

EXPLORING PATTERNS OF HETEROGENEITY IN ACTIVITY-TRAVEL BEHAVIORS OF OLDER PEOPLE

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ABSTRACT

The travel behavior and mobility needs of older people have been topics of much interest to transport planners and policy makers for a number of reasons. The desire to provide mobility to older people even as their capabilities diminish, and the need to recognize their vulnerability when they do attempt to navigate the transportation network on their own, has motivated a rich stream of research dedicated to studying their activity-travel behavior. Many studies in the past, and most travel models to date, consider older people as a single market segment of 65 years of age or over. To better understand differences among various subgroups of the older population, this paper presents a detailed analysis and comparison of older population subgroups using data derived from the 2017 National Household Travel Survey (NHTS) of the United States. The paper includes a review of earlier studies on the activity-travel patterns of the older segment of our population, and a detailed descriptive statistical analysis on technology and time use patterns with a view to identify how these behaviors evolve as people age. In addition, the paper presents three modeling efforts to understand the differential effects of age on the action space, the use of transportation modes, and the activity participation and time allocation behavior of older people. The analysis suggests that there is considerable heterogeneity among older people, which calls for more targeted policy interventions and a more disaggregate treatment of older population subgroups in travel models. The analysis reveals that an individual's medical condition and need for use of a medical device are significant explanatory variables affecting all three of the choice dimensions modeled in this study. This calls for the development of policies and mobility options that serve the disabled regardless of age, while recognizing the inherent correlation between age and disability status.

Keywords: travel of older people; heterogeneity; action space; time use; technology use; activity-travel engagement

1. INTRODUCTION

Studying the mobility choices and needs of older people is increasingly important as the older population continues to grow. In 2016, there were 46 million people over the age of 65 years, comprising 15 percent of the total US population, and this share is expected to rise to 21 percent by the year 2030 (Federal Interagency Forum on Aging-Related Statistics, 2016). As people age, health-related issues, cessation of driving, and fear of uncomfortable travel situations further contribute to their decreased mobility (Marin-Lamellet and Haustein, 2015), putting them in a vulnerable position for social exclusion and further deterioration in health. Current seniors are, however, more active, retire later, and may even work full-time or part-time well beyond traditional retirement age when compared to earlier generations (Goulias et al. 2007; Rosenbloom, 2001, 2003). They are also healthier, more financially secure, and more mobile than previous generations (Chen and Millar, 2000; Zhou et al., 1997). In 2015, 85 percent of the senior population aged 65-84 had driver's licenses, and of those older than 85 years, 70 percent had driver's licenses (FHWA, 2016), indicating that a majority of older individuals either choose to or are compelled to drive well past retirement age, even into their 80s (Hwang et al, 2015). While these statistics suggest that the automobile is the predominant mode of travel for this group (as in most other age groups in the USA), older people have greater health and mobility challenges than their younger counterparts, which renders driving a dangerous and sometimes even impossible task.

Older people can face myriad barriers including declines in strength, flexibility, vision, and reaction time (Zuin et al., 2002; Carr et al., 2005, 2006; Green et al., 2013), contributing to significant safety challenges when navigating an auto-oriented transportation system. These issues limit their participation in activities, rendering life less enjoyable for individuals who would otherwise desire to stay active in their communities (Rosenbloom, 2003). Health-related mobility restrictions are linked to driving cessation, which is linked to fewer out-of-home activities and symptoms of depression (Whelan et al., 2006). These restrictions on mobility, which are less prevalent in younger people, intensify issues related to social isolation and depression (Church et al., 2000; Schönfelder and Axhausen, 2003). One out of four seniors over the age of 80 has uncorrectable vision problems (Congdon et al., 2004) and some form of dementia afflicts about 35 percent of those aged 85 years or older (Plassman et al., 2007). Deficits in cognitive domains related to physical mobility are predictive of injurious falls, and deficits in physical function related to the ability to walk are predictive of falls in general (Welmer et al., 2017) – suggesting that even walking can be a challenging mode of transportation for those in the upper age ranges of the older population.

Older people do not make the same kind of trips or travel at the same frequency as people in other age groups. They may also react to changes in technology and new services differently than younger people. Studying their behavioral differences is vitally important to planning and designing a built environment and transportation system of the future that provides equitable mobility. Providing optimal mobility for older people – where they have the ability to safely and reliably go where, when, and how they want to – is directly related to healthy aging and well-being (Satariano et al., 2012). To provide mobility for older people, it is important to quantify their action spaces, identify patterns of travel mode usage, and understand how activity-travel and time use patterns evolve as people age.

The primary objective of this study is to examine mobility patterns of the elderly in general and to investigate differences among subgroups of the older population in particular to recognize the heterogeneity in activity-travel behaviors that exist within this cohort. The study of older people's activity-travel has often treated individuals aged 65 or older as a monolithic group. These

studies often use age as an explanatory variable, but do not focus on explicit differences among disaggregate groups of older people (Stone et al., 2017). More recently, there have been a number of attempts to unravel differences among different subgroups within the older population (Hwang et al, 2015; O’Hern and Oxley, 2015), and this study aims to contribute significantly to this body of literature by presenting an analysis of the latest household travel survey data available in the United States. With advances in medicine and the emergence of new mobility options, smartphone technologies, and online services, it would be of value to examine the extent to which activity-travel choices and technology use patterns differ among subgroups of older people in the current context.

The 2017 National Household Travel Survey (NHTS) data set collected in the United States is used in the current paper. The analysis in this paper focuses on a multitude of key aspects of activity-travel behavior. The paper offers a detailed descriptive analysis of patterns of technology use among older population subgroups. With the increasing role that technology is playing in people’s activities and lifestyles, it is of value to understand how patterns of technology use differ across older population subgroups. The paper then proceeds to present a number of models to capture a variety of activity-travel behaviors. The first is a model of action space, which represents the spatial extent of activity engagement outside the home. The second is a model of mode usage by activity purpose, to capture differences in mode usage patterns that may exist among different subgroups. The third dimension of interest in this paper is that of time use allocation for various activities, with a view to investigate differences among subgroups. Essentially, these three measures capture a spatial dimension (action space), a temporal dimension (time use), and a travel dimension (mode use). By examining these three diverse measures of behavior, this paper aims to offer a rich set of insights into differences that exist (or not) among the subgroups of older people using the latest version of the NHTS data set. The study considers the ages of 65 to 74 years, 75 to 84 years, and 85 years or older. In addition, the age group 55 to 64 years is included, both as a basis for comparison and because some people in this age group retire early. These individuals may exhibit activity-travel patterns similar to those of persons aged 65 to 74.

The remainder of the paper is organized as follows. A review of literature is furnished in the next section, recognizing previous efforts into the study of the activity-travel behavior and unique mobility of older people. The third section presents a description of the data, while the fourth section presents an exploratory analysis of technology use for the target sample. The three subsequent sections constitute an analysis and modeling of the three dimensions of interest in this study. The final section offers concluding thoughts.

2. RECOGNIZING HETEROGENEITY WITHIN SUBPOPULATIONS

By 2020, around 19 percent of suburban households are expected to have at least one person with a physical disability over 65 years of age (Smith et al., 2008). These disabilities contribute to unsafe driving conditions as older people experience both higher rates of crash occurrence and higher rates of injury and death in crash events. In 2016 alone, over 7,400 senior adults were killed due to vehicle crashes and the vehicle death rate for those aged 65 and older is substantially higher than the rate for most other age groups (CDC, 2017). The highest death rates are for individuals aged 80 to 84 years as well as 85 years and above. There were 20.7 and 20.2 deaths (due to vehicle crashes) per 100,000 people for these older age groups (CDC, 2017) – values that are comparable to that exhibited by those aged 20 to 24 years (19.7 deaths per 100,000 people in 2016). These statistics suggest that the study of the mobility patterns of older populations is critically important, particularly with increasing proportions of older people in societies around the world. In addition,

and more pertinent to this study, is the notion that there is considerable heterogeneity in mobility and safety statistics among older population subgroups.

Despite gerontological research recognizing age heterogeneity in studies of older people for several decades (Nelson and Dannefer, 1992), the study of older people's activity-travel has often treated individuals aged 65 or older as a monolithic group. A number of gerontological research studies of psychological and social outcomes continue to neither report nor discuss age-based variability (Stone et al., 2017). Based on their review of a number of empirical studies, Stone et al. (2017) note that research in social gerontology is not paying adequate attention to intra-age variability. This study is motivated by the need to obtain deep insights into variability that exists within the older age group (65 years and over).

