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Factors Affecting Driving Decisions and Vehicle Miles Traveled by Americans with Travel-Limiting Disabilities: Evidence from the 2022 National Household Travel Survey (NHTS) Data

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Abstract

Using the 2022 National Household Travel Survey data, this study explores the socioeconomic and demographic factors influencing vehicle miles traveled and driving decisions of Americans with travel-limiting disabilities. It employs descriptive statistics, independent sample *t*-tests, multiple linear regression, and logistic regression. The study finds a higher prevalence of travel-limiting disabilities in urban areas compared to rural areas, and the prevalence of travel-limiting disabilities increases with age. The study also finds evidence of statistically significant differences in the means of trip-related factors for Americans with travel-limiting disabilities across geographic locations with higher vehicle miles traveled, total trip miles, and number of vehicles in households in rural areas compared to urban areas. Across genders, males drive higher total trip miles and represent a higher proportion of drivers in households, while females have higher vehicle miles traveled. The study concludes that in rural areas, there are higher group means for trip-related variables, there are more females with travel-limiting disabilities, the higher the age, the higher the prevalence of travel-limiting disabilities, and age and number of drivers in the household are the two common significant predictors of vehicle miles traveled and driving decisions of Americans with travel-limiting disabilities.

Keywords: travel-limiting disabilities; National Household Travel Survey; driving decisions; vehicle miles traveled; logistic regression

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1. Introduction

Mobility and accessibility are two of the most important words in medical geography and agricultural geography because when the issue of food insecurity is discussed globally, particularly in the United States, the most common barrier is inequality in accessibility and not necessarily the unavailability of food. On the other hand, inequality in accessibility to healthcare facilities is also a big concern for people with disabilities. Access to transportation, either a personal vehicle, public transportation, paratransit, or rideshare, is particularly important for people with disabilities to access essential opportunities in their communities. People with disabilities are less mobile compared to people without disabilities because of the limited transportation options available to them [1–3]. Wasfi et al. [4] found significant challenges faced by people with disabilities in accessing transportation, particularly public transportation and paratransit. One of the notable consequences of the inequality in access to transportation between people with disabilities and people without disabilities is the longer travel times to healthcare facilities for the former, especially in rural areas [5].

Reichard et al. [6] affirm that there are concerns about inequality in mobility and accessibility for Americans living with disabilities. Giuliano and Hanson [7] found a positive correlation between mobility and access to job opportunities. For people living with disabilities, studies show that they are marginalized in access to job opportunities, and they experience unequal access to food and healthcare facilities and programs [8–11].

Access to opportunities is of great concern, and having access to a reliable source of transportation is very crucial [2]. However, there have been reports of inequalities in accessibility to school, jobs, food, and healthcare for people with disabilities [12–14]. Studies have also found barriers to access to paratransit systems and air transportation for this vulnerable population [15,16]. It has been reported that people with disabilities are usually physically less active than those without disabilities, although this improves their overall health [17,18]. Active travel improves physical activity, but people with disabilities, especially those with mobility-related disabilities, find this difficult [19]. Corran et al. [20] found evidence of declining levels of mobility and travel for people with disabilities in London, United Kingdom, while Eisenberg et al. [21] also found evidence of reduced active travel done by people with disabilities in the United States.

"Travel-limiting disabilities" is used throughout this study to describe any medical condition or disability that makes traveling difficult, either visible (physical disabilities) or invisible (cognitive or psychological disabilities). Ibukun and Alam [1] comparatively quantify travel-limiting disabilities across geographic locations (rural vs. urban) and genders (male vs. female) in the United States using the National Household Travel Survey (NHTS) data and found that the top two trip purposes of Americans with travel-limiting disabilities are made for shopping and medical/dental reasons. They also explore that during the COVID-19 fourth wave pandemic, people with travel-limiting disabilities made less use of public transit, with 70% and 61.9% reporting less use in rural areas and urban areas, respectively. Zhang et al. [3] found inequality in access to public transit and paratransit during the COVID-19 pandemic. Ibukun and Alam [1] also investigated the driving decisions of the same group and concluded that across geographic locations, Americans with travel-limiting disabilities drove more in rural areas compared to urban areas, and males with travel-limiting disabilities drove more compared to their female counterparts. While a lot has been done in the areas of mobility and accessibility of people with disabilities, as of now, no study has explored the driving characteristics, behavior, patterns, and factors influencing the driving decisions of people with travel-limiting disabilities. This study seeks to address this critical gap in previous studies about the factors affecting the vehicle miles traveled (VMT) of people with disabilities despite their mobility challenges. "Driving decision" in this study refers to the decision or choice that Americans with travel-limiting disabilities make either to drive or not to drive. Whilst previous studies have ascertained that people with disabilities mostly use paratransit and public transit to move from origin to their various destinations [1,19,22], not a lot has been done to abstract factors responsible for them deciding to drive or to opt for other travel modes. Although Deka [22] investigated the role of household members in transporting people with disabilities, this is the first study to explore the factors impacting the vehicle miles traveled (VMT) of Americans with travel-limiting disabilities and their decision to drive despite their disabilities.

The study explores the factors responsible for the mobility of Americans with travel-limiting disabilities, emphasizing VMT, total trip miles, and their decisions to either drive or not. It aims to analyze the socioeconomic and demographic characteristics of Americans with travel-limiting disabilities across geographic locations and genders, determine if there are significant differences in means of VMT, Trip Miles, and other selected trip-related variables across geographic locations and genders, investigate factors contributing to the VMT of Americans with travel-limiting disabilities, and determine the predictors influencing their decision to drive. The study aims to not only contribute to the existing body of work on the marginalization of people with disabilities in accessing opportunities, transportation, and healthcare, but it also explores a new perspective by focusing on Americans with travel-limiting disabilities. Exploring these mobility constraints for this population would be instrumental for equitable accessibility planning in the future. Previous studies have shed light on people with disabilities in general; this study differs as it focuses on only people with travel-limiting disabilities in the United States to investigate the factors that determine the amount of driving that Americans with travel-limiting disabilities engage in across geographic locations and genders. This is the first study to evaluate the driving characteristics of people with travel-limiting disabilities using the 2022 NHTS dataset. Understanding these intricacies could be important in data-driven policy formulation for this vulnerable population.

