40.00
60.00
Serv_Freq

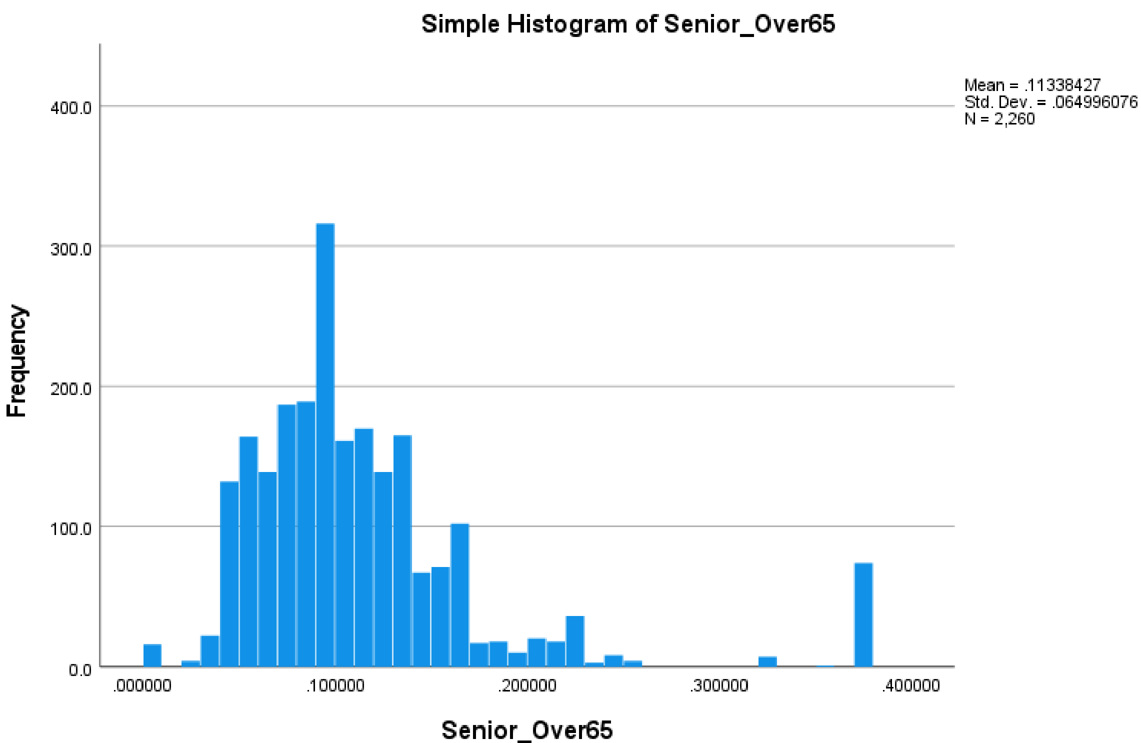

Simple Histogram of BuildingVolume
Mean = 6810.7506061305320
Std. Dev. = 27032.0533393223850
N = 2,260
Frequency
2,500.0
2,000.0
1,500.0
1,000.0
500.0
0.0
.000000000000
100000.000000000000
200000.000000000000
300000.000000000000
400000.000000000000
BuildingVolume


Simple Histogram of Tree_Canopy_at_Stop
Mean = 1606.47
Std. Dev. = 1883.057
N = 2,260
Frequency
800.0
600.0
400.0
200.0
0.0
0
2500
5000
7500
10000
12500
Tree_Canopy_at_Stop