Studies of mode choice behavior of older people often use age groups as explanatory variables, but do not focus on heterogeneity within age groups. Liu et al. (2017) studied older people as a homogenous group by age, defining them as those aged 60 or older (60 is the official statutory retirement age in China). They used a combination of descriptive statistical analysis and linear regression models to measure the effects of environment factors on travel, focusing on the differences between the population 60 years and older and people aged 18 to 59 years. In another study, Feng (2017) studied the activity-travel of older people in Nanjing, China using a mixed-methods approach with regression models and qualitative interviews to tease out the impacts of demographic, built environment, and accessibility variables on activity frequency and distance traveled for shopping and leisure activities. They used the base age group of 50 to 59 years to study the differences in travel for all individuals aged 60 or older. They found that those aged 60 or older used public transit at a greater rate than those aged 50-59 years, in part because public transportation is half-priced for persons older than 60 and free for people older than 70 (Nanjing Civil Affairs Bureau, 2010). In treating the older demographic as a single group, these studies did not investigate heterogeneity within the older age group.

Similarly, a number of studies of activity patterns of older people have not considered heterogeneity explicitly. Meyer and Speare (1985) investigated moving patterns for older people without accounting for potential variation among different older people subgroups, and this may have contributed to their finding that age has little effect on total mobility after controlling for other variables. Habib and Hui (2017) used an activity-based approach to study the scheduling and activity type and location choices of older people in the National Capital Region (NCR) of Canada. They modeled the effect of spatial accessibility (i.e., the distance between the central business district (CBD) and trip destinations) on activity type choice. Other studies have concluded that older people rely on private vehicles for most trips (as do people of most age groups), but they use public transit at a higher rate than adults younger than 65 years of age (Lynott and Figueiredo, 2011). Another study (Enam et al., 2018) examined differences between working and non-working individuals and found that working older people pursue more social out-of-home activities than non-workers. This study suggested that further research is necessary to determine the factors that contribute to mobility losses among individuals in retirement. Their analysis explores activity-travel differences by age, working status (non-workers, part-time workers and full-time workers), and other socio-demographic characteristics. Haustein (2012) analyzed the mobility behavior of older people and employed cluster analysis to identify key market segments, labeled as captive car users, affluent mobiles, self-determined mobiles, and captive public transport users. The mobility patterns of older people were found to be influenced more so by health measures, social status, infrastructure conditions, and access to transportation systems than by age.

In virtually all of the studies cited so far, the older age group has been treated as a single bloc without adequate consideration of the heterogeneity that may be prevalent within this demographic segment. However, this is not to say that prior research has completely ignored the potential prevalence of heterogeneity among older population groups. Boschmann and Brady (2013) investigated activity-travel behavior in the Denver metropolitan area, splitting older population into disaggregate groups of ages 65-74, 75-84, and 85+ and comparing them to the base group of pre-retirement persons aged 60-64 years. They studied the differences in trip frequency, travel distances, and mode choice of these disaggregate groups, and analyzed the effects of Transit Oriented Development (TOD) proximity on trip frequency, travel distance, and mode choice. In another study, Hjorthol (2013) analyzed the differences in winter and summer seasonal activity-travel behavior of older people in five communities of Norway using the 2005 National Travel Survey. Using linear regression and descriptive analysis techniques, the study examined the effects of weather-related hazards, such as decreased road maintenance, on the activity-travel behavior of different age groups (65-69, 70-74, 75-79, and 80-84) across seasons. They also studied the prevalence and impact of health-related issues on travel attitudes and frequency across genders and age groups.

Hu et al. (2013) studied the travel behavior of older people in Changchun, China, a developing region where the travel behavior of older people was hypothesized to be influenced by cultural and economic factors (which are themselves not influenced by age). They studied the number of trips per day, travel mode choice, and activity-travel purposes of older people across age groups including ages 61-65, 66-70, 71-75, and 75+. The study also examined variations in trip frequency by destination activity type between males and females for the different age subgroups. Hwang et al. (2015) studied travel patterns and characteristics of the older population in the State of New York. Their study documented differences in travel by age subgroups (65-69, 70-74, 75-79, 80-84, and 85+) through a descriptive analysis of the 2009 National Household Travel Survey (NHTS) New York State subsample. The analysis helped uncover differences in older individuals' driver status between urban and rural areas, between males and females, and among age groups. Goulias et al. (2007) split the older population in the Puget Sound Regional Travel Survey into age subgroups: 50-64, 65-79, and 80+ years old. They studied the activity-travel patterns of the "baby-boomer" generation (people aged 50 to 64 years at the time of the study) and found differences in the activity-travel patterns of baby-boomers compared to individuals of older generations (age subgroups). The study concluded that further investigation of subgroups of older people was needed to unravel heterogeneity in such aspects as working status, land use impacts on travel, and household composition.

Many studies of the built environment recognize that features such as walkability, street connectivity, land use mix, and pedestrian-friendly elements are positively associated with active travel by older adults (Cerin et al, 2017). Maximizing and maintaining cognitive functioning, physical mobility, and functioning of underlying physiological systems is directly related to well-being (Ferruci et al, 2016). In this context, O'Hern and Oxley (2015) examined several travel behavior phenomena associated with active transportation (i.e., involves physical activity) among older subgroups (ages 65-74, 75-84 and 85+) in the Melbourne, Australia area. They note that identifying the factors that motivate and contribute to active travel can help inform strategies that encourage more active travel, particularly among older people.

In recent years, technology has played an increasingly important role in shaping mobility patterns and activity-travel choices. In addition, new sharing- and hailing-based mobility options (made possible by technology) have emerged. Given this rapid transformation of the transportation

and technology landscape, it is critical to conduct analysis of recent data to better understand differences among older population subgroups to identify those that are truly at risk of social exclusion and mobility poverty. For this reason, this paper aims to study differences in the use of technology for fulfilling activity needs (e.g., online shopping) among older age groups. As an increasing number of older people continue to work past the traditional retirement age, understanding technology usage patterns and activity-travel behaviors of older workers and non-workers may help shed light on the specific mobility needs of different subgroups. This study employs the latest version of the National Household Travel Survey (NHTS), thus providing a robust basis to uncover differences across older people subgroups while recognizing the very different technological landscape prevalent in 2017 (when the latest NHTS data was collected). Unique dimensions of older people's activity-travel behavior, that have not been studied extensively in the context of seniors in the past, are examined in this study (including, for example, virtual activities and technology usage). In addition, model estimation efforts presented in this paper shed light on the socioeconomic, behavioral, health-related, and built environment influences on mode choice, activity engagement, extent of action space, and time use for older people, while recognizing the heterogeneity that may be prevalent.

3. DATA DESCRIPTION

The data source for this study is the 2017 National Household Travel Survey (FHWA, 2017; NCTCOG, 2018). This dataset includes information about the number of trips by all modes including walking, cycling, personal vehicle, public transit, ride-hailing, and car share. The current study focuses on examining travel behavior of older people during weekdays in the Dallas-Fort Worth (DFW) Metropolitan area. In the DFW metro sample, information from 18,426 people is available, 7,522 (40.8 percent) of whom are aged 55 or older. In this subsample of 7,522 individuals, differences in activity-travel patterns are examined by socioeconomic factors, built environment variables, attitudes, and medical condition status and duration. Key descriptive statistics for the different age groups are summarized in Table 1, with the age group 25-54 years included for comparison. The study focuses on uncovering activity-travel pattern variations across four different older age groups (55-64 years, 65-74 years, 74-85 years, and 85 years and older), along several dimensions such as gender and working status.

Key differences by age group in Table 1 suggest that the older old people are less likely to be full-time and part-time workers than the younger old people. Also, most individuals, regardless of age, are drivers. A drop-off in driving license holding status significantly occurs only for the 85+ age group. As age increases, the prevalence of medical conditions increases as well, with higher rates of medical challenges for those aged 75-84 years and 85+ years. The oldest old people are more white than their younger peers, and are also slightly less educated than younger old people, with a higher share of individuals in the oldest age groups indicating High School graduate or less as the highest level of education achieved. A higher proportion of the older old people live alone (based on the household size distribution), potentially contributing to social isolation and the inability to obtain assistance for travel and activity engagement. Consistent with the smaller household sizes and lower driver's licensing holding in older stages of life, the number of household vehicles shows a steep drop-off for the 85+ year group. The average number of household drivers follows the pattern seen for average number of vehicles in the household. Overall, there is a gradual change in socio-economic characteristics until the age of 74, with more dramatic shifts happening at 75+ and 85+ years.