The vision of forward-looking transportation planning is not only technological sophistication but also the inclusiveness of every resident. There is a need to draw data-driven insights from the past and understand the present to predict the future. With the advent of autonomous vehicles gaining popularity, it becomes increasingly important to understand the transportation needs, barriers, and travel patterns of Americans with travel-limiting disabilities. This study aims to provide evidence-based insights from the 2022 NHTS dataset to understand the role socioeconomic and trip-related factors have played in travel behavior in the post-COVID-19 pandemic. This will help to ensure an all-inclusive accessibility planning that can culminate in future mobility equality.

2. Data and Methodology

2.1. Data

This study utilizes the NHTS modified version 2.0 dataset released in March 2024 that covers the 24 h travel history of the representative households of noninstitutionalized residents in the United States. The dataset consists of four files: household, person, trip, and vehicle. Each household is randomly selected, and electronic surveys are sent to obtain socioeconomic, demographic, and travel data. The household file contains variables peculiar to the 27,290 households surveyed, including their socioeconomic status. The person file contains socioeconomic and demographic information about each member of the household aged five and above. The trip file houses details about trips, including trip purpose and other trip-related variables. The vehicle file contains detailed information about the modes of travel. For the sample to be representative of the entire U.S. population, the data were weighted using the 7-day national household weight to give a total population size of 290,183,796. Purposive sampling was implemented to extract databases for people with travel-limiting disabilities and those without travel-limiting disabilities. The study merged the person and trip files using primary keys named HOUSEID and PERSONID to create a single database containing 176 trip and person variables. From this database, the researchers extracted two new databases: one for Americans with travel-limiting disabilities and the other for those without travel-limiting disabilities. The total sample size for people with and without travel-limiting disabilities was 18,647,931 and 271,535,865, respectively. From the NHTS dataset, travel-limiting disability data is obtained from the answers of respondents to the question "Do you have any condition or disability that makes traveling difficult?" Those who respond "yes" represent those with travel-limiting disabilities, and their respective socioeconomic and trip-related variables are merged into a single database. On the other hand, those who respond "no" to the question are also put into another database, alongside their socioeconomic and trip-related variables. Although the 2022 NHTS user guide suggests that a survey is considered complete when all respondents answer the required questions and not more than 20% of non-required questions are missing for every household member, this study adopted Multiple Imputation (MI) in Python using the scikit-learn package to manage missing numerical data to reduce bias.

2.2. Methodology

Both descriptive and analytical approaches are used in this study. Descriptive statistics were used to describe selected socioeconomic, demographic, and trip variables for Americans with travel-limiting disabilities across genders and geographic locations. *t*-tests were employed to compare selected numerical trip variables across genders and geographic locations. Multivariate regression analysis was employed to identify factors determining VMT for Americans with travel-limiting disabilities. Logistic regression analysis was employed to model predictors influencing the choice of Americans with travel-limiting disabilities, whether to drive or not.

2.2.1. Descriptive Statistics

Descriptive statistics like percentages are used to describe the selected socioeconomic and demographic variables, such as age, race, education, and household income. Percentages are also used to explore trip purposes and travel behavior during the fourth wave of the COVID-19 pandemic. Bar charts were used to describe the distribution of travel-limiting disabilities and driving decisions by geographic locations and genders. Pie charts are utilized to describe the length of time Americans with travel-limiting disabilities have had the condition. The descriptive analysis was done for Americans with travel-limiting disabilities across geographic locations and genders using SPSS version 29, Python version 3.13.7, and R statistical packages.

2.2.2. Independent Samples *t*-Test

Independent samples *t*-test, which is also known as Student's *t*-test, is a test statistic that is used to check if the difference between two groups is statistically significant. It compares the means of two independent groups [23]. It is computed using Equation (1).

$$\mathrm{t} = \frac{\overline{x}_1 - \overline{x}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{1}$$

where $\overline{x}_1$ is the sample mean of the first group, $\overline{x}_2$ is the sample mean of the second group, s_1^2 is the variance of the first group, s_2^2 is the variance of the second group, and n_1 and n_2 are the sample sizes of the first and second groups, respectively.

The study employs independent samples *t*-tests to compare the mean differences for selected trip-related variables like total trip miles, VMT, and number of drivers in households between Americans with and without travel-limiting disabilities. It also adopts independent sample *t*-tests to check if the differences between the means of these trip-related variables for Americans with travel-limiting disabilities between rural and urban areas and between males and females are significant.

2.2.3. Regression Analysis

Multiple Linear Regression

Linear regression models the linear relationship between a dependent variable and one or more predictor variables. When there is a singular predictor and a dependent variable, it is called simple linear regression, but when there are multiple independent variables, it is referred to as multiple linear regression. According to Seal [24], the concept of multiple linear regression was developed by Gauss in 1795. The relationships between the dependent variable and the predictors are modeled via a linear function of the independent variables, where the model parameters are estimated from the sample data (Equation (2)).

$$y_i = \beta_0 + x_1\beta_1 + x_2\beta_2 + x_3\beta_3 + \ldots + x_i\beta_i + \varepsilon_i \tag{2}$$

where y_i is the dependent variable, $x_1, x_2, x_3, \ldots, x_i$ are the independent variables, β_0 is the intercept, $\beta_1 \ldots \beta_i$ are the regression coefficients or slopes, and ε_i is the error term.

