CIVIL ENGINEERING STUDIES
Illinois Center for Transportation Series No. 13-026
UILU-ENG-2013-2027
ISSN: 0197-9191

Modeling Seniors’ Activity-Travel Data

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Research Report No. FHWA-ICT-13-026

A report of the findings of
ICT-R27-113
Modeling Seniors’ Activity-Travel Data
Illinois Center for Transportation

August 2013

Technical Report Documentation Page

1. Report No. FHWA-ICT-13-026	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Modeling Seniors' Activity-Travel Data		5. Report Date August 2013
		6. Performing Organization Code
7. Author(s) Kouros Mohammadian, Behzad Karimi, Zahra Pourabdollahi, and Martina Frignani		8. Performing Organization Report No. ICT-13-026 UILU-ENG-2013-2027
9. Performing Organization Name and Address Department of Civil and Materials Engineering University of Illinois at Chicago 842 W. Taylor St. Chicago, IL 60607-7023		10. Work Unit No. (TRAIS)
		11. Contract or Grant No. R27-113
12. Sponsoring Agency Name and Address Illinois Department of Transportation Bureau of Materials and Physical Research 126 E. Ash Street Springfield, IL 62704		13. Type of Report and Period Covered
		14. Sponsoring Agency Code

15. Supplementary Notes

16. Abstract

The United States is experiencing an increase in its elderly population. According to Census Bureau estimates, this population should increase by 104.2% from 2000 to 2030, which translates into 72.1 million elders by 2030. This demographic change will affect the transportation system, like any other socioeconomic system. Thus, this study seeks to understand the dynamics of elderly activity-travel behavior and its potential effects on the transportation system to better identify and meet seniors' transportation needs. The Urban Travel Route and Activity Choice Survey (UTRACS), an automated, Internet- and GPS-based prompted-recall survey that was coupled with learning algorithms, was employed for that purpose. In this report, the study team analyzes elderly tour formation, activity-trip planning, mode-choice selection, and activity timing.

17. Key Words Seniors, travel behavior, travel survey	18. Distribution Statement No restrictions. This document is available to the public through the National Technical Information Service, Springfield, Virginia 22161		
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 69 pp.	22. Price

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

ACKNOWLEDGMENT, DISCLAIMER, MANUFACTURERS' NAMES

This publication is based on the results of ICT-R27-113, **Modeling Seniors' Activity-Travel Data**. ICT-R27-113 was conducted in cooperation with the Illinois Center for Transportation, the Illinois Department of Transportation, Division of Highways, and the U.S. Department of Transportation, Federal Highway Administration.

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EXECUTIVE SUMMARY

In 2010, there were nearly 40.3 million individuals age 65 and older in the United States, representing more than 13% of that year's population. According to Census Bureau estimates, this population is expected to increase by 104.2% from 2000 to 2030, which translates into 72.1 million people age 65 and older in 2030. This increase has become a serious concern in the United States because of the potential social and economic effects that an increasing elderly population can have on socioeconomic systems.

The projected increase in the elderly population will affect the transportation system, like any other socioeconomic system. Thus, it is crucial to understand the dynamics of elderly activity-travel behavior and its potential effects on the transportation system to better identify and meet their transportation needs. The lifestyle of senior citizens differs dramatically from that of younger people. Elderly people rarely perform the basic home–work–home travel pattern and often have mobility restrictions that make their travel needs more complicated. These facts show the importance of understanding how elderly population affects transportation planning.

In the 1970s, when the aging phenomenon was not yet a critical issue, several researchers studied the relationship between elderly activity-travel behavior and the transportation system. In 2002, the Transportation Research Board of the National Academies identified the aging population as a critical phenomenon in the 21st century. Since then, aging has become an important research topic, and there have been many studies to investigate elderly travel behavior and how it differs from non-elderly travel behavior.

This study addresses several issues related to elderly activity-travel behavior. Chapter 1 presents a literature review on elderly travel behavior. Chapter 2 contains a general descriptive analysis of the activity-travel data obtained from the Urban Travel Route and Activity Choice Survey (UTRACS), an automated Internet- and GPS-based, prompted-recall survey with learning algorithms. The UTRACS sample includes two age groups, one-half of elderly and the other of non-elderly people, who were asked to participate in the survey for 14 days. Participants responded daily to survey questions about their activity-travel patterns, planning perspectives, travel attributes, and other factors. The survey used multi-day activity diaries combined with GPS traces and an activity pre-planning and scheduling survey. The survey was conducted for one year in the Chicago region from March 2009 to March 2010.