TABLE 1 Socio-Demographic Characteristics by Age Group

Characteristic	Age Groups				
	25-54	55-64	65-74	75-84	85+
Number of Individuals (N)	7,265	3,303	2,674	1,195	350
Person-Level Characteristics					
<i>Working Status</i>					
Full-time working status (%)	72.72	55.31	17.24	3.85	1.71
Part-time working status (%)	8.80	10.41	10.66	6.03	3.43
Licensed driver (%)	96.48	96.52	94.73	86.69	64.29
Has a medical condition (%)	3.06	8.57	12.83	23.43	46.29
Medical condition limits mobility (%)	2.26	6.36	9.42	25.02	53.71
Travels with a medical device (%)	0.74	3.21	5.53	9.96	24.57
Black (%)	10.06	10.26	8.56	6.86	4.57
White (%)	74.49	82.62	85.53	87.70	92.00
Hispanic (%)	13.28	7.05	5.12	4.35	4.29
<i>Highest Level of Education</i>					
Less than High School graduate (%)	2.60	3.06	3.14	5.86	9.43
High school graduate or GED (%)	12.42	16.32	18.03	22.93	31.43
Some college or associates degree (%)	25.34	32.03	31.45	28.87	24.57
Bachelor's degree (%)	34.80	28.61	25.92	22.43	20.00
Graduate or professional degree (%)	24.80	19.95	21.43	19.83	14.29
Household-Level Characteristics					
Own home (%)	71.58	85.01	87.81	86.19	74.57
<i>Household Size (HHSIZE)</i>					
HHSIZE = 1 (%)	12.07	18.65	23.34	27.28	38.86
HHSIZE = 2 (%)	30.49	58.37	64.44	61.51	47.14
HHSIZE = 3 (%)	22.74	14.65	7.82	7.78	11.71
HHSIZE = 4 (%)	23.33	5.87	2.39	1.76	1.14
HHSIZE = 5+ (%)	11.37	2.45	2.01	1.67	1.15
Average HHSIZE	2.97	2.16	1.96	1.91	1.79
<i>Number of Household Vehicles (HHVeh)</i>					
HHVeh = 0 (%)	1.42	2.12	2.06	2.43	10.29
HHVeh = 1 (%)	18.20	19.65	27.60	37.49	52.57
HHVeh = 2 (%)	49.69	43.90	47.64	43.68	28.00
HHVeh = 3 (%)	19.82	22.28	15.03	11.13	8.00
HHVeh = 4+ (%)	10.87	12.05	7.67	5.27	1.14
Average HHVeh	2.26	2.29	2.03	1.81	1.38
Household in urban area (%)	92.51	91.49	89.79	91.46	93.43
<i>Household Income</i>					
Less than \$35,000 (Low) (%)	13.65	15.80	22.51	30.04	37.43
More than \$100,000 (High) (%)	45.79	42.90	26.03	18.66	13.71
Average number of HH Drivers	2.06	1.96	1.78	1.66	1.32
Average number of adults in household	2.11	2.05	1.91	1.87	1.77
Average number of children <5 years	0.23	0.02	0.01	0.00	0.00
Average number of children 6-17 years	0.63	0.09	0.04	0.04	0.02

There are also differences in the activity-travel characteristics of older people compared to those of younger aged people as shown in Table 2. Nearly 40 percent of those aged 85 years or older reported zero trips on the travel day compared to about 12 percent of those aged 25 to 55 years. Staying at home on a travel day may indicate social exclusion, mobility barriers, or lack of exercise – all of which influence health and quality of life. The total average daily travel distance for each age group shows a sharp decline with age. This may suggest a serious shrinkage of the action space of an individual in old age. In terms of mode shares, the automobile consistently accounted for the largest mode share across all age groups. In fact, mode shares appear to show a rather gradual change across the age groups in comparison to many other statistics that show a more dramatic shift. The transit mode share steadily declines with age, suggesting that accessing and using transit services may be challenging for older people. In other words, it is unlikely that transit will experience a boost in ridership with the aging of the US population, unless transit agencies significantly alter the nature of the service.

TABLE 2 Activity-Travel Characteristics by Age Group

Characteristic	Age Groups				
	25-54	55-64	65-74	75-84	85+
Number of Individuals (N)	7,265	3,303	2,674	1,195	350
Activity-Travel Characteristics					
<i>Count of Person Trips on Travel Day (%)</i>					
0	11.75	15.05	20.34	26.69	38.29
1	2.08	2.79	1.50	2.26	0.86
2	23.85	22.65	18.06	20.17	24.29
3	12.17	11.81	12.64	12.47	12.00
4	16.23	15.47	15.18	12.64	10.00
5+	33.92	32.24	32.27	25.77	14.57
Average total daily trips	3.86	3.62	3.58	3.00	2.15
<i>Average total daily miles traveled</i>	52.92	53.40	35.16	23.76	14.98
<i>Mode Shares for Person-Trips</i>					
Private vehicle (car, van, SUV, truck) (%)	92.85	92.25	92.50	93.18	91.63
Active transport (walking, cycling) (%)	5.80	6.50	6.53	6.33	8.14
Public transport (bus, rail, etc.) (%)	1.36	1.25	0.97	0.49	0.23
<i>Daily (Weekday) Time Use by Activity</i>					
Average time working (min)	321.8	260.8	96.7	25.4	14.8
Average time use shopping/eating out (min)	37.1	43.1	50.2	48.7	31.9
Average time use social/recre./health (min)	72.4	83.8	96.8	78.5	52.1
Average time use at home (min)	727.8	726.4	812.3	824.8	731.7
<i>Average Trip Counts by Purpose</i>					
Work/school	0.81	0.69	0.36	0.17	0.12
Shopping/eating out	0.91	1.09	1.27	1.11	0.81
Social/recreational/health	0.76	0.56	0.64	0.55	0.36

Finally, the time use and average trip counts per weekday reveal, as expected, a drop-off in work activity with age. However, for shopping and eat-out, and the social/recreation/health purpose, there is an increase until age 74, after which there is a drop-off, perhaps reflecting the onset of some physical and mobility challenges at about 75 years. The analysis conducted for this paper focuses on these three trip purposes (noted in Table 2), and does not consider other purposes

that may be more difficult to categorize or constitute low time-budget activities (that is why the sum across activity purposes in Table 2 is not 1440 minutes).

The 2017 NHTS dataset was cleaned and filtered to produce a sample that had complete information on variables of interest and was suitable for modeling activity-travel dimensions of the older population. Only records of individuals, households, and trips in the Dallas-Fort Worth-Arlington statistical area were retained in the analysis sample. The trip file was further filtered to include only weekday trips. This paper is not focused on comparing activity-travel patterns between weekdays and weekend days but is rather focused on uncovering the characteristics of and differences among older population subgroups in terms of activity-travel during weekdays. Missing information that led to omission of records in the analysis sample includes both responses where a respondent chooses not to answer, and where the respondent does not know the answer.

In other studies of the activity-travel patterns of older people, driver status, worker status, income, household structure, and public transportation availability have all been found to be influential in explaining mobility (Miranda-Moreno and Lee-Gosselin, 2008; Nordbakke and Schwanen, 2015). In this paper, these factors are examined in detail to determine underlying drivers of older population mobility, given the newest national travel survey and the presence of new modes of transportation for travel (such as mobility-on-demand services). The analysis in this paper focuses on three key aspects of mobility: action space (spatial extent of travel), mode use, and time allocation to activities (temporal dimension of activity engagement). Before proceeding to an analysis of these three behavioral phenomena, however, the paper offers a detailed examination of technology use patterns for different older age groups. With the growing influence that technology is playing in people's lives and activity-travel patterns, examining patterns of technology use may prove useful in understanding differences in mobility between groups.

4. TECHNOLOGY USE AND MEDICAL/HEALTH LIMITATIONS

Virtual activities, such as the use of the internet for online shopping, telecommuting, and interacting virtually with friends and family members may provide the ability for older people to stay connected and enjoy a high degree of well-being even in the absence of the ability to travel physically between places. With services such as Amazon's grocery delivery and similar services (Pomranz, 2018), there are many options for older people and those with limited mobility to engage in activities and access services they desire without the hassle and danger of physical travel. It is increasingly important to analyze the choices of individuals in the use of new technology and participation in virtual activities, along with their physical activity-travel episodes, to get a more holistic picture of their lifestyle and societal engagement (Lavieri et al., 2018). Mokhtarian (2009) identifies twelve reasons why telecommunications can increase travel and four reasons why telecommunications can substitute for travel. With the rapid evolution of technology, these two sides of the coin are still at play. On the one hand, telecommunications technologies enable individuals (especially seniors who may no longer have the ability to drive) to access ride-hailing and other mobility-on-demand services through a convenient mobile app. On the other hand, telecommunications technologies also allow older individuals to interact and engage with society without necessarily having to undertake physical travel. Thus, the ownership and use of telecommunications technologies is an important facilitator of mobility and social interaction that is worthy of investigation, particularly for older individuals.