The study uses multiple linear regression analysis to model the relationship between VMT for noninstitutionalized Americans with travel-limiting disabilities and selected predictors. Before modeling, all the assumptions of ordinary least squares were tested: Q-Q plots were used to check for normality of residuals, multicollinearity was assessed using the variance inflation factor (VIF) with a threshold value less than 5, and Breusch-pagan tests were employed to check for homoskedasticity. The independent variables included in the model are urban, medium income (\$25,000–\$51,000), high education (Bachelor's and graduate degree), high income (More than \$51,000), medium education level (high school and associate degree), age, household size, and number of drivers in households. The natural logarithm of VMT was taken and used as the dependent variable in the model. The multiple linear regression model adopted in this study can be expressed mathematically as shown by Equation (3).

$$\begin{aligned} \ln(y_i) = \ln(\text{VMT}) = \beta_0 + \beta_1 \text{ urban} + x_2\beta_2 + \text{medium income} + \beta_3 \text{ high education} + \beta_4 \text{ high income} \\ + \beta_5 mediumeducation + \beta_6 age + \beta_7 householdsize + \beta_8 number of driversinhousehold + \varepsilon_i \end{aligned} \tag{3}$$

Logistic Regression

Logistic regression is used to model the relationship between a dependent variable that has a binary response and several independent variables [25]. The dependent variable is usually represented with dummy variables, dividing the group into two: 1 if it belongs to the first group, and 0 if otherwise. The coefficient of the model measures how much one group differs from the other. Logistic regression is represented mathematically with the log-odds as shown in Equation (4).

$$\text{logit (p)} = log\frac{P}{1-P} = \beta_0 + x_1\beta_1 + x_2\beta_2 + x_3\beta_3 + \ldots + x_i\beta_i + \epsilon_i \tag{4}$$

where p is the probability of the event occurring, $\frac{P}{1-P}$ is the odds of the event happening, β_0 is the intercept, $\beta_1 \ldots \beta_\mathrm{i}$ are the coefficient estimates of the predictors $x_1 \ldots x_\mathrm{i}$.

The probabilistic function of the log-odd is given by Equation (5).

$$\text{p} = \frac{1}{1 + b^{-(\beta_0 + x_1\beta_1 + x_2\beta_2 + x_3\beta_3 + \ldots + x_i\beta_i)}} \tag{5}$$

This probabilistic function converts the log odds into a probability that varies between 0 and 1 of the events happening.

Logistic regression is adopted to model the factors that influence the dependent variable, the driving decisions of the Americans with travel-limiting disabilities, and a set of selected predictors. The binary dependent variable is 1 if the people with travel-limiting disabilities drive and 0 if they do not. The binary dependent variable (driving decision) is obtained by extracting the travel mode of Americans with travel-limiting disabilities. Those who drive primarily are represented as 1, and those who use other modes of transit are categorized as 0. The independent variables included in the model are male, number of people on the trip, number of workers in households, medium income ($25,000-$51,000), age, high income (more than $51,000), number of drivers in households, and number of household members older than 18 years.

3. Results and Discussion

3.1. Descriptive Statistics of Travel-Limiting Disabilities in the United States

Overall, there are more females with travel-limiting disabilities compared to males, as shown in Figure 1. Also, there are more Americans with travel-limiting disabilities in urban areas, with eight out of every ten people belonging to this group compared to two out of every ten residing in rural areas. Figure 2 explores that out of the 18 million Americans with travel-limiting disabilities, 73.4% reported having been living with the disability for more than six months, 7.5% have been living with this condition for six months or less, while 19.1% reported living with the disability their entire life.

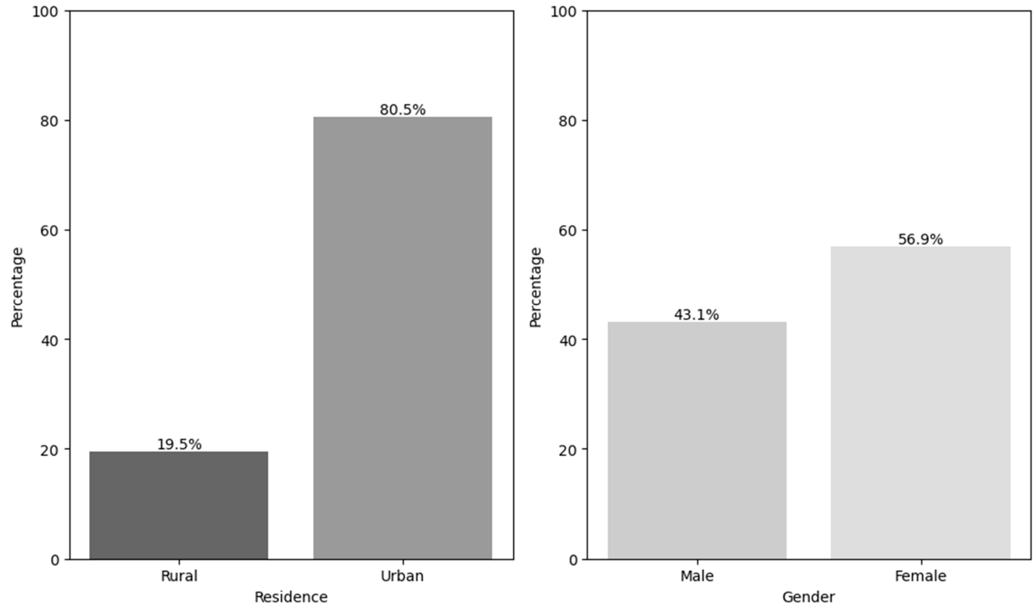

Figure 1. Travel-Limiting Disabilities by Geographical Locations and Genders.