Although activity-travel planning behavior is an important aspect in understanding individual activity-travel behavior, only few studies have addressed it. Chapter 3 explores activity-travel decision-making and planning behavior, and presents a descriptive analysis of choice of activity location, activity time, travel mode, and route. This chapter also investigates activity-travel planning more closely for two consecutive age groups—baby boomers and young-old seniors (ages 65 through 74).

Chapter 4 explores seniors' trip and tour formation, based on UTRACS data analysis, and presents an advanced model for interactivity duration, focusing on shopping activities. The latent segmentation model was run for elderly and non-elderly people to compare rhythmic patterns and to examine the duration between successfully executed shopping activities.

Chapter 5 describes a copula-based joint model the study team developed to model elderly people's mode choice. This copula-based model has been extensively used in recent years to model two or more decisions jointly and determine their interdependence.

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CHAPTER 1 LITERATURE REVIEW

Public health, medical care, diet, and economic circumstance are among the factors influencing life expectancy. In developed countries, with better public health and stronger economies, life expectancy has significantly increased in recent decades. This increase in life expectancy and an accelerating decrease in birth rates have resulted in a higher proportion of elderly people in developed countries.

The United States, like many other nations, is experiencing an increase in the number of elderly residents. The United States has the third-fastest-growing proportion of senior citizens among developed countries, after Japan and the European Union (Turner et al. 1998). Increasing life expectancy is one reason for accelerating growth in the American elderly population. Figure 1.1 shows how life expectancy at birth has changed from 1970 to 2010. Over that 40-year period, life expectancy has gradually increased from 70.8 to 78.7 years.

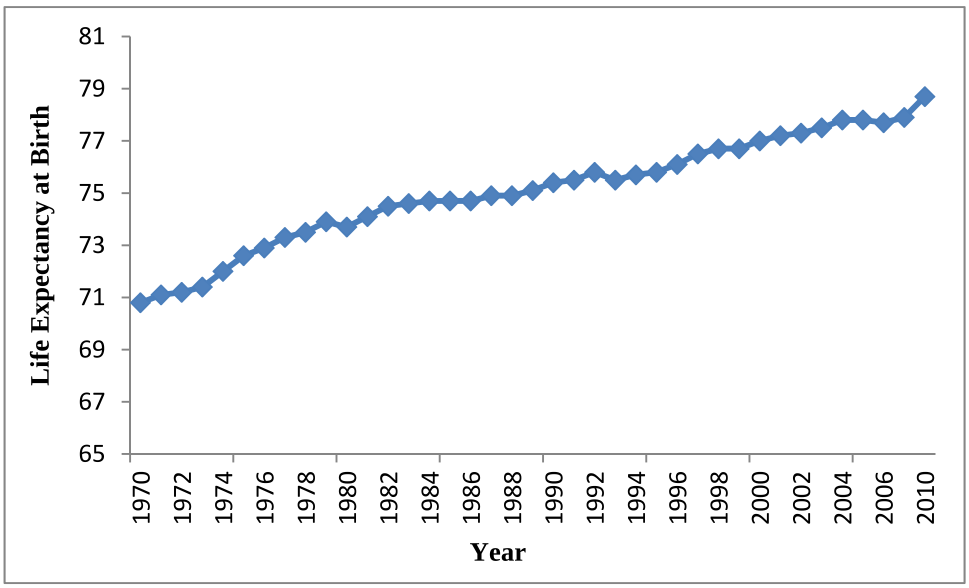


Figure 1.1 Life expectancy at birth in the United States, 1970 to 2010 (National Center for Health Statistics 2012).

The aging of the postwar “baby boom” generation is another important contributor to accelerating growth in the American elderly population (U.S. Census Bureau 2009). The term “baby boomer” refers to people born between 1946 and 1965. Baby boomers, as illustrated in Figure 1.2, represent the peak rate of U.S. births dating back to 1930 (Jones and Hoffmann 2003; National Center for Health Statistics 1994). The oldest baby boomers began turning 65 years old in 2011, resulting in a considerable increase in the elderly population (Wan et al. 2005).