Many of the virtual activity variables in the 2017 NHTS are only asked of the survey respondent and not of all members in a respondent household. For instance, the frequency of internet use is asked only of the survey respondent and not of all household members. This is also

true of attitudinal questions such as the variable measuring the degree of agreement with the statement that the individual walks to reduce the financial burden of traveling. Selected attitudinal variables are discussed in a later section of this paper. Because the technology use and attitudinal questions are only asked of the person responding to the survey, the number of individuals in this analysis sample is 4,569, compared to the total of 7,522 older individuals available for study in the DFW sample.

Frequency of Internet Access

Household travel survey respondents aged 55 and older were segmented by different age groups, gender, and working status to determine differences in internet use and virtual activity engagement among different subgroups. Table 3 presents a comparison of the distribution of frequency of technology use among age groups. The categories are “Never”, “Sometimes”, and “Daily”. The category “Sometimes” is an aggregation of the following categories: “a few times a week”, “a few times a month”, and “a few times a year.”

The youngest subgroup of the analysis sample report almost universal frequent internet use, with 98.1 percent of those aged 55-64 years and 94.9 percent of those aged 65-74 years reporting using the internet at least a few times a week (combination of sometimes and daily). For those aged 75-84 years, the percentage drops to 86 percent; and for those 85+ years, the percentage shows a more substantial drop to 71.8 percent. While the drop in percent of individuals using internet is undoubtedly tangible, it is nevertheless noteworthy that more than 70 percent of those 85+ years use internet on a fairly regular basis. In addition, it can be expected that cohorts in the younger age groups will sustain their level of internet use frequency even as they age into the older subgroups. Thus, it would appear that the internet could serve as a powerful tool to keep older people connected and engaged in society and able to access goods and services. It is clear that transportation agencies should leverage the internet as much as possible to provide older people information about their mobility options, ways to connect and access services, and communicate transportation needs and desires. Providing more information to older individuals about their safe mobility options is likely to increase the likelihood that they will be able to continue pursuing activities into their older years.

There are gender differences in the frequency of internet use among older individuals (not shown in table). While males and females tend to have similar frequencies of internet use in the age groups of 55-74 years, differences begin to appear in the 75+ year age groups. While 77.7 percent of females aged 75-84 years report accessing the internet at least once a week, the corresponding percentage for males is 85.3 percent. The gender discrepancy in internet use increases for those aged 85+ years, with 60.7 percent of females and 77.3 percent of males reporting internet use at least a few times a week respectively. It is found that 32 percent of females aged 85+ report never use the internet compared to 17.9 percent of males in this age group. The reasons for this may be myriad, including lingering and historic gender norms and differences that often see males using technology more than females. It is likely that these gender differences will fade with the passage of time, and this fading of differences is already seen among those under 75 years of age. In other words, policymakers can feel confident that any internet-based information campaign is likely to reach and impact males and females uniformly in the future.

TABLE 3 Frequency of Technology Use for Respondents 55+ Years of Age

	Total (N = 4,569)		55 to 64 years (N = 1,946)		65 to 74 years (N = 1,667)		75 to 84 years (N = 750)		85+ years (N = 206)	
	%	Frequency	%	Frequency	%	Frequency	%	Frequency	%	Frequency
Frequency of Internet Use										
Never	5.9	268	1.8	35	4.8	80	13.2	99	26.2	54
Sometimes	7.9	361	5.3	103	8.0	133	11.5	86	18.9	39
Daily	85.8	3,922	92.8	1,805	86.9	1,449	74.5	559	52.9	109
Not Ascertained	0.4	18	0.2	3	0.3	5	0.8	6	1.9	4
Frequency of Computer Use										
Never	9.5	433	4.6	89	8.7	145	16.9	127	35.0	72
Sometimes	17.0	777	15.3	297	18.6	310	18.0	135	17.0	35
Daily	71.6	3,271	79.2	1,541	70.8	1,180	61.7	463	42.2	87
Not Ascertained	1.9	88	1.0	19	1.9	32	3.3	25	5.8	12
Frequency of Tablet Use										
Never	39.8	1,817	31.0	604	40.5	675	52.8	396	68.9	142
Sometimes	23.5	1,073	27.9	543	22.9	381	17.1	128	10.2	21
Daily	31.4	1,436	37.6	731	31.7	529	20.5	154	10.7	22
Not Ascertained	5.3	243	3.5	68	4.9	82	9.6	72	10.2	21
Frequency of Smartphone Use										
Never	20.3	929	9.5	185	19.7	329	38.7	290	60.7	125
Sometimes	11.7	535	11.1	216	12.2	204	12.4	93	10.7	22
Daily	65.0	2,969	78.1	1,520	65.4	1,090	42.5	319	19.4	40
Not Ascertained	3.0	136	1.3	25	2.6	44	6.4	48	9.2	19
Frequency of Online Shopping										
	N = 7,522		N = 3,303		N = 2,674		N = 1,195		N = 350	
Infrequent	46.2	3,472	37.1	1,224	45.7	1,223	63.0	753	77.7	272
Low	11.7	2,490	35.6	1,176	35.0	935	26.6	318	17.4	61
Medium	65.0	965	16.6	547	12.3	330	6.6	79	2.6	9
High	3.0	595	10.8	356	7.0	186	3.8	45	2.3	8

Full-time workers of all older age groups almost universally access the internet at least a few times a week (97.9 percent). Likewise, 96.5 percent of part-time workers of all older age groups access the internet at least a few times a week. Whether they access the internet because of their job or despite it, workers typically tend to be “plugged-in” to society and connected via the internet. In contrast, non-workers are less likely to use the internet as frequently as their working counterparts across all age groups. Among non-workers across all age groups, 87.2 percent report using the internet at least a few times a week, which reflects a high rate of internet connectivity and usage (although lower than that for workers). The share of frequent users in the non-working group does differ by age. The share of non-workers aged 85 or older reporting internet use at least a few times a week is just 66 percent. The corresponding percentage among those 75-84 years of age is considerably higher at 80 percent.

Computer Use, Tablet, and Smartphone Usage

This subsection focuses on use of devices that facilitate connectivity and provide pathways to access goods and services virtually. Older people exhibit variation in the use of devices to access the internet across different subgroups defined by age, gender, and working status. The age-based variation in device usage is shown in Table 3.

More than one-half of the older people in every age group report using a personal computer daily, except for the 85+ age group (of which 42.2 percent report using a personal computer daily). While there is a substantial drop in percent of individuals using a personal computer daily as age progresses, the percent of individuals using a personal computer “sometimes” is very similar across the age groups. However, while only 4.6 percent of those 55-64 years report never using a personal computer, the corresponding percent is 35 percent for those 85+ years. Although age and computer literacy are likely to play a role in explaining these differences, it is plausible that exiting the workforce also plays a role in diminished personal computer usage among the older age groups.

Older individuals use newer technology devices (tablets and smartphones) less frequently than personal computers. It is found that 68.9 percent of those 85+ years never use a tablet; and 60.7 percent of those in this age group never use a smartphone. These percentages are quite high, and sit in stark contrast to the corresponding numbers for those 55-64 years (31 percent and 9.5 percent respectively). Smartphones are used more frequently than tablets by all age groups, and the percent using smartphones daily is consistently higher than the percent using smartphones sometimes. This suggests that, if individuals acquire a smartphone, then it is more likely that they will use it daily than “sometimes”. Nevertheless, there is a substantial proportion of individuals 75-84 years and 85+ years who never use a smartphone. This is somewhat troublesome, given that many emerging mobility options can only be accessed via a mobile app, rendering older people who do not have a compatible device unable to use such mobility options.

Full-time workers use computers, tablets, and smartphones at a considerably higher frequency than non-workers (not shown in table). The shares of non-working males who access the internet daily by personal computer do not differ noticeably across age segments in the 55-84 year age range. More substantial differences are seen, however, for females. Non-working females who access the internet daily constitute about 60 percent of those in the age ranges of 55-74 years, but this share drops to 48.2 percent for those aged 75-84 years. Non-working males in the age groups spanning 55-84 years access the internet with nearly uniform daily frequency (about 72 percent). There is a marked drop-off among the 85+ year group. However, with 75-84 year old individuals gradually transitioning into the 85+ year category, it is reasonable to expect the 85+ year old individuals of tomorrow to be more like the individuals aged 75-84 years today.