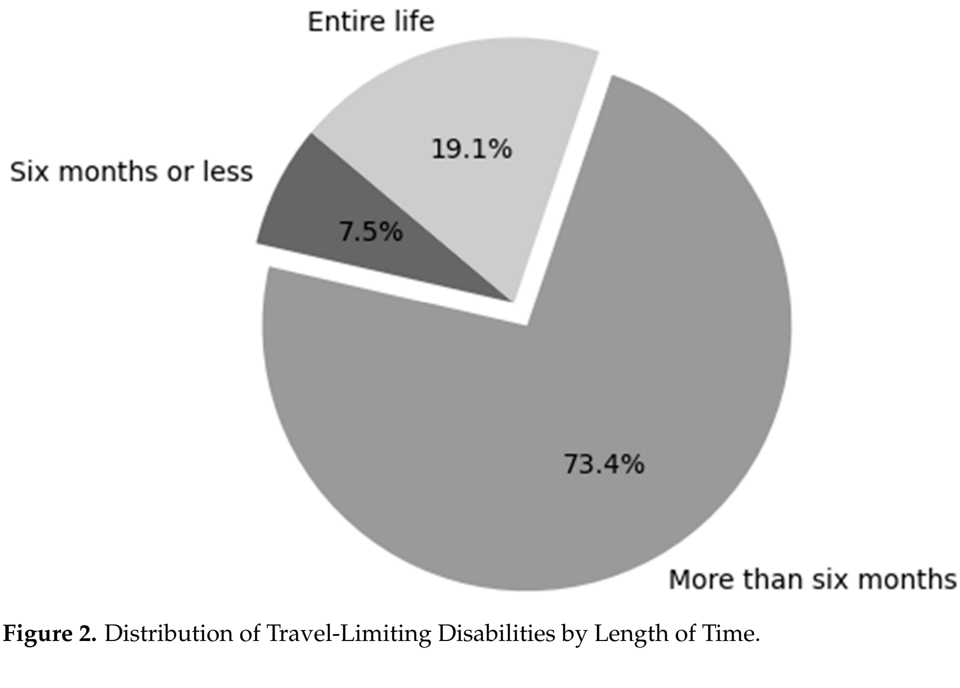

Figure 2. Distribution of Travel-Limiting Disabilities by Length of Time.

Table 1 explores the socioeconomic and demographic variables of Americans with travel-limiting disabilities across geographic locations and genders. It can be inferred that the older an individual gets, the higher the prevalence of travel-limiting disabilities, with a higher prevalence in urban areas across all age groups except for those 65 and above, for which there is a higher prevalence in rural areas. Across geographic locations, there is a higher prevalence of travel-limiting disabilities in urban areas in age groups 1–15 years and 16–64 years, with 4.8% and 56.9%, respectively, compared to 2.4% and 44.7% prevalence rates in these groups in rural areas. Across genders, travel-limiting disabilities are highest in the age group 16–64 years, with 57.6% and 52.2% for both males and females, respectively. The rates significantly drop in the age group 65 and above, with 36.2% and 44.8%, respectively.

Table 1. Distribution of Socioeconomic and Demographic Characteristics of Americans with Travel-Limiting Disabilities by Geographical Locations and Genders.

Socio-Demographic Variables		**Americans with Travel-Limiting Disabilities**			
		Rural (%)	**Urban (%)**	**Male (%)**	**Female (%)**
Age (years)	1–15	2.4	4.8	6.1	3.0
	16–64	44.7	56.9	57.6	52.2
	65 and above	53.0	38.3	36.2	44.8
Education level	Less than high school	9.1	9.8	10.0	9.4
	Some high school, no diploma/GED	11.6	11.1	10.4	11.8
	High school graduate	32.1	33.2	36.0	30.8
	Some college, no degree/some trade school	25.3	19.3	18.4	22.0
	Associate degree (2-year)/trade school certificate	10.9	9.0	7.7	10.6
	Bachelor's degree	6.7	9.5	9.1	8.7
	Master's degree	2.8	5.9	5.7	5.0
	Professional/Doctorate degree	1.5	2.3	2.7	1.6
Race	White	86.9	72.1	74.6	75.2
	Black or African American	6.2	12.5	8.5	13.4
	Asian	0.0	3.2	2.9	2.3
	American Indian/Alaska Native	0.8	2.6	3.4	1.3
	Native Hawaiian/Pacific Islander	0.0	0.6	0.3	0.7
	Multiple races selected	1.1	0.0	0.0	0.4
	Other race	5.0	9.1	10.3	6.7
Household Income ($)	Less than 10,000	5.0	9.6	9.6	5.0
	10,000–14,999	7.7	9.6	9.6	7.7
	15,000–24,999	18.1	12.4	12.4	18.1
	25,000–34,999	10.1	10.8	10.8	10.1
	35,000–49,999	12.5	9.8	9.8	12.5
	50,000–74,999	19.6	17.0	17.0	19.6
	75,000–99,999	11.9	9.8	9.8	11.9
	100,000–124,999	3.6	6.0	6.0	3.6
	125,000–149,999	4.4	5.6	5.6	4.4
	150,000–199,999	4.4	5.2	5.2	4.4
	200,000 or more	2.6	4.2	4.2	2.6

It can also be deduced from Table 1 that Americans with lower education levels (high school and GED) have higher travel-limiting disabilities prevalence across geographic locations and genders, with high school graduates having the highest prevalence across the board. Across geographical locations, overall, the total household income of Americans with travel-limiting disabilities is less than their counterparts in urban areas. In rural areas, 15% of the people with travel-limiting disabilities have an annual household income of $100,000 or more, compared to 21% in urban areas. A similar proportion of the population has an annual total income of less than $25,000, with 30.6% and 31.6% in rural and urban areas, respectively. White people have the highest travel-limiting disabilities across geographic locations and genders, followed by Black people. The prevalence of disabilities decreases drastically when the annual total household income crosses the cohort of $50,000–$74,999.