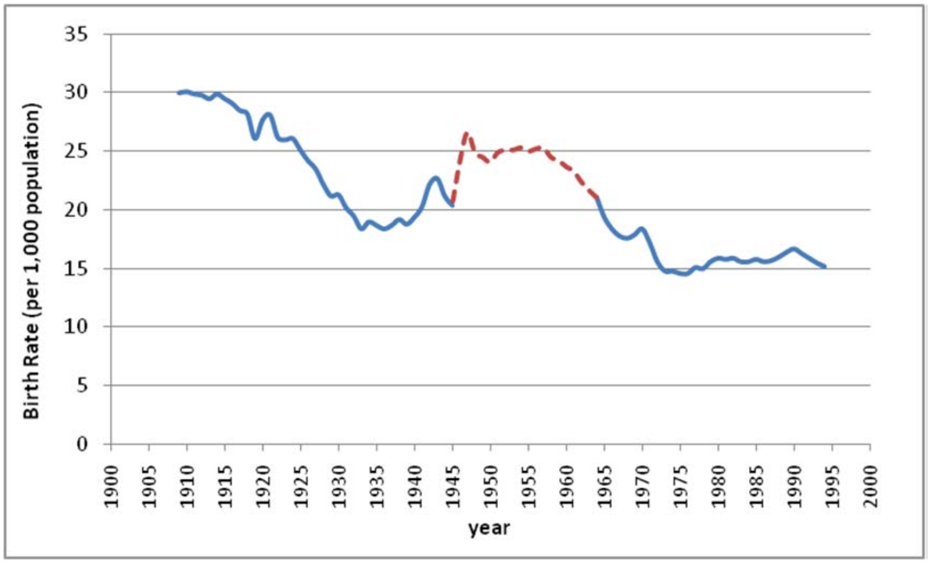


Figure 1.2 U.S. birth rate plot; The dotted line indicates baby boomers' birth rate (National Center for Health Statistics 1994).

In 2010, there were nearly 40.3 million individuals age 65 and older in the United States. This represents more than 13% of that year's population. According to Census Bureau estimates, the number of elderly people is expected to increase 104.2% from 2000 to 2030. This translates into 72.1 million elderly in 2030. Meanwhile, the total population is estimated to increase 29.2%. This translates into an additional 33.5 million seniors in the United States by 2030, compared with 2010. This increase has become a serious concern in the United States because of the potential social and economic effects that an increasing elderly population can have on socioeconomic systems.

These increases in the older American population will affect this country's transportation system. It is therefore crucial to understand the dynamics of seniors' activity-travel behavior and its potential effects on the transportation system to better identify and meet seniors' transportation needs. Senior lifestyles are very different from that of younger people. Unlike younger people, elderly individuals rarely perform the basic home–work–home travel pattern. Instead, they have very different daily activity-travel patterns. Elderly people also often have mobility restrictions that make their travel needs more complicated.

In the 1970s, several researchers studied elderly peoples' activity travel behavior and its relationship with the transportation system, when the aging phenomenon was not a critical issue (Bell and Olsen 1974; Hanson 1977; Stirner 1978). In 2002, the National Academies' Transportation Research Board (TRB) listed aging as a critical phenomenon in the 21st century (Pisarki 2003). Since then, aging has become an important research topic. Many studies have investigated seniors' activity-travel behavior and compared these differences with those of the non-elderly (Giuliano et al. 2003; Mercado and Páez 2009; Páez et al. 2007).

Elderly driving behavior and the impacts on traffic safety is one of the issues most often addressed in previous studies about seniors' travel behavior. In 2010, older drivers were 16% of all licensed drivers in America, a 2% increase since 2001 (NHTSA 2012). The increased convenience of driving as a result of technological advances, individual's inclinations to maintain their choice travel mode, the elderly population's improving health conditions, and more disposable income are several factors contributing to the increasing share of elderly drivers (Alsnih and Hensher 2003).

Previous studies indicated that increased reaction time, loss of visual and hearing abilities, increased mobility constraints, and decreased cognitive capacity are among the most frequent factors negatively affecting elderly peoples' driving ability (McGwin et al. 2000; Lyman et al. 2001; Dobbs 2005). Elderly drivers are more often involved in side-impact and angle collisions at intersections (Robertson and Vanlaar 2008) and in traffic crashes per each mile driven. They also have a higher fatality rate (Rosenbloom 2003). In the United States, 17% of the traffic fatalities and 8% of the people injured in traffic crashes in 2010 were elderly people (NHTSA 2012).

Driving is the most frequent travel mode among elderly Americans (Collia et al. 2003). They drive more than young people (Rosenbloom 2003) and do not use public transit very often (Collia et al. 2003). Rosenbloom (2003) partly explained the elderly's preference for driving by indicating that most elderly people (79%) live in suburban and rural areas, where public transit or other alternative modes are limited.