Online Shopping

There is considerable interest in the impacts of online shopping on physical store-based shopping and the implications for activity engagement and traffic patterns (Xi et al., 2018). In a study of adult internet users in China, Xi et al. (2018) found that there is a positive association between online and in-store shopping, with e-shopping serving as an important information channel that promotes in-store shopping. For older people, online shopping may not only enable them to access goods and services more easily (without the need for physical travel), but also instigate physical shopping episodes – thus engendering greater levels of out-of-home activity engagement and interaction.

In the 2017 NHTS, the frequency with which an individual purchased items online in the previous 30 days is measured for all respondents. Unlike the frequency of internet and device use, this variable was collected for all persons in the respondent households. Four categories of online shopping frequency are considered: infrequent (0 times in the last 30 days), low (1 to 3 times in the last 30 days), medium (4 to 6 times in the last 30 days), and high (7+ times in the last 30 days). There are noticeable differences across age groups in the frequency of online shopping, suggesting that those 85+ years of age are less inclined and/or less able to access and use online shopping portals to obtain goods and services. The last major row of Table 3 shows the distribution of shopping frequency online in the past 30 days for all older persons in the DFW subsample of NHTS. Individuals in the oldest age category (85+) are more likely to be infrequent online shoppers when compared with the groups in younger age categories. It is found that 77.7 percent of individuals in the 85+ category shop online infrequently; the corresponding percentage for those 55-64 years is just 37.1 percent. However, as with internet use, the differences across age groups may fade over time. Those aged 55-64 years will eventually transition into the older age groups and are likely to maintain higher levels of online shopping than the very old people of today.

Differences in the online shopping habits of older people were examined across gender lines (not shown in table). The share of males aged 55-64 years who report infrequent online shopping is 41 percent; the corresponding percent for females is 33.7 percent. In the older demographic segments, however, the trend is reversed. The share of females who report infrequent online shopping is larger than the corresponding share of males for both age groups 75-84 years and 85+ years. Working status plays a role in shaping online shopping behavior. In the age groups of 55-64 and 65-74 years, non-working males are more likely to have shopped online in the last 30 days than non-working females. It is found that 66.3 percent of non-working females aged 75-84 years and 80.8 percent of non-working females aged 85+ years report infrequent online shopping. The corresponding percentages for non-working males are 62.6 percent and 76.6 percent respectively, suggesting that some gender differences are present at this time with females slightly less inclined to engage in online shopping than males (in the 75+ age ranges). It is expected that these differences will fade as people currently under 75 years of age transition into the older age groups and the gender norms that have traditionally contributed to differences between males and females becomes less pronounced over time.

Working from Home

Table 4 presents the percent of individuals in various market segments and age groups who work from home. As expected, the number of individuals aged 75+ years who are workers is very small and hence the statistics should be interpreted with caution for the oldest two age groups. Of the 7,522 individuals aged 55 or older in the sample, 3,053 are workers.

TABLE 4 Working From Home by Age, Gender, and Working Status

	Total		55 to 64 years		65 to 74 years		75 to 84 years		85+ years	
	%	Number	%	Number	%	Number	%	Number	%	Number
Male Full-Time Workers	(N = 1,314)		(N = 1,002)		(N = 277)		(N = 29)		(N = 26)	
Yes	17.4	229	15.9	159	20.9	58	34.5	10	33.3	2
No	82.6	1,085	84.1	843	79.1	219	65.5	19	66.7	4
Male Part-Time Workers	(N = 288)		(N = 100)		(N = 138)		(N = 44)		(N = 6)	
Yes	45.8	132	47.0	47	46.4	64	34.1	15	100.0	6
No	54.2	156	53.0	53	53.6	74	65.9	29	0.0	0
Female Full-time Workers	(N = 1,026)		(N = 825)		(N = 184)		(N = 17)		(N = 0)	
Yes	13.5	139	13.1	108	13.6	25	35.3	6	--	--
No	86.5	887	86.9	717	86.4	159	64.7	11	--	--
Female Part-time Workers	(N = 425)		(N = 244)		(N = 147)		(N = 28)		(N = 6)	
Yes	30.8	131	29.5	72	34.7	51	21.4	6	33.3	2
No	69.2	294	70.5	172	65.3	96	78.6	22	66.7	4
All Male Workers	(N = 1,602)		(N = 1,102)		(N = 415)		(N = 73)		(N = 12)	
Yes	22.5	361	18.7	206	29.4	122	34.2	25	66.7	8
No	77.5	1,241	81.3	896	70.6	293	65.8	48	33.3	4
All Female Workers	(N = 1,451)		(N = 1,069)		(N = 331)		(N = 45)		(N = 6)	
Yes	18.6	270	16.8	180	23.0	76	26.7	12	33.3	2
No	81.4	1,181	83.2	889	77.0	255	73.3	33	66.7	4
All Workers	(N = 3,053)		(N = 2,171)		(N = 746)		(N = 118)		(N = 18)	
Yes	20.7	631	17.8	386	26.5	198	31.4	37	55.6	10
No	79.3	2,422	82.2	1,785	73.5	548	68.6	81	44.4	8

Table 4 summarizes the differences in working from home among different subgroups of older workers. For both males and females, a higher proportion of part-time workers (than full-time workers) work from home. Nearly one-half of male part-time workers aged 55-64 and 65-74 years work from home, but only about 30% of female part-time workers in these age groups work from home. Male full-time workers also work from home at a greater rate than female full-time workers. The rate of working from home appears to increase with age for most worker subgroups. This finding is consistent with expectations. Workers in the more advanced age brackets are likely to be placed in more flexible jobs and these individuals may seek jobs with work-at-home option so that they do not have to endure a commute on a daily basis. Both males and females tend to work from home more as they age. An interesting exception to this pattern is that the share of male or female part-time workers working from home decreases for those 75-84 years of age. This might indicate that the nature of part-time work available to those aged 75-84 years requires them to be outside of the home. This may include, for example, service-industry work. However, caution should be exercised in drawing conclusions, given the small sample sizes of part-time workers in the 75-84 year age band. Overall, it appears that work from home options are somewhat limited, with the majority of workers (in all age ranges) not working at home. While this may be positive from a social interaction perspective, it may also present challenges for those who are unable to commute to a workplace on a regular basis. Being able to work from home may offer older people the opportunity to interact with individuals (at least virtually) and be intellectually stimulated.

Attitudes and Medical Limitations

This subsection covers some findings related to attitudes and medical limitations reported by the NHTS respondents. Responses to the questions that measured attitudes towards travel were recorded on a likert scale with options of strongly disagree, disagree, neither agree nor disagree, agree, and strongly agree. Only the survey respondent's opinions were collected. These variables were analyzed descriptively to gain insights on the differences among subgroups of older people.

The NHTS presented questions that explored the extent to which individuals considered travel to be financially burdensome. It was found that older people tend to be split into one-thirds when it comes to attitudes toward travel as a financial burden. One-third of the individuals agree that travel is a financial burden, one-third neither agree nor disagree, and one-third disagree that travel is a financial burden. For the question as to whether the price of gasoline affects amount of travel they undertake, a larger percentage of individuals in each age subgroup agree with this statement. This suggests that, because gasoline prices are more critical in a car-dependent metro area such as DFW, older people (who may not be earning any longer as they exited the workforce) are likely to be more sensitive to the specific factor that affects out-of-pocket travel cost. Even though there is sensitivity to the price of gasoline and travel for all subgroups of older people, very few agree with the statements that they bicycle or use public transit to reduce the financial burden of travel. This suggests that price-sensitive older people may reduce the financial burden of travel by other means such as traveling less or traveling with a fuel-efficient vehicle.

Disability and health status are important determinants of activity-travel patterns. In prior research (Sener et al., 2011), it has been reported that individuals with a disability are more likely to engage in physically active episodes in-home and with family members (who can presumably provide assistance they need in the home environment). In the 2017 NHTS, respondents self-reported health status on a five-point scale from Excellent to Poor. A higher share of individuals aged 55-64 years report an excellent opinion of their health (22.7%) compared to those aged 65-74 (17.3%) and those aged 75 or older (11.5%). There are very few gender-related differences in

the opinion of health, and full-time and part-time workers of all ages tend to be more likely to report being in Excellent or Very Good health than non-workers. While this is indicative of a correlation between working and health status, the direction of causation merits further exploration. Individuals in good health may be able to work, but those who work may experience better health by virtue of the physical and mental benefits that work can provide.