Figure 3 shows driving decisions of the Americans with travel-limiting disabilities across geographic locations and genders. It can be claimed that a higher proportion of people with travel-limiting disabilities drive in rural areas (68.1%) compared to urban areas (60.2%). This could be attributed to better public transportation and paratransit services in urban areas compared to rural areas. The same trend is observable across genders, with six out of every 10 females with travel-limiting disabilities opting to drive compared to 6.4 out of every 10 males.

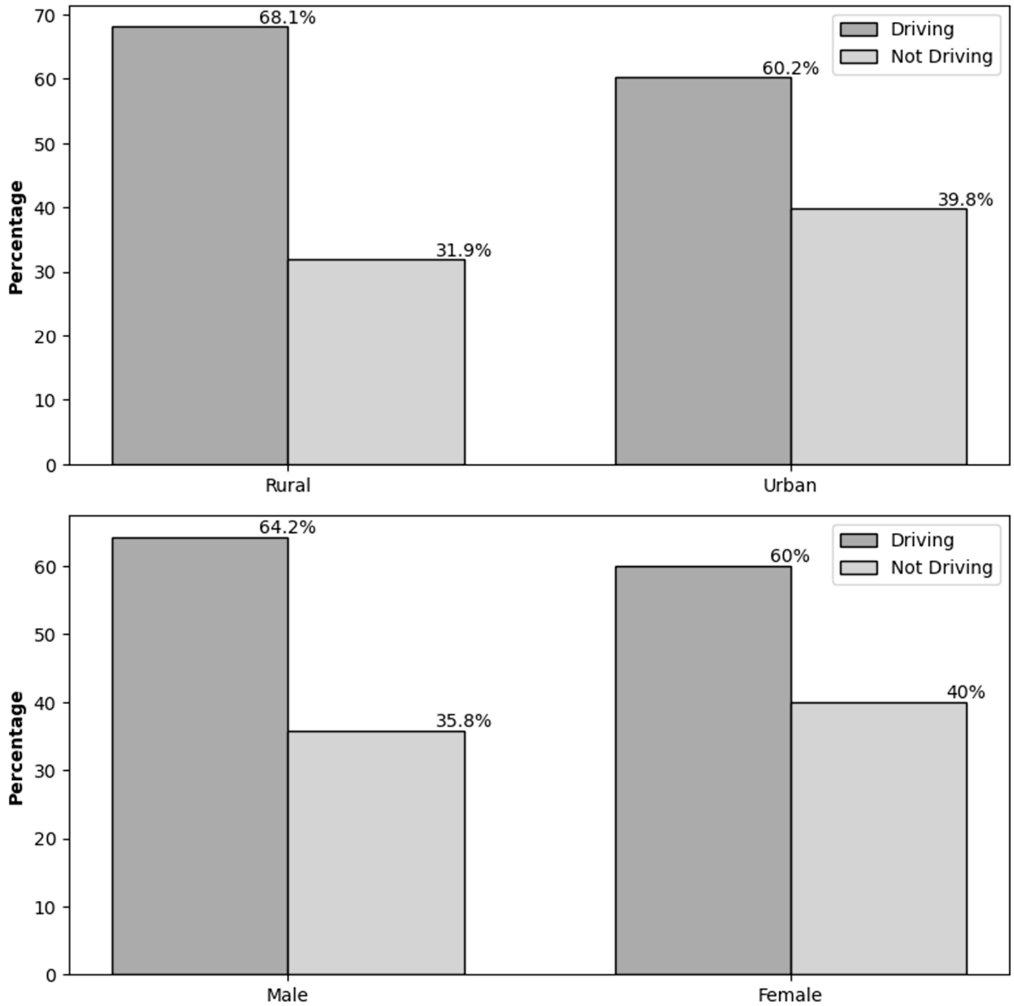

Figure 3. Description of Driving Decisions of Americans with Travel-Limiting Disabilities by Geographic Locations and Genders.

3.2. *t-Test Result of Mean Differences In Travel-Related Variables*

The study compares trip-related variables among people with travel-limiting disabilities and those without such disabilities. The same variables were also compared across geographical locations and genders for the people with travel-limiting disabilities. The selected variables are VMT, total miles traveled, and the number of drivers in households. The variables' normality was verified using Q-Q plot and Kolmogorov–Smirnov test.

The result shows that the mean daily VMT for the group with travel-limiting disabilities is 3.279 miles, while that for those without travel-limiting disabilities is 9.396, during the 24 h survey period, which could be a weekday or a weekend, which is indicative of the gap in travel behavior across the two groups. This is expected because people with travel-limiting disabilities rely more on public transit and share rides when compared with people without disabilities. This reduced VMT exhibited by people with travel-limiting disabilities corroborates the findings of Deka [22] and Wasfi et al. [4], which document reduced mobility among people with disabilities. Another explanation for this is that the average number of vehicles in households for Americans without travel-limiting disabilities is higher than that of households with travel-limiting disabilities, as indicated in the independent *t*-test for the number of drivers in households (DRVRCNT). With a *p*-value of 0.001, one can conclude that there is a statistically significant difference between the VMTs of the two groups.

The same conclusion can be made when total miles traveled for the day (TRIP_MILES) are compared between the two groups. Total trip miles traveled consists of both miles driven plus the number of miles traveled using other modes of transportation within the 24 h survey window. The result from the independent sample *t*-test indicates that the mean of the total trip miles traveled for people without travel-limiting disabilities is 6.369 miles more (15.277) than that of people with travel-limiting disabilities (8.908), with a standard deviation of 37.890 and a *t*-test Cohen's d of 0.164, which has a small effect. This is because the top two trip purposes for people with travel-limiting disabilities are shopping and medical visits, and they rarely travel for recreational purposes. This is supportive of the findings of Zhang et al. [3], who found that most of the trips made by people with disabilities are health-related and only a small proportion of their trips are made for recreational purposes (1.2%). Cohen's d statistic is closer to the threshold value of 0.2 for small effects. It implies for this study that although there is a significant difference in total trip miles traveled between the people with and without travel-limiting disabilities, the significance of this difference is small. For Americans without travel-limiting disabilities, a substantial proportion of their trips is made for work, shopping, and recreational purposes [1]. The *p*-value (0.002) is also less than the chosen alpha level of 0.05, and as such, one can conclude that there is a statistically significant difference between the total trip miles traveled by the two groups.