Most elderly people travel within suburban areas (Mohammadian et al. 2007) where public transit is frequently unavailable or not appropriate for their typical travel purposes (Collia et al. 2003). In the same context, Giuliano et al. (2003) explored the relationships between elderly peoples' travel patterns and their residences, using the 1995 Nationwide Personal Transportation Survey. The authors found a strong relationship between land use and senior travel patterns. They also analyzed the effects of different land use strategies on elderly mobility. Xinyu et al. (2008) and Hough et al. (2008) also explored the effects of urban design on elderly mobility.

Although walking is a healthy transportation mode for all ages (Yaffe et al. 2001), for a large number of the elderly with mobility restrictions, walking is not the preferred travel mode. People age 65 or over comprise 19.3% of all pedestrian fatalities (NHTSA 2012). However, studies showed that general improvements in the transit system, such as increasing service frequency and providing real-time notices or booklets on transit information and the schedule, are highly appealing to the elderly and would increase their transit ridership (Mohammadian et al. 2007). Paratransit is another public transit alternative that is more convenient but also more costly. Owing to its high operational costs, this service is only available for elderly people with severe disabilities (Rosenbloom 2001).

In Sweden, "community buses" (Stahl 1992) are another public transit alternative for elderly people. They use small buses with low-height floors on fixed routes designed to better serve seniors' origins and destinations. The community buses more successfully served the older population in Sweden than transit and paratransit services (McLarry et al. 1993). However, community bus implementation in Madison, Wisconsin was unsuccessful because it could not cover a diverse range of destinations, given the city's sprawl (Rosenbloom 2001).

Collia et al. (2003) used 2001 NHTS data to compare the average number of trips for elderly and non-elderly people. They showed that older individuals take 3.4 trips per day on average, compared with 4.4 trips per day on average for young individuals. They also discovered that gender differences are important factors in travel behavior. Typically, adult men travel more than adult women and have a lower tendency to use public transit (Collia et al. 2003). The same behavior was observed among the elderly, with older men traveling 27 miles per day on average and older women traveling 10 miles per day on average (Collia et al. 2003). However, they found that the distance traveled decreases significantly as age advances. For men, the distance traveled decreases from 42 miles for young men to 27 miles per day for older men, while for women it decreases from 25 miles for young women to 10 miles per day for older women (Collia et al. 2003).

In another study, Mercado and Páez (2009) used data from Canada's Hamilton Census Metropolitan Area (CMA) to examine what determined the average distance different age groups traveled. They showed travel distance decreased as age increased. Gender, employment constraints, and household characteristics were other significant factors for distance traveled. They also showed that elderly people drove considerably less. Páez et al. (2007) used mixed-ordered probit models to conduct a demographic and spatial analysis of trip generations of different age groups, including elderly people. Newbold et al. (2005) conducted a generational analysis on Canada's elderly population. They used the 1986, 1992, and 1998 General Social Survey databases and found tangible changes over time in elderly travel behavior.

Several studies have investigated elderly travelers' tour-based characteristics. These studies showed the number of tours decreasing significantly as age increases (Golob and Hensher 2007; Mercado and Páez 2009). Golob and Hensher (2007) also compared the number of tours for different modes. They found that the number of auto-driver tours decreases more significantly as people age, in comparison with auto-passenger or transit tours (Golob and Hensher 2007). The number of auto-driver tours peaks between ages 40 and 44 and considerably decreases as people age. This results in an increase in the use of auto-passenger or transit modes in tours (Golob and Hensher 2007). It implies that elderly peoples' loss of driving ability reduces the number of tours, rather than a decline in the desire to perform these activities. Mercado and Páez (2009) argued that older individuals prefer independent and affordable travel modes like public transit rather than dependent modes, such as accepting a ride from family or friends. In another study, Frignani et al. (2011) compared the decision-making and tour formation processes of elderly and non-elderly people and found substantial differences in the activity-travel behavior of the elderly and the non-elderly. They used the Urban Travel Route and Activity Choice Survey (UTRACS) (Frignani et al. 2010) data as their database. This database provided very detailed information on travel activity planning horizons and flexibilities for these age groups. All the facts and findings on the travel behavior differences between elderly and non-elderly people and the social and safety issues associated with the increasing number of elderly, show the importance of providing attractive alternative transportation to fulfill elderly peoples' activity-travel needs.