Responses to the reasons for not walking more were not collected for all persons participating in the NHTS. The survey attempted to capture the extent to which people did not walk more due to infrastructure reasons on the one hand and due to safety reasons on the other hand. However, because of small sample sizes, it is not possible to uncover differences by gender and working status for these two attitudinal variables related to walking. Comparisons are therefore limited to those between age subgroups. There are three infrastructure-related reasons for not walking more: no nearby paths or trails, no nearby parks, and no sidewalks or sidewalks are in poor condition. Additionally, all four unique combinations of these variables are listed as responses, including the ability to select all three as reasons for not walking more. Older people overwhelmingly consider the largest barrier to walking more to be sidewalks that are missing or in poor condition. Over one-half of individuals in each age subgroup report sidewalks as a reason for not walking more. Similar to infrastructure-related reasons, there are three safety-related reasons that individuals may consider for not walking more. The biggest concern for all age groups is that there is not enough lighting, with over one-half of the individuals in each age group reporting lighting as a reason for not walking more. The data show that older people do not walk more because of poor walking infrastructure in their neighborhoods, or at least the perception of poor infrastructure in their neighborhoods.

5. A MULTIVARIATE LOG-LINEAR REGRESSION MODEL OF ACTION SPACE

This section presents an analysis of the action space of an individual, recognizing that the size of the action space is likely influenced by the time-space accessibility of individual (Yoon and Goulias, 2010). With advancing age (and potential inability to drive an automobile), and depending on the built environment in which an individual resides, time-space accessibility may diminish over time, resulting in a smaller action space for older individuals. In an effort to determine the extent to which the action space of an individual is affected by age, a multivariate log-linear regression model of the farthest distance from home that a person travels to participate in an activity is estimated. It is recognized that the farthest location visited on the travel survey day may not necessarily be representative of the true action space of the individual. One may not have traveled far on a specific day because there was no need to, or because of myriad other reasons. The action space of such an individual may, in fact, be much larger than what is implied by the farthest distance to an out-of-home location visited on a specific day. Likewise, an individual may have made a special trip to a faraway place to fulfill a special purpose, causing an over-representation of the true action space. However, it was felt that the distance to the farthest location visited on the travel survey day may be used as a reasonable surrogate measure of action space for purposes of this analysis. Future research should focus on developing more accurate measures of action space, consistent with theories of time geography (Habib and Hui, 2017).

This study employs a multivariate multiple log-linear regression approach to model the effects of different socioeconomic and household variables on action spaces for different activity types. The natural logarithm of distance is used to transform the distance variable and control the effects of outliers on distance measures. Activity types are aggregated into three key categories: work/school, commercial/shopping, and social/recreational/health. One limitation of the action

space computation is that the data set does not provide the true home location coordinates or activity location coordinates. Given the need to protect privacy of survey respondents, location data is only available at the aggregated Traffic Survey Zone (TSZ)-level. Therefore, the action space is computed as the road network distance between the centroids of the home TSZ and the activity location TSZ. Location data and TSZ files were obtained from NCTCOG (2018).

The log-likelihood of the multivariate multiple regression model of action space at convergence was -32,001.4, and the log-likelihood of the constants-only model with covariances restricted to zero was -33,771.6. The log-likelihood ratio test statistic for this model is greater than the chi-square value with sixteen restrictions at any reasonable level of significance, rejecting the constants-only model in favor of the full regression model.

Model estimation results are presented in Table 5. Age was tested as a continuous variable and as a dummy variable for the age ranges 65-74, 75-84, and 85+. For most age groups, age does not significantly impact action space for different activities. When compared to those aged 55-64, people aged 65-74 are more likely to have a larger action space for shopping/eating trips. Those aged 65 or older have a smaller work action space compared to those aged 55-64, which makes sense as fewer individuals choose to work after age 65 compared to those aged 55-64; and among those who do, many may search to engage in work activities closer to home than when they were employed prior to retirement. As expected, those aged 85 or older travel shorter distances for social/recreational/health activities, suggesting that individuals in this older age subgroup may tend to locate in neighborhoods where such amenities are close-by. It appears that the action space tends to diminish for older subgroups, consistent with their poorer health status.

Interestingly, gender did not play a significant role in determining action space for any activity type. Individuals with a medical condition tend to have diminished action spaces, particularly for discretionary and maintenance activity purposes where the individual can exercise some control on the locations visited. Work/school locations are less flexible and hence medical condition does not significantly affect the distance measure from home (it may affect whether a person works at all). Working status affects action space in ways that are to be expected. Being a full-time worker increases the space for work activities and decreases the action space for social/recreational/health activities. It is likely that full-time workers are willing and able to travel farther to find good full-time employment and the longer commute is justified by the full-time job. Schedule constraints likely diminish their action space for discretionary social-recreational activities. Being a part-time worker also contributes to a larger action space for work/school activities, but not to the same degree as full-time worker status. Part-time workers are likely to have schedules that are more flexible and find work locations closer to home, and hence they do not depict smaller action spaces for social/recreational/health activities as full-time workers do.

Other household characteristics affect revealed action space, as measured by the distance to the farthest location visited outside home. Individuals residing in urban areas have diminished action spaces; this is likely a manifestation of the greater access to and concentration of activities in urban settings. Thus, individuals in urban areas do not have to travel far to access appealing amenities and destinations. Lower income individuals, on the other hand, may be constrained due to limited monetary resources, thereby leading to a smaller action space for social/recreational/health activities. Online shopping purchases for home delivery in the past 30 days also has an impact on action space. Interestingly, it is found that this variable positively impacts the action space for shopping/eating out trips. This indicates that older people who are tech-savvy and shop online with greater frequency are more likely to shop or eat out further away from home than those who shop online with less frequency.

TABLE 5 Log-linear Multivariate Multiple Regression of Action Space by Aggregated Activity Type

	Work/School Action Space		Shopping/Eating Action Space		Social/Recreational/Health Action Space	
Explanatory Variables	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Constant	0.2086	5.66	1.1362	31.31	0.8218	20.08
Age is 65-74	--	--	0.1071	4.29	--	--
Age is 65+	-0.0548	-2.16	--	--	--	--
Age is 85+	--	--	--	--	-0.1448	-2.10
Individual has a medical condition	--	--	-0.2666	-6.89	-0.1560	-4.09
Individual is a full-time worker	1.3633	37.03	--	--	-0.2014	-7.37
Individual is a part-time worker	0.7777	19.60	--	--	--	--
Household is in an urban area	--	--	-0.3003	-8.60	-0.1394	-3.94
Household income below \$35K	--	--	--	--	-0.1202	-3.97
Online Purchases for delivery, last 30 days	-0.0090	-3.06	0.0169	5.44	--	--
Variance/Covariance Matrix						
Work/School Action Space	0.9038		0.1191		-0.0017	
Shopping/Eating Action Space	0.1191		1.1295		0.2507	
Social/Recreational/Health Action Space	-0.0017		0.2507		1.0451	
Implied Correlation Matrix						
Work/School Action Space	1.0000		0.1179		-0.0017	
Shopping/Eating Action Space	0.1179		1.0000		0.2307	
Social/Recreational/Health Action Space	-0.0017		0.2307		1.0000	

There may be an unobserved variety-seeking attitude (further enabled by technology) that influences this behavior. Although a substitution effect would suggest that shopping online would decrease the need to shop further away from the home location, it appears that there may be a more complementary effect between online shopping and the action space for physical shopping.

The error variance-covariance matrix and the implied correlation matrix are also presented in Table 5. Error correlations represent the presence of common unobserved attributes that simultaneously affect action spaces of different activity types. Significant correlations were found between work/school and shopping/eating (0.1179), between work/school and social/recreational (-0.0017), and between shopping/eating and social/recreational (0.2307). As expected, the covariance between the action spaces of discretionary activities is the strongest of the three, indicating that the action space for discretionary activities is influenced in the same direction by unobserved factors. The somewhat unexpected positive correlation between error terms for shopping/eating and work/school action spaces suggests that there may be an unobserved connection between these activity types. For example, those who work may engage in shopping, running errands, and eating meals (such as lunch) close to the work location. This may lead to a positive correlation between the action space for work and the action space for shopping/eating activities.

6. A MULTIVARIATE ORDERED MODEL OF MODE USE BY ACTIVITY PURPOSE

Mode use is a fundamental behavioral dimension of much interest in the field of traveler behavior and values, with a number of studies dedicated to analyzing mode choices of specific demographic groups. For example, Blumenberg and Pierce (2014) analyzed the 2009 National Household Travel Survey to understand mode use patterns of low income individuals and find that they are less multimodal than higher income individuals (counter to initial expectations). They conclude that providing multimodal options may enhance mobility for low income individuals, particularly if they do not have access to an automobile. A similar case may be made for older individuals, particularly as they age. Also, understanding factors influencing the use of active travel modes by older individuals may help communities design built environments that promote active travel.