For the number of drivers in households (DRVRCNT) for the Americans with travel-limiting disabilities compared to those without travel-limiting disabilities, the *t*-test indicates that the average number of drivers in households for Americans with travel-limiting disabilities is 1.65 with a standard deviation of 1.048, compared to 2.13 with a standard deviation of 0.935 for those without travel-limiting disabilities. The low *p*-value (0.001) indicates that there is a statistically significant difference between the number of drivers in households among the two groups. Cohen's d for the number of drivers in households is 0.935, which means that the effect size is large.

After the study establishes that there are significant differences in VMT, TRIP_MILES, and DRVRCNT between Americans with and without travel-limiting disabilities, it also investigates if these significant differences are maintained across geographic locations (rural areas vs. urban areas) and genders (males vs. females) for Americans with travel-limiting disabilities. The study compares the trip-related variables for Americans with travel-limiting disabilities in rural areas with those with travel-limiting disabilities in urban areas.

The result from the *t*-test shows that the average daily VMT for people with travel-limiting disabilities in rural areas is 6.644 miles, while that of the people with travel-limiting disabilities in urban areas is 2.861 miles with standard deviations of 11.863 and 19.450, respectively, which implies that people with travel-limiting disabilities in rural areas drive approximately four miles more than their counterparts in urban areas. Urban areas are typically less spatially segregated and more compact compared to rural areas, and as such, this result is not surprising. Also, urban destinations are closer to their origins compared to rural areas. This may indicate that the distance to the destination is less of a deterrent to driving than dealing with congestion. The low *p*-value (0.003) indicates that there is a statistically significant difference between the VMTs for people with travel-limiting disabilities in rural areas and people with travel-limiting disabilities in urban areas. The Cohen's d statistic of the *t*-test is 0.206, implying that the effect size is small.

The study explores the variability in VMT as well among males and females with travel-limiting disabilities. When compared across genders, the *t*-test reveals that among people with travel-limiting disabilities, women drive more miles than men, with group means of 3.678 and 3.266 miles, respectively. These findings diverge from the usual general pattern of men driving more than women [26–28], which indicates different observable dynamics across genders for people with travel-limiting disabilities. The standard deviations of the independent sample *t*-test were 23.676 and 8.234, respectively, with Cohen's d statistic of 0.022 indicating a small sample effect. The *p*-value of 0.001 indicates that there is a statistically significant difference between the VMTs of men and women with travel-limiting disabilities.

After establishing that Americans with travel-limiting disabilities have statistically significant differences in the VMTs across genders and geographic locations, the study investigates whether this difference exists between the total trip miles across genders and locations. *t*-test results show that people with travel-limiting disabilities in rural areas travel 19.781 miles on average, while their counterparts in urban areas travel only 7.011 miles on average, with standard deviations of 25.690 and 21.341, respectively, with a *p*-value of 0.002 and a Cohen's d value of 0.577. It can be implied that there is a statistically significant difference in total trip miles for people with travel-limiting disabilities across geographic locations with a medium effect size. This difference in total miles traveled can be attributed to the close proximities between origins and opportunities in urban areas compared to the spatially segregated rural areas.

There is also a statistically significant difference ($p < 0.05$) in total trip miles for people with travel-limiting disabilities across genders, with men having a group mean of 10.392 miles compared to women having a group mean of 8.147 miles, with standard deviation values of 19.574 and 24.789, respectively. A Cohen's d value of 0.099 implies that the independent sample effect is small.

However, while comparing the number of drivers in households for the Americans with travel-limiting disabilities in rural areas versus urban areas, the *t*-test shows that the group mean in rural areas is 1.92, which is higher than 1.56 in urban areas with standard deviations of 0.954 and 1.051, respectively. The low *p*-value (0.001) with Cohen's d value of 0.347 indicates that the independent sample effect size is small. However, when the same variable is compared among men and women with travel-limiting disabilities, results indicate that the men have a group mean of 1.68 with a standard deviation of 1.083, while the women have a group mean of 1.60 with a standard deviation of 1.011. This difference is statistically significant ($p< 0.05$, $t = 168.678$) with a Cohen's d value of 0.081, indicating a small effect size.

3.3. Multiple Linear Regression of Factors Determining Vehicle Miles Traveled of Americans with Travel-Limiting Disabilities

To comprehend the mobility of Americans with travel-limiting disabilities as it relates to their travel and driving patterns, this study explores the factors predicting VMT using multiple linear regression analysis. The study starts by checking for outliers using the boxplots, and the only observation that was three standard deviations or more away from the mean in the dependent variable (VMT) was removed. Subsequently, the researchers also checked for normality by employing a Q-Q plot, a Histogram, and the Shapiro–Wilk test. None of the Q-Q plots and histograms indicates perfect normality. As such, we took the natural logarithm of VMT, and the result of the Shapiro–Wilk test indicated normality as the p-value is greater than 0.05.