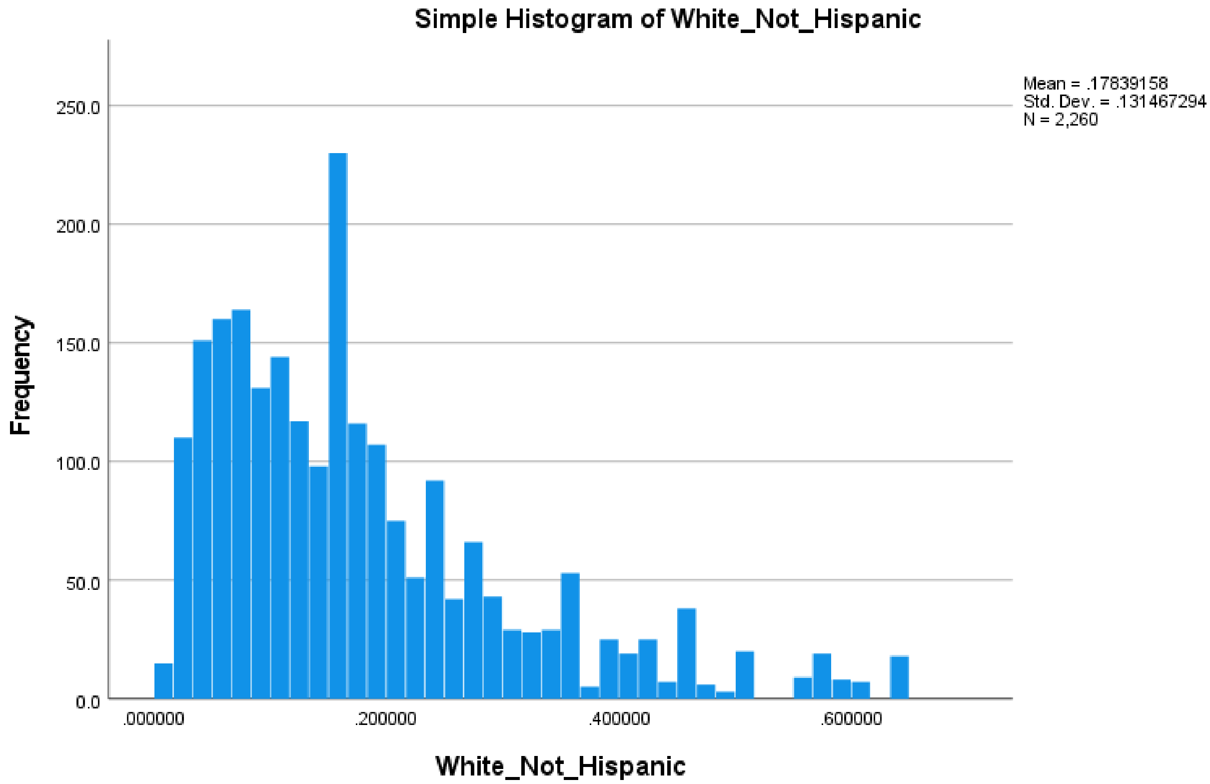

Simple Histogram of Tree_Canopy_Cover
Mean = .09929577
Std. Dev. = .032436963
N = 2,260
Frequency
200.0
150.0
100.0
50.0
0.0
.000000
.050000
.100000
.150000
.200000
Tree_Canopy_Cover