This section is concerned with understanding the factors that influence the counts of trips by mode by purpose for older people. A multivariate ordered probit model is estimated to identify socio-demographic, household, and travel characteristics that impact the number of trips undertaken by different modes of transport for various activity purposes. The three modes considered include active transport (biking and walking), private vehicle (car, van, truck, SUV), and public transportation (bus, rail); and the four activity types considered include home, work/school, shopping/eating out, and social/recreational/health. Mode use is modeled using a count modeling approach to determine the factors influencing different levels of use of each mode by activity type.

The modeling framework used here is a direct application of the one found in Ferdous et al (2010). This model uses a pairwise marginal likelihood estimation approach, which involves using a composite marginal approach based on bivariate margins (see Bhat et al, 2010 for details). Because this model has 12 dependent variables (four purposes by three modes) and up to 13 explanatory variables per outcome, displaying the estimation results of the full model in table format is rather prohibitive. Therefore, key findings and results are summarized in this section. The model was found to offer a goodness-of-fit consistent with models of this nature. The predicted log-likelihood for the full model at convergence was -15,537.3, while that for the null model was -18,877.4. The likelihood ratio test statistic is 6,680, indicating that the specified model is a very

significant improvement over the null model. Comparisons of model performance showed that the estimated model was also better than the null model in predicting aggregate shares of mode use by activity type. Thus, the estimated model performed better than the null model on both aggregate and disaggregate measures of performance.

The focus of this paper is on understanding the effects of age-related variables on mode use patterns for different activity purposes. As such, the discussion here will be limited to the subset of explanatory variables that pertain to this class of explanatory factors. The three age categories of 65-74 years, 75-84 years, and 85+ years were included in the model specification while treating the age group of 55-64 years as the base. It is found that age has a differential impact on the propensity to use active transport modes for the “home” trip purpose. The coefficients corresponding to the three age bands for this mode-activity combination are -0.1004, -0.1604, and -0.3425 respectively. In other words, as the age of the individual increases and progresses from one band to the next, the propensity to use active transportation modes for home trips decreases. The drop in propensity when transitioning from 75-84 years to 85+ years is substantially larger than the drop in propensity when transitioning from 65-74 years to 75-84 years. It is this type of heterogeneity that this study aims to unravel and explicitly recognize; by revealing this type of heterogeneity, it is possible to see the specific contexts where the older subgroups have difficulty relative to younger subgroups.

Another negative coefficient (of value -0.2089) is associated with the age group of 75-84 years for the propensity to use active transport modes for shopping/eating out. Individuals in this age band are still interested in traveling to farther locations for shopping/eating activities but are less likely to use active transportation modes to do so. A similar negative coefficient (-0.2376) appears for the same age group for the propensity to use active transportation modes for social/recreational/health activities. Once again, it appears that this group is not yet ready to shrink their action space dramatically, and as a result, their propensity to use active transportation modes is diminished relative to other age groups. The one other situation where age variables turned out to be significant is that for the private vehicle mode – home purpose combination. The variable representing 65-74-year-old group has a positive coefficient for this combination; on the other hand, the variable 85+ years has a negative coefficient. It appears that those 65-74 years are very much inclined to use the private vehicle. Those 85+ years have diminished auto driving capabilities and show a decreased propensity to use the auto mode, thus calling for the establishment of alternative mobility options that can help fulfill mobility needs, especially in contexts lacking good modal alternatives (such as public transit). In this realm, mobility-on-demand services appear to be filling a critical role of providing mobility to older people who are no longer able to drive or use public transit. Age variables did not significantly affect the propensity of engaging in any other mode-purpose combination. In general, it may be concluded that differences among the subgroups of the older population exist, but those differences are specific to certain modes, activity types, and contexts. An understanding of the modes and contexts where differences across age subgroups exist will help in the design of strategies and modal alternatives that could ameliorate the deleterious effects of aging.

Several other socio-economic and demographic variables were found to be significant in explaining mode usage for various activity purposes. Given the size of the model specification, and in the interest of brevity, a detailed explanation is not provided here. Variables that turned out significant include working status, gender, existence of a medical condition, level of education, race, income, built environment attributes (density measures), driver’s license status, household tenure, and residential location type. Full time employees have a higher propensity to use the

automobile for work, those with a medical condition (especially one that limits driving) are negatively inclined to use all three modes of transportation, and minority groups are more inclined to use public transportation relative to other groups. Built environment attributes (housing density measures) are critical to the propensity to use active modes of transport and public transportation for various trip purposes. Overall, the model offered reasonable and behaviorally intuitive results consistent with expectations.

An examination of the error correlation matrix revealed a pattern of correlations in which the association between frequencies of use of different modes of transportation for the same activity types is rather weak. However, as expected, there is a positive correlation between the count of active transport for work and shopping/eating out activities, and between the count of public transport use for home, work, and shopping/eat out activities. There are strong negative correlations between errors associated with the count of private vehicle trips for home and work purposes and the count of the same activity purposes by public transit modes. In other words, unobserved factors that positively contribute to auto use are likely to negatively contribute to public transport mode use, suggesting that public transport modes need to offer a very high level of service to attract riders away from the private vehicle mode. A result that is along expected lines is the positive relationship between a mode use for one activity and the same mode use for a different activity. That is, individuals who travel using one type of mode are more likely to travel with a greater frequency by the same mode for other activities. This suggests that it may be difficult to bring about multimodal travel patterns among the older population.

7. A MODEL OF ACTIVITY PARTICIPATION AND TIME USE ALLOCATION

The final dimension studied in this paper is that of time use allocation. Time use is modeled using the multiple discrete continuous extreme value (MDCEV) model proposed by Bhat (2005, 2008), with the in-home time expenditure treated as the outside good (which must be consumed at least to some degree by every individual in the sample). The MDCEV model essentially allocates a total available time budget to various activity categories, while accommodating satiation (i.e., diminishing marginal utility) and corner solutions (zero allocation of budget to certain categories other than the outside good, which must be consumed). The model formulation is omitted here in the interest of brevity, but complete details are available in Bhat (2005, 2008) and many other papers that have applied the Kuhn-Tucker based demand model systems in recent years (e.g., Shamshiripour and Samimi, 2017; Imani et al., 2014; Habib, 2009).

Model estimation results are presented in Table 6. As in the other models developed in this paper, three activity categories are considered (besides the outside good). The three activity categories are rather broad in nature: work/school, shopping/eating, and social/recreational/health. The translation parameters (see bottom of table) represent the preference for an alternative; a higher value of a translation parameter implies lower satiation; that is, the individual will consume more of that alternative relative to the others. As expected, work/school has the highest translation parameter, suggesting that individuals in this sample allocate the most time to this particular activity. This is not surprising given that the sample includes 55-64 year-old individuals who are presumably working to a very significant extent. The translation parameter for social/recreational/health activity is larger than that for shopping/eating, suggesting that older people allocate more time to social and recreational activities than to maintenance type activities.

Among the explanatory variables, the age variables are of interest in the context of this study. The continuous age variable has a negative coefficient for shopping/eating and social/recreational/health activities, suggesting that the time allocated to these activities decreases

with advancing age. The variable representing age range of 65-74 years has a positive coefficient on shopping/eating, suggesting that this group dedicates more time to these activities. The effect of this variable needs to be considered together with the continuous age effect, which is calculated as $-0.0122 \times 64 = -0.7808$ (at 64 years of age). When people reach 65 years, the results indicate a positive bump in this negative effect by 0.1305 to -0.6503 , which then goes back down to -0.7808 at the age of about 75 years. Effectively, the results indicate that individuals in the 65-74 years age group are more likely to spend time in shopping/eating than their immediate age-adjacent peers on either side. Those in this age group are likely to be just retired and experiencing a new phase of life, enabling the allocation of more time to shopping/eating activities relative to their younger peers. They are also relatively healthy and capable of undertaking activities outside the home relative to their older peers. The variable representing the age range of 75-84 years has a negative coefficient for work/school, suggesting that this is the age in which individuals truly relinquish working (perhaps some continue to work at least part-time during the 65-74 years). Strangely, the 85+ year variable does not have a negative coefficient on work/school time allocation, or any activity time allocation for that matter. It is possible that the two variables representing medical condition and use of medical device are capturing the 85+ age effect. Both variables have negative coefficients on activity time allocation, with the medical condition variable having negative coefficients across the table for all activities.