Seniors' lifestyle and characteristics have changed over time. The elderly population today has a more active lifestyle, enjoys better health, and lives longer than past generations. Their active life style today results in more out-of-home activities and more activity trips. In total, seniors' vehicle trips increased 77% over a period of 12 years from 1983 to 1995, which translates into a 98% increase in miles driven and a 40% increase in driving time (Rosenbloom 2001). However, transit ridership among elderly people declined over the same period and, according to Rosenbloom (2001), will likely continue decreasing. These significant changes in seniors' behavior over time indicates that future generations of seniors might not have the same lifestyle and behavior as those in the past, which should be considered and studied carefully for any long-term planning.

In the same context and considering the ongoing trends, Arentze et al. (2008) used the microsimulation model ALBATROSS to investigate possible alterations in activity-travel behavior of future elderly populations, (Arentze and Timmermans 2003). Their findings implied that future elderly populations would conduct more out-of-home social and leisure activities. They also found that future seniors would work longer and increasingly choose to live in suburban areas. Their findings would result in an increase in kilometers traveled as a mobility indicator and possible growth in transit ridership among the Dutch elderly.

Other studies exploring the elderly populations' relationship with the transportation system have focused on elderly activity-travel choice. These studies have tried to define separate models for seniors (Hilderband 2003; Chang and Wu 2005; Van den Berg et al. 2010). Highly capable activity- and tour-based models have provided the basis for separately capturing and integrating different homogenous population groups' travel behavior. These models are composed of diverse sub-models and try to approach real daily travel behavior. Some efforts in modeling aspects of elderly travel behavior are moving in this direction.

Chang and Wu (2005) used a multinomial logit model (MNL) to illuminate the mode-choice behavior of elderly Taiwanese. They found that age, gender, and living environment are significant factors in elderly people's mode-choice decisions. Van den Berg et al. (2010) studied elderly citizens' travel demand in the Netherlands, to model number of trips, travel mode, and travel distance. They used paper-and-pencil and social-activity diary data collected for two days. Su et al. (2009) examined elderly peoples' mode choice behavior for shopping trips. They ran multinomial logit and nested logit models on the London Area Travel Survey. Their analysis revealed that most elderly people relied on the auto-passenger mode for shopping trips. Mercado and Newbold (2009) also focused on the development of an elderly mode-choice model. Hibino et al. (2007) and Roorda et al. (2009) also investigated factors influencing elderly travel demand.

Some studies have shown that categorizing the elderly population into more homogenous subpopulations with unique specifications can provide more accurate output on elderly travel behavior (Karimi et al. 2012; Hilderband 2003; Wachs 1979; Meyer 1981). Generally, seniors are categorized in two major ways: lifestyle or age. Sociodemographic characteristics categorize the elderly population using lifestyle. Hilderband, for example, identified six lifestyle clusters: workers, mobile widows, granny flats, mobility-impaired, affluent males, and disabled drivers (Hilderband 2003). In the latter categorization method, which is widely used, the elderly population is usually categorized into three age groups, the young-old (65 through 74 years old), old (75 through 84 years old), and oldest-old (≥ 85 years old).

This study addresses several elderly activity-travel behavior issues. This approach includes a general descriptive analysis on the activity-travel data obtained from UTRACS, an automated GPS-based, prompted-recall survey with learning algorithms over the Internet, and a discussion on the differences between elderly and non-elderly activity-travel behaviors. The study team also explores activity-travel decision-making and planning behavior.

Although activity-travel planning behavior is important for understanding individuals' activity-travel behavior, only a few studies have addressed it. The study team, therefore, analyzes the UTRACS data and proposes an advanced model for the intershopping duration of the elderly population to explore seniors' activity-travel planning behavior. Moreover, they use UTRACS data to explore and analyze senior trip and tour formation. Finally, using advanced and cutting-edge modeling techniques in transportation studies, they develop a model for elderly mode choice and present the results of these analyses and proposed models.

CHAPTER 2 DATA PROCESSING AND DESCRIPTIVE ANALYSIS

Collecting data about travel activity and attributes has become easier and more interesting because of the development of cell phone and global-positioning system (GPS technology (Wolf et al. 2001; Wolf 2006). GPS-based travel surveys have many advantages including creating maps for activity-travel patterns to help respondents recall their activity travel when answering survey questions (Bachu et al. 2001; Clark and Doherty 2009).