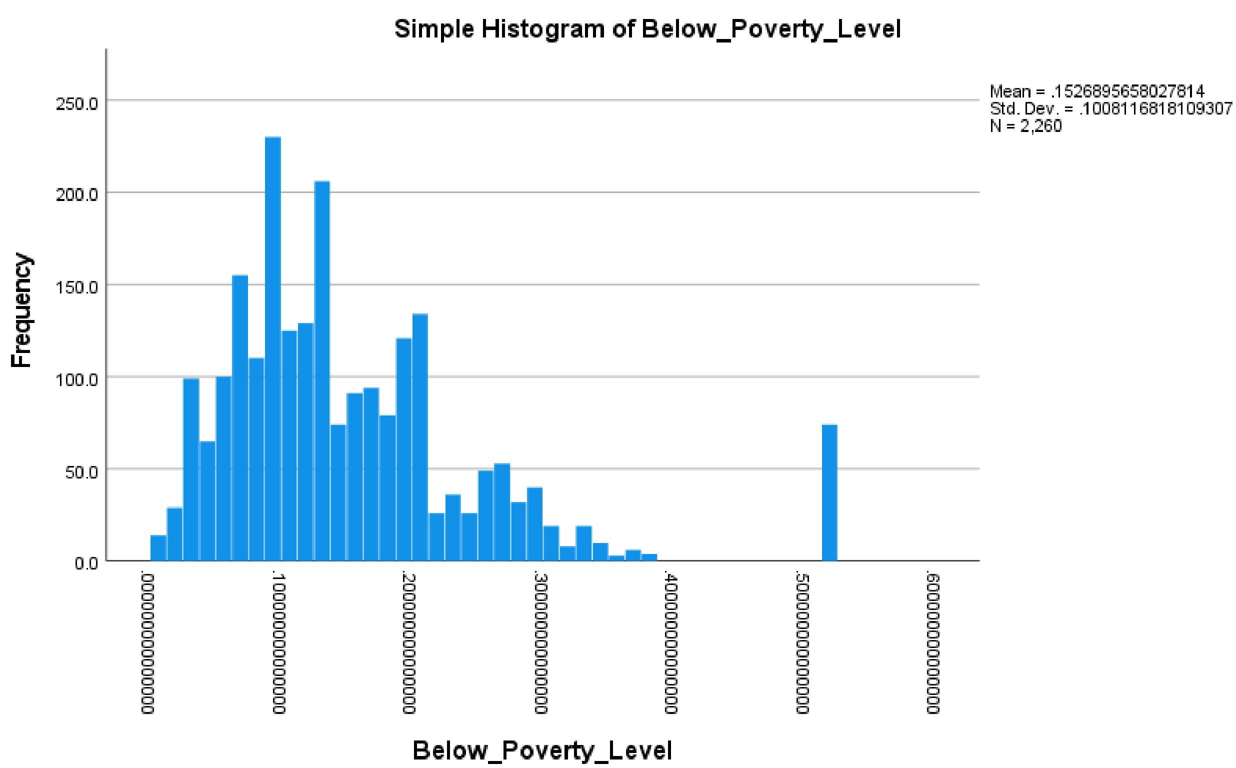


Simple Histogram of Youth_Under18
Mean = .24235661
Std. Dev. = .055936221
N = 2,260
Frequency
250.0
200.0
150.0
100.0
50.0
0.0
.000000
.100000
.200000
.300000
.400000
.500000
Youth_Under18



Simple Histogram of Senior_Over65
Mean = .11338427
Std. Dev. = .064996076
N = 2,260
Frequency
400.0
300.0
200.0
100.0
0.0
.000000
.100000
.200000
.300000
.400000
Senior_Over65


Simple Histogram of White_Not_Hispanic
Mean = .17839158
Std. Dev. = .131467294
N = 2,260
Frequency
250.0
200.0
150.0
100.0
50.0
0.0
.000000
.200000
.400000
.600000
White_Not_Hispanic


Simple Histogram of Below_Poverty_Level
Mean = .1526895658027814
Std. Dev. = .1008116818109307
N = 2,260
Frequency
250.0
200.0
150.0
100.0
50.0
0.0
.0000000000000
.1000000000000
.2000000000000
.3000000000000
.4000000000000
.5000000000000
.6000000000000
Below_Poverty_Level

Generalized Linear Mixed Models

Case Processing Summary

	N	Percent
Included	2260	100.0%
Excluded	0	0.0%
Total	2260	100.0%

Model Summary

Target		Shelter_0_1
Probability Distribution		Binomial
Link Function		Logit
Information Criterion	Akaike Corrected	1846.377
	Bayesian	1920.615

Information criteria are based on the -2 log likelihood (1820.215) and are used to compare models. Models with smaller information criterion values fit better.