TABLE 6 MDCEV Model of Time Use by Activity Type (Base is Time for Home Activities)

Explanatory Variable	Work/School		Shopping/Eating		Social/Recreational/Health	
	Value	t-stat	Value	t-stat	Value	t-stat
<i>Socio-Demographics</i>						
Constant	-10.8877	-86.57	-5.4058	-25.78	-5.8843	-26.39
Household size	--	--	-0.2386	-9.36	-0.1499	-5.46
Age (continuous)	--	--	-0.0122	-4.39	-0.0144	-4.86
Age 65-74 years	--	--	0.1305	3.18	--	--
Age 75-84 years	-0.4151	-2.92	--	--	--	--
Age 85+ years	--	--	--	--	--	--
Female	--	--	--	--	--	--
Full-time worker	4.6101	35.47	-0.1099	-2.01	-0.3474	-5.97
Part-time worker	3.8582	28.18	0.1933	2.89	--	--
Medical condition	-0.6154	-3.99	-0.3821	-3.90	-0.5378	-7.48
Medical device	--	--	-0.3105	-2.62	--	--
HH income < \$35,000	-0.1832	-2.07	-0.2931	-5.48	-0.4486	-7.53
<i>Translation Parameters</i>						
	Value				t-stat	
G02- Work/school	365.2490				20.190	
G03 - Shopping/eating	27.4677				35.856	
G04 - Soc/rec/health	79.7798				30.328	

In other words, it appears that the activity participation and time allocation behavior is not only a matter of age, but more significantly a matter of medical fitness and condition. To the extent that older people are afflicted to a greater degree by maladies, their activity-travel engagement patterns become constrained. So, with advances in medicine, if people can stay healthy into later ages of life, it is plausible to expect that the age effect will increasingly diminish. If the correlation between age and medical condition diminishes over time, then age could become an increasingly inconsequential variable in travel models; rather, medical condition and medical device usage will dictate what people can and cannot do, and the lifecycle stage (empty nest, out of work force, and reduced family obligations) governs the types of activities that people undertake. Age has merely served as a surrogate for these effects in travel models to date. From a transportation policy standpoint, the profession should pay more attention to those who are disabled, those who have medical conditions and device constraints, and those who need assistance *regardless of age*, rather than focus on age alone.

The MDCEV model offered reasonable goodness-of-fit. The log-likelihood function corresponding to the constants only model is -68,655.4542 while the log-likelihood function value corresponding to the full model is -66,259.0078. These values can be used to calculate a likelihood ratio test statistic of 4792.8929, which is greater than the critical χ^2 value with 18 degrees of freedom at any level of significance. The ρ^2 value is rather low at 0.0349, but this is not all that unexpected given the disaggregate nature of the model and the many unknowns and unobserved variables that are likely to impact activity time allocation behavior of older people.

8. DISCUSSION AND CONCLUSIONS

This paper aims to describe how different subgroups of the older population differ with respect to their activity-travel characteristics and mobility patterns. The latest 2017 National Household Travel Survey (NHTS) data set of the United States is used to study heterogeneity among the older population subgroups by considering and comparing those 55-64 years, 65-74 years, 75-84 years, and 85+ years of age. A descriptive comparison shows that heterogeneity continues to exist; those in the older subgroups are less likely to have driver's licenses, are less likely to use the internet and devices such as smartphones, depict lower levels of mobility and trip making, exhibit lower levels of car ownership, and undertake fewer activities and spend less time outside the home. In other words, the fading of activity-travel engagement with age continues to be an issue confronting individuals as they advance into the later stages and ages of life.

A descriptive analysis of different groups of the older population found there are some groups less likely to be "plugged-in" than others. Women aged 85 or older in particular have among the lowest internet usage compared to all other groups. It would be a desirable goal to connect non-internet users, as those without access to internet might be missing out on activities such as shopping or spending time with friends and family as these activities become increasingly accessible through online applications and smartphones. Similarly, non-working older people are less likely to own smart phones. Although individuals in this group could potentially gain mobility from the use of Transportation Network Company (TNC) services, they may not have the means to access these services when compared to their working peers who are more likely to have smart phones. In other words, there are factors other than age (e.g., working status) that contribute to an individual's mobility and technology choices, contributing to considerable heterogeneity even among people of the same age group and gender.

The analysis also showed that older men are more likely to work from home than older women across all age groups, and part-time working men are substantially more likely to work

from home than part-time working women. This may point to a difference in the type of jobs that older men and women hold, and merits further study. There may be systematic gender differences in employment opportunities for older populations, allowing older men greater flexibility to work from home than women. This gender gap may be partially explained by the results of the analysis of technology use - older women are less likely to use the internet and smartphones than older men, which implies that they may not have the same level of tech-savviness as men to be able to work virtually from home. In summary, it should not be assumed that all members of an age group will have the same propensity to work from home. There is heterogeneity within age groups that can be attributed to gender and whether an individual works full-time or part-time. Future gerontological research should study and address the gaps in working from home between older men and women and between full-time and part-time workers. Such an analysis would help identify strategies that enable working from home for all subgroups, especially for individuals who still wish to contribute to society and provide an income for their households, but are limited by health-related barriers to mobility in their older years.

To better characterize the heterogeneity while controlling for various other socio-economic and demographic effects, the paper includes three modeling efforts. First, the paper includes a multivariate log-linear regression model of action space, which is defined as the farthest location that individuals visit outside home. Second, the paper presents a multivariate ordered probit model of the frequency of mode use for various trip purposes. Third, the paper presents a multiple discrete continuous extreme value model of activity participation and time use allocation for different activity purposes. For simplicity, three activity purposes are considered in this paper: work/school, shopping/eating, and social/recreational/health. Similarly, three modes are considered: private vehicle, active modes, and public transit.

The results suggest that there is heterogeneity among age groups even after controlling for various other effects; however, the degree of heterogeneity varies among the choice dimensions considered and the age-specific dummy variables are selectively significant in different choice alternatives. For example, the 65-74 age variable contributes negatively to work/school action space while the 85+ year age variable contributes negatively to the social/recreational/health action space. In the multivariate ordered probit model, the age specific variables negatively impact propensity to use active transportation modes for home trips, but to different degrees for different age groups. The variable representing 75-84 year old age group depicts a negative coefficient for the propensity to use active transport modes for shopping/eating activity. On the other hand, none of the age variables are statistically significant for the frequency of public transit mode use for any activity purpose. With respect to activity time allocation, age variables are selectively significant; for example, the variable representing 75-84 years has a negative influence on activity time allocation to work/school, while the variable representing 65-74 years has a positive influence on activity time allocation to shopping/eating. The results suggest that efforts aimed at enhancing density and diversity of opportunities and amenities in space would help older people continue to engage in activities even as their action spaces shrink. Providing convenient mobility options (virtually on par with the private automobile) would enable seniors to travel even when their physical and cognitive capabilities diminish and they are no longer able to drive or use transit on their own.

Interestingly, variables representing the medical condition of the individual and whether the individual uses a medical device are statistically significant, and often to a greater degree than the age-specific variables. It appears that activity-travel choices are determined to a significant degree by the physical and cognitive abilities of the individual; as these abilities generally diminish

with age, the age variables serve as surrogates to represent the diminished capacity of individuals to undertake activities and travel. As medical advances allow individuals to remain active into later years of life, age may become less of a factor in explaining activity-travel behavior in the future; rather the lifecycle stage and medical capacity of the individual will govern and drive activity-travel choices. Transport surveys should explicitly collect such information, and variables representing these dimensions should be explicitly incorporated in travel forecasting models. Transport policy interventions should be aimed at assisting and providing options to all who have disabilities and medical needs, regardless of age, so that mobility and equal opportunity is truly provided to all. Future research should aim to unravel the relative size effects of different explanatory factors; i.e., to what extent is the lower mobility among the older population due to age, medical conditions and devices, lifecycle stage, and household structure? Such an exercise will help policy makers target interventions strategically and assess the extent to which lower mobility depicted by older individuals is truly representative of social exclusion or merely an artifact of their lifecycle stage representing a voluntary choice.

The analysis in this paper has clearly shown the presence of considerable heterogeneity in activity and mobility choices within the older population. This suggests that treating the 65 and over age group as a single bloc (just because 65 years is the traditional retirement age) is not appropriate in travel analysis and travel demand forecasting models. Travel analysis methods should explicitly consider older population subgroups defined by separate age bands to recognize the varied needs and mobility challenges faced by different segments of the older population. Traditional age-based market segmentation definitions used in travel demand models are inadequate to forecast the mobility needs and choices of older population subgroups, thus limiting the ability to develop strategies, interventions, and mobility options that specially cater to their well-being. The advent of mobility-on-demand services and automated vehicle technologies holds considerable promise to enhance mobility for the older populations. However, these services must be designed to accommodate the specific needs of the older populations (with appropriate features needed by physically challenged individuals) so that the convenience afforded by these emerging technologies and services can be fully leveraged.

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