Table 2 presents the results of the multiple linear regression of the determinants of VMT for Americans with travel-limiting disabilities. It can be inferred from the results that out of the seven predictors, three (urban, age, and number of drivers in households) show a statistically significant impact on VMT. When compared to their counterparts in rural areas, people with travel-limiting disabilities in households in urban areas are associated with 44.8% lower VMT. This could be because there is more spatial segregation in rural areas and more access to public transit in urban areas. The results also indicate that for every additional one-year increase in the age of the population, there is a 1.09 percent reduction in VMT. The implication of this is that older individuals with travel-limiting disabilities drive slightly less. This aligns with the findings of Deka [22], who ascertained that older people with disabilities often share rides with other members of the household who drive.

Table 2. Regression Results of the Determinants of Vehicle Miles Traveled.

Predictor	Estimate	Std Error	t-Value	Pr(>|t|)	VIF
Intercept	2.834970	0.453958	6.245	1.90×10^{-9} ***	
Urban (baseline rural)	−0.806282	0.179634	−4.488	1.11×10^{-5} ***	1.082277
Medium Income (baseline Low Income)	−0.031053	0.222672	−0.139	0.8892	1.642891
High Income (baseline Low Income)	0.336773	0.196451	1.714	0.0878	1.795676
Low Education (baseline High Education)	−0.947892	0.701491	−1.351	0.1779	1.099517
Medium Education (baseline High Education)	0.051379	0.166112	0.309	0.7574	1.157884
Age	−0.010958	0.005106	−2.146	0.0329 **	1.092516
Number of Drivers in Household	−0.193185	0.096347	−2.005	0.0461 **	1.121420
R^2	11.07				
F-statistic	4.287				

Note: *** Significant at 99% confidence level; ** Significant at 95% confidence level.

Each additional driver in the household results in a decrease in VMT. This also buttresses the findings of Ibukun and Alam [1] about shared driving in households with people with travel-limiting disabilities, reducing the burden of driving. It can be deduced from the regression results that there are no meaningful differences in the VMT of the people with travel-limiting disabilities who have low annual household income (less than $25,000) and medium annual household income ($25,000–$51,000). However, there is a marginally significant difference (p-value 0.088) between the VMT of people with travel-limiting disabilities with high annual household income compared to those with low annual household income, with those residents in households with high annual income driving about 40% higher VMT.

Finally, low education level correlates to lower VMT when compared to those with higher education levels, and there is little to no difference in VMT of the people with travel-limiting disabilities with medium education and higher education levels. Although the education level attained by the people with travel-limiting disabilities may be instrumental in giving insights into their travel patterns, the relationship is weak and not statistically significant. A VIF of less than 5 indicates no presence of multicollinearity among the predictor variables included in the regression model.

3.4. Logistic Regression of Factors Affecting Driving Decisions of Americans with Travel-Limiting Disabilities

Ibukun and Alam [1] explored that the Americans with travel-limiting disabilities drive mostly for medical/dental and grocery/shopping purposes. This study aims to determine the factors that influence their driving decisions using a logistic regression model. The dependent variable is driving decisions, the value of which is 1 for Americans with travel-limiting disabilities who drive and 0 for those who do not drive. The selected predictors were subjected to logistic regression, and the result is shown in Table 3. With a McFadden pseudo R-squared value of 49.5%, this model shows strong explanatory power in explaining the driving decisions of the people with travel-limiting disabilities.

Table 3. Determinants of Driving Decisions of Americans with Travel-Limiting Disabilities.

Predictor	Estimate	Std Error	z-Value	Pr(>|z|)	Odds Ratio	VIF
Intercept	−0.185949	0.730499	−0.255	0.7991		
Male (baseline Female)	−0.491749	0.324008	−1.518	0.1291	0.61155601	1.035054
Number of people on the trip	−0.804219	0.171281	−4.695	2.66×10^{-6} ***	0.44743727	1.122658
Count of workers in the household	−0.421381	0.247711	−1.701	0.0889	0.65613993	1.652877
Medium Income (baseline Low Income)	0.471860	0.483560	0.976	0.3292	1.60297355	1.649843
High Income (baseline Low Income)	−0.309018	0.430723	−0.717	0.4731	0.73416771	1.827912
Age	0.041089	0.008874	4.630	3.65×10^{-6} ***	1.04194451	1.443769
Number of Drivers in Household	4.010761	0.401400	9.992	2×10^{-16} ***	55.18886853	3.317787
Count of adult household members at least 18 years old	−2.434275	0.349097	−6.973	3.10×10^{-12} ***	0.08766124	2.690539
Pseudo R^2	0.4948764					
AIC	279.08					

Note: *** Significant at 99% confidence level.

The study implemented a backward induction logit model, and the final model selected had the lowest Akaike information criterion (AIC) of 279.08. This means that this model has the best fit among the different models explored in the backward induction. Out of all the predictors included in the model, four are found to have statistically significant effects on the dependent variable, driving decision. The significant predictors are the number of people on the trip, respondent age, number of drivers in the household, and the count of adult household members at least 18 years old. It can be deduced that for each additional person on a trip, the log odds of driving reduce by 0.80, with the odds of the outcome increasing by approximately 0.45 times when other variables are constant.

For every year increase in age, the odds of driving increase by 4.2%. As traveling for people with disabilities is more focused on midday activities and traffic congestion is comparatively low during these times, it makes sense that older people, including those with disabilities, can drive as they get older, specifically to get medical care. Also, as people get older, there is increased independence and income, which may result in improved access to vehicles. Furthermore, they also have fewer alternatives, especially in rural areas, as rural transit options tend to be comparatively sparse.