Responding to transportation planners' concerns about the aging population's unique travel behavior and transportation needs, the study team conducted and combined UTRACS with traditional activity-travel data to provide a comprehensive dataset on individuals' travel behavior and decision-making processes. UTRACS is an automated GPS-based, prompted-recall survey with learning algorithms over the Internet. This survey asked respondents how and when they planned their activity and travel attributes and their perceived constraints on those decisions. It also collected information (such as activity purposes, travel modes, times, distances, etc.) from the activity-travel diaries that respondents kept for this study.

The survey respondent sample included half elderly and half non-elderly households. The study team asked individuals to participate in the survey for 14 days. These respondents daily answered the survey questions about their activity-travel patterns, planning perspectives, travel attributes, etc. The collected data should contribute to an understanding of elderly activity-travel behavior and decision-making processes and allow for analysis of the differences in elderly and non-elderly travel behavior.

2.1 SURVEY METHODOLOGY

The study team collected the data in three major steps. First, respondents joined the survey, registered as the user, and completed a survey about their socio-demographics, routine activities, and frequently visited locations. This step allowed the survey software to automatically build respondents' routine activity and travel patterns and decrease the propensity for repetitive queries. This diminished some of the difficulties respondents would have in the long-run. Survey-registered participants could enter their routine activities' attributes (such as activity type, partner involved, location, start and end times, and their variability) using a tabular-format page. They input the day-of-the-week when each activity was regularly performed. Respondents also used a Google Maps display and a pointer tool for locating frequently visited places.

In the second step, respondents completed a periodic activity-planning survey. This step collected data on activity type, start and end times, location, people involved, and travel mode for a fixed day in the near future, with an 8-day gap from the user registration date. The respondents completed the same survey three days and one day before the "pre-planning day." Figure 2.1(a) shows the activity-planning survey display.