Classification
Overall Percent Correct = 81.2%
a

		Predicted	
Observed		1	0
1	Count	234	341
	% within Observed	40.7%	59.3%
0	Count	83	1602
	% within Observed	4.9%	95.1%

a. Target: Shelter_0_1

Fixed Effects[a]

Source	F	df1	df2	Sig.
Corrected Model	23.853	12	2239	.000
Ridership	33.857	1	2239	<.001
Serv_Freq	3.026	1	2239	.082
TransitCenter	5.870	1	2239	.015
TransferStop	3.165	1	2239	.075
Space_for_Shelter	200.749	1	2239	.000
BuildingVolume	5.409	1	2239	.020
Tree_Canopy_at_Stop	1.939	1	2239	.164
Tree_Canopy_Cover	4.438	1	2239	.035
Youth_Under18	.893	1	2239	.345
Senior_Over65	.352	1	2239	.553
White_not_Hispanic	.007	1	2239	.934
Below_Poverty_Level	2.311	1	2239	.129

Probability distribution: Binomial
Link function: Logit
a

a. Target: Shelter_0_1

Fixed Coefficients[a]

Model Term	Coefficient	Std. Error	t	Sig.	95% Confidence Interval Lower	95% Confidence Interval Upper
Intercept	-2.591	.5558	-4.662	<.001	-3.681	-1.501
Ridership	.025	.0042	5.819	<.001	.016	.033
Serv_Freq	-.015	.0087	-1.740	.082	-.032	.002
TransitCenter=1	3.079	1.2707	2.423	.015	.587	5.571
TransitCenter=0	0[b]	.	.	.	.	.
TransferStop=1	.406	.2281	1.779	.075	-.041	.853
TransferStop=0	0[b]	.	.	.	.	.
Space_for_ Shelter=1	2.392	.1688	14.169	.000	2.061	2.723
Space_for_Shelter=0	0[b]	.	.	.	.	.
BuildingVolume	-8.461E-6	3.6380E-6	-2.326	.020	-1.560E-5	-1.327E-6
Tree_Canopy_at_Stop	5.419E-5	3.8918E-5	1.393	.164	-2.213E-5	.000
Tree_Canopy_Cover	-5.307	2.5194	-2.107	.035	-10.248	-.367
Youth_Under18	1.493	1.5795	.945	.345	-1.605	4.590
Senior_Over65	.904	1.5229	.593	.553	-2.083	3.890
White_not_Hispanic	-.056	.6723	-.083	.934	-1.374	1.263
Below_Poverty_Level	-1.388	.9129	-1.520	.129	-3.178	.402

Fixed Coefficients[a]

Model Term	Exp(Coefficient)	95% Confidence Interval for Exp(Coefficient)	
		Lower	Upper
Intercept	.075	.025	.223
Ridership	1.025	1.016	1.034
Serv_Freq	.985	.968	1.002
TransitCenter=1	21.731	1.798	262.589
TransitCenter=0	.	.	.
TransferStop=1	1.500	.959	2.347
TransferStop=0	.	.	.
Space_for_ Shelter=1	10.932	7.851	15.221
Space_for_Shelter=0	.	.	.
BuildingVolume	1.000	1.000	1.000
Tree_Canopy_at_Stop	1.000	1.000	1.000
Tree_Canopy_Cover	.005	3.543E-5	.693
Youth_Under18	4.449	.201	98.520
Senior_Over65	2.469	.125	48.919
White_not_Hispanic	.946	.253	3.535
Below_Poverty_Level	.250	.042	1.495

Probability distribution: Binomial
Link function: Logit
a. Target: Shelter_0_1
b. This coefficient is set to zero because it is redundant.

Covariance Parameters Summary

Covariance Parameters	Residual Effect	1
	Random Effects	0
Design Matrix Columns	Fixed Effects	16
	Random Effects	0[a]
Common Subjects		1

Common subjects are based on the subject specifications for the residual and random effects and are used to chunk the data for better performance.
a. This is the number of columns per common subject.

Residual Effect

Residual Effect	Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
					Lower	Upper
Variance	1.410	.000	.	.	1.410	1.410

Covariance Structure: Scaled Identity
Subject Specification: (None)