As the number of household members at least 18 years old increases by one person, the odds of driving for people with travel-limiting disabilities decrease by approximately 91%. This decrease in the odds of driving for individuals with travel-limiting disabilities could highlight shared responsibilities in households with more adults in the household. The household members with travel-limiting disability are the passengers on trips. This agrees with the findings of Deka [22]. Also, for each additional person on the trip, the odds of the respondent with travel-limiting disability being the driver on the trip drop by 55%. This might be attributable to the fact that a larger group of travelers may opt for ridesharing and public transit, or someone else drives when they carpool. Like the findings of Deka [22] that people with disabilities made trips as passengers when there were other drivers in the households, and every additional increase in household members increases the probability of giving rides to people with travel-limiting disabilities by 2.3%, the results of this study reaffirm the reliance of people with travel-limiting disabilities on other household members without disabilities for mobility. There is a marginal significance in the relationship between the count of workers in a household and the driving decision (p-value 0.0889), which suggests that as the number of workers in the household increases, the odds of the individual with travel-limiting disabilities to drive decrease by 34%. This leads to the thought that as the number of workers increases, driving duties may be shared in the household, culminating in fewer individual trips for those with travel-limiting disabilities.

It can also be inferred that people with travel-limiting disabilities with medium income ($25,000–$51,000) have about 60% increased odds of driving compared to those with low income (less than $25,000). On the other hand, Americans with travel-limiting disabilities with annual income greater than $51,000 (high income) are 26% less likely to drive compared to those with low annual household income. This could be that as income increases up to a certain threshold, Americans with travel-limiting disabilities can comfortably afford rideshare services for their trips. However, this relationship between income and driving decision is not statistically significant, and no strong conclusions can be drawn. Finally, men with travel-limiting disabilities are 39% less likely to drive compared to their female counterparts, although this relationship is also not significant. With VIF values less than 5, one can conclude that there is no multicollinearity among the predictors included in the model.

4. Conclusions

Using the 2022 NHTS version 2.0 data, this study employs descriptive statistics, independent samples t-tests, multiple linear regression analysis, and logistic regression techniques to explore the driving decisions of Americans with travel-limiting disabilities. The objectives of the study include describing the socioeconomic and demographic variables, determining significant differences in the means of VMT and other selected trip-related variables, determining the predictors driving VMTs, and identifying factors responsible for driving decisions for the noninstitutionalized U.S. population with travel-limiting disabilities.

The results of the analysis reveal that travel-limiting disabilities increase with age across locations and genders, and the prevalence is higher among low-educated Americans in both categories. Whites have the highest travel-limiting disabilities, followed by Black people. The prevalence rate drops at an increasing rate as the household income group reaches $50,000–$74,999. Independent samples t-tests reveal statistically significant differences in VMT, total trip miles, and number of drivers in households across genders and geographic locations. Americans without travel-limiting disabilities exhibit a higher group mean for all trip-related variables compared to those with travel-limiting disabilities. Isolating Americans with travel-limiting disabilities, the study finds statistically significant evidence of higher group means for trip-related variables in rural areas compared to urban areas. On the other side, when considered across genders, men have a significantly higher group mean for total trip miles and number of drivers in the household, but women have higher VMT than men.

Multiple linear regression model results identify urban, respondent's age, and number of drivers in the household as the significant predictors of VMT for the Americans with travel-limiting disabilities, while logistic regression model results reveal that the number of adult household members at least 18 years old, respondent's age, and number of people on trip are statistically significant factors in explaining the odds of Americans with travel-limiting disabilities to drive compared to not drive.

This study has some gaps and limitations that may impact the generalizability of the findings, which future studies can fill. Firstly, future studies should include a spatial aspect in the modeling to identify the factors that cause spatial variations in both VMT and driving decisions for Americans with travel-limiting disabilities. Spatial modeling could not be adopted in this study because the NHTS data is not spatially referenced. The absence of a spatial identifier in the NHTS dataset hinders one's ability to identify geographical variation in travel patterns, behavior, and mobility across space. This culminates in the researchers' inability to identify spatial disparities in travel limiting disabilities at a finer geographic scale.

Secondly, the separation of travel-limiting disabilities into visible and invisible disabilities should be a focus of future research in disability studies. Although the 2022 NHTS dataset made it possible to identify respondents with travel-limiting disabilities, it is impossible to segregate those with visible disabilities (e.g., physical mobility disabilities) and invisible disabilities (e.g., cognitive and psychological disabilities). One can expect that people with physical mobility disabilities face infrastructural barriers and other barriers not experienced by those with cognitive and psychological disabilities, and vice versa. The absence of this segregation has made it impossible for us to ascertain the difference in travel behavior between the two groups.

Furthermore, the study recognizes the under-specification of the models due to the absence of important confounders and interaction effects like geographic accessibility, vehicle ownership details, and disability severity. As stated earlier, the researchers also could not include geographic accessibility in the models because of the absence of spatial identifiers in the data. Vehicle ownership details were also missing in the dataset at the individual level. To make up for this, the study included the household structure. In addition to this, the survey only factored in the presence of travel-limiting disabilities and the length of time the respondents have had the disabilities; no emphasis was placed on the severity. These confounders and unobserved factors, like behavioral convolution, may be responsible for the small R^2 (11.07%) of the multiple linear regression.

5. Policy Recommendations

The study reveals that there are significant differences in VMTs for Americans with travel-limiting disabilities in rural and urban areas, specifically with higher VMT in rural areas, which stems from limited choices in access to public transportation and paratransit. Policymakers should consider improving public transit and paratransit networks in rural areas, as this could reduce the dependence of Americans with travel-limiting disabilities on driving their vehicles. Furthermore, although the study finds evidence of reduced reliance on driving personal vehicles for people with travel-limiting disabilities in urban areas stemming from spatial compactness and availability of public transportation, they still face challenges in accessing opportunities and even still drive for medical purposes. Due to the preceding, regular audits and improvements should be conducted to ensure that sidewalks and public transportation systems are inclusive of people with travel-limiting disabilities. Finally, given the limitations in access to public transportation and paratransit in rural areas, policies that encourage subsidized ridesharing for people with travel-limiting disabilities could help bridge the inequality gap that exists between them and people without travel-limiting disabilities in accessing varied opportunities.

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