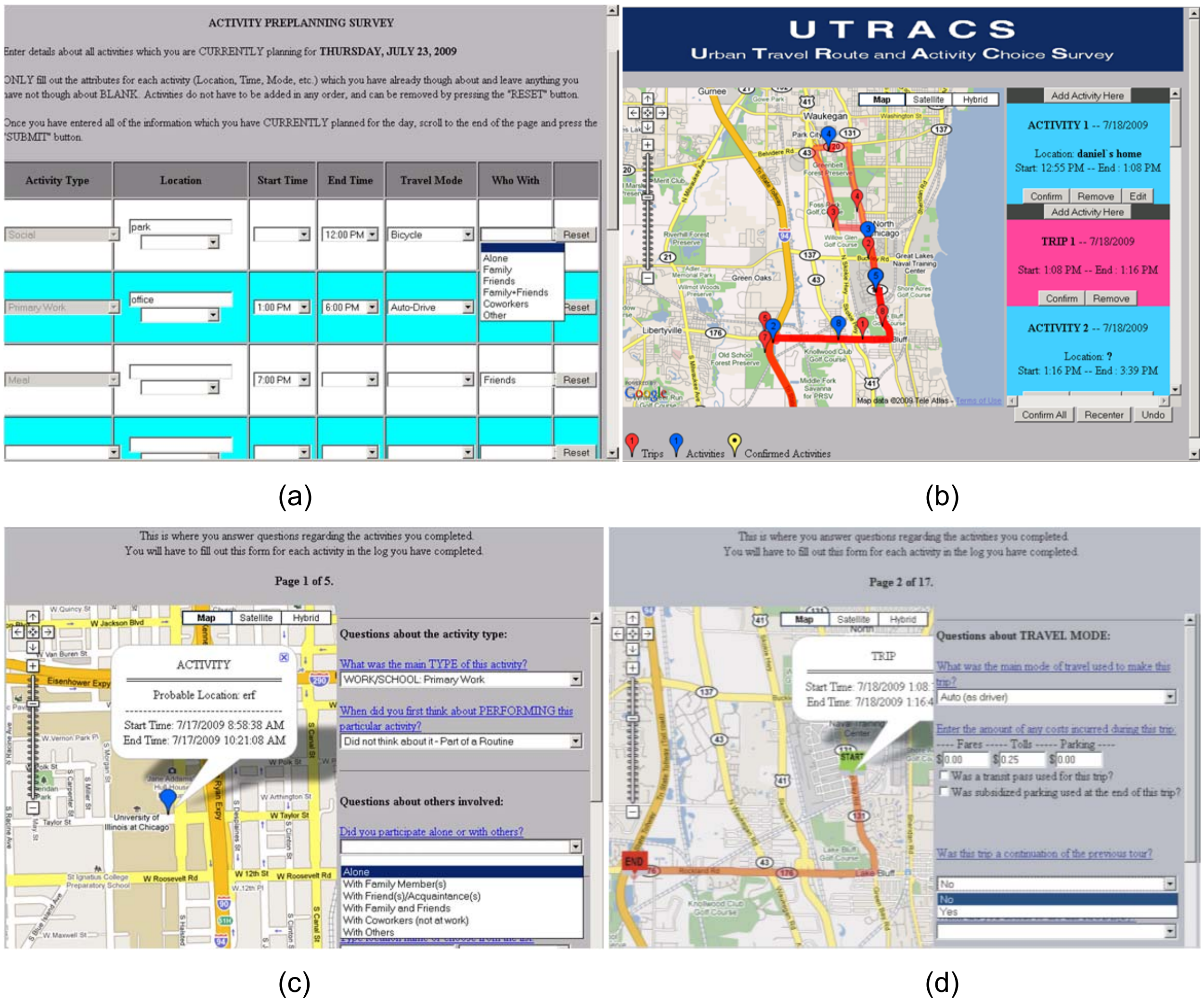


Figure 2.1 Survey website: (a) planning day survey, (b) activity-travel pattern confirmation, (c) questionnaire about activities, (d) questionnaire about trips (Frignani et al. 2010).

Because different activity attributes have dissimilar planning horizons (Clark and Doherty 2008), respondents could skip questions about unknown activity attributes in each of the three planning-activity surveys.

In the final step, respondents carried a small personal GPS logger for 14 days to record their activity-travel patterns, including the planning day outcome. They would nightly upload data recorded on their logs onto the survey website. The survey software was designed to make the uploading process as easy as possible. After connecting the logger to the computer using a USB cable, respondents clicked the “OK” button in an auto-play window to start processing the GPS data. After running the processing code, an auto-play login page was loaded with the respondent’s user name, asking him or her to enter the password and select a processed file to upload.

The uploaded data were transferred to a Web server and analyzed to build a timeline for the respondent’s activities and trips. A map automatically detecting the respondent’s activity-travel patterns was displayed next to the timeline. Respondents were thus able to review their trips and activities and correct errors in the data caused by any faults of the location-finding algorithm, signal-acquisition delay, or bad satellite fixes. Testing results showed that GPS devices detected 97% of all activities. Eighty-seven percent of these automatically captured activities were precise (Auld et al. 2009).

Respondents could modify their activities using tools to add, delete, and edit. After each update, a modified and interactive map could be zoomed in and out, scrolled, and visualized as a satellite image was displayed for respondents to verify the changes. The website page displayed the activity-travel pattern map presented in Figure 2.1(b). This exercise showed that using such an interactive activity-travel pattern map and activity timeline would attract participants and make modifications easier.

After the user modified the data, a questionnaire was generated for each verified trip and activity. It was displayed beside a map of the activity location or travel route referred to in the questionnaire. The known information on the activity or trip, including respective dates, start and end times, and location name were presented next to the map and questionnaire to prompt the respondent to recall the trip and activity details and to accurately answer the questions.

The questionnaire asked respondents about mode choices (including multiple modes), costs, and when and why they decided to choose a particular mode and route. It also asked respondents about activity type, people involved, location, start time, and duration-planning horizons, as well as location, start time, and duration flexibilities. All answers were multiple-choice, and each questionnaire included a comment box at the end for a more elaborate answer.

A learning algorithm was used to auto-populate answers for the travel mode, location name, activity type, and people involved to make the process easier and faster for respondents (Auld et al. 2009). Auto-population suggestions were only made when the predicted answer was known with a high degree of confidence. Respondents could choose the correct choice to modify any wrong, auto-populated answers. Figure 2.1(c) and 2.1(d) respectively show the website pages with the activity and trip questionnaires.

2.2 SURVEY EQUIPMENT AND IMPLEMENTATION

The GPS trackers, chargers, rechargeable AAA batteries, and computers with an Internet connection were the equipment used in the survey. The Taiwanese AMOD Technology Co., Ltd. manufactured the GPS trackers used for this study. They are model number AGL3080 Photo Tracker. The device is driverless and has a storage capacity of 128 megabytes, which can hold 360 hours of tracking data. The codes, used for processing the recorded raw data, were written in Java programming language and stored in the GPS trackers. The device uses three AAA batteries and can operate continuously for 15 hours. The dimensions are 90 x 45 x 23 millimeters. It weighs approximately 50 grams, not including batteries. The device has 20 parallel channels and a tracking sensitivity of –158 dBm. It is capable of recording data every 1, 5, or 10 seconds; but the research team used only the 5-second mode because it provided better visualization of trip routes.

The survey software was stored on a Web server to eliminate the need for installing any software on the computer where the survey is taken. The server-side Web application framework ASP.NET was used to run the survey code; and the computer programming language JavaScript was used to run the Google Maps API mapping software. Using Java as the programming language for the survey and hosting the survey on a Web server allowed respondents to use any computer with basic equipment (including a USB port, mouse, screen, Internet connection, and Java Runtime Environment) for the survey.

Because of the experimental procedure of GPS- and Internet-based surveys at the time (Stopher et al. 2008), no standardized guideline existed for methods of drawing samples and sample size, and for equipment deployment and retrieval for these survey types. In this study, the research team used the methodology and implementation procedures recommended in previous studies for traditional travel surveys.

2.3 SURVEY RESPONDENTS

A total of 112 respondents living in 101 households in the Chicago area participated in the survey. The study team recruited participants from a random, stratified sample of the Chicago area population. Half of the sample consisted of people age 65 and over and the other half of people ages 16 through 64.

The geographical area surveyed comprises Cook, DuPage, Lake, and Will Counties, covering a land area of 2,565 square miles with more than 6,600,000 inhabitants. This sample was stratified by county and by four categories of income. The sample followed the geographic population distribution in Census 2000. However, because of past experience of obtaining a lower response rate among lower-income and lower-education households (Mohammadian et al. 2009), households falling in the lower-income categories were oversampled in an attempt to yield a final income distribution similar to that of Census 2000.

People age 16 and above were eligible survey participants. This age limit existed because children under 16 typically do not have full control over their schedules and depend on others for being picked up and dropped off at activity locations, especially in the suburban areas, where travel options other than driving are limited. People who were unable to leave home or to complete the survey because of health conditions were also considered ineligible. Only English-speaking people could take the survey because the questionnaire was available in only this language, but this limitation affected only a small number of potential respondents. The survey team did not require respondents to be familiar with computers because the survey required only basic computer knowledge and the study team provided training and assistance.

For households that did not possess a working computer and Internet connection, the study team provided laptops with dial-up or wireless broadband. They either left the laptops and Internet data card in the households for use during the survey period or visited the households every 2 or 3 days, bringing the equipment with them. In the first case, having a computer and an Internet connection for 2 weeks was an extra incentive to participate. In the second case, even if respondents answered the survey a couple of days after the trips and activities occurred, the prompted-recall method of displaying the events on a map was expected to strongly reduce the amount of information lost (Bachu et al. 2001). The GPS tracker storage capacity was not a concern because it could hold 360 hours of data.

The incentives for participation were a $25 debit card for each respondent in the household and the entry into a drawing to win one grand prize of $500 or one of two first prizes of $250 dollars, also in form of debit cards. Respondents were entitled to the $25 card after they completed the upfront surveys and two days of survey participation. The drawing of the three prizes incentivized continued participation throughout the 14-day survey period. The respondents received one entry for each day they uploaded data and completed the associated questionnaires.

The steps in the recruitment of respondents and their participation in the survey were as follows:

1. Invitational material sent,
2. Invitational phone call made,

3. Initial visit conducted to deliver equipment and demonstrate its use,
4. Assistance offered during the course of the survey, and
5. Final visit conducted to retrieve equipment and deliver the participation incentive.

2.4 DATA VALIDATION

The data collected in a travel survey are primarily used to analyze travel behavior patterns and to calibrate and validate travel-demand models. Because the quality of analysis and models are mainly dependent on the quality of the input data, any travel survey's ultimate goal is to produce high-quality data that can be used to estimate a reliable demand model. Therefore, the survey instrument and the implementation procedures used in this project were designed to ensure the highest-quality data possible. This section assesses the quality of the data collected by performing a cross-validation analysis for trip and activity attributes and looking at the response rate, sample bias, and trip-rate indicators.

The study team surveyed a total of 112 respondents living in 101 households. Fifty-four percent of these respondents were seniors (≥ 65 years old) and the other 58 were between 18 and 64 years old. They also collected details for 2,401 trips and 2,622 activities from the seniors and 2,938 trips and 3,419 activities from the younger respondents. The study team thus collected data for 5,339 trips and 5,771 activities. Figure 2.2 shows the geographic trip distribution. It shows good coverage of the Chicago metropolitan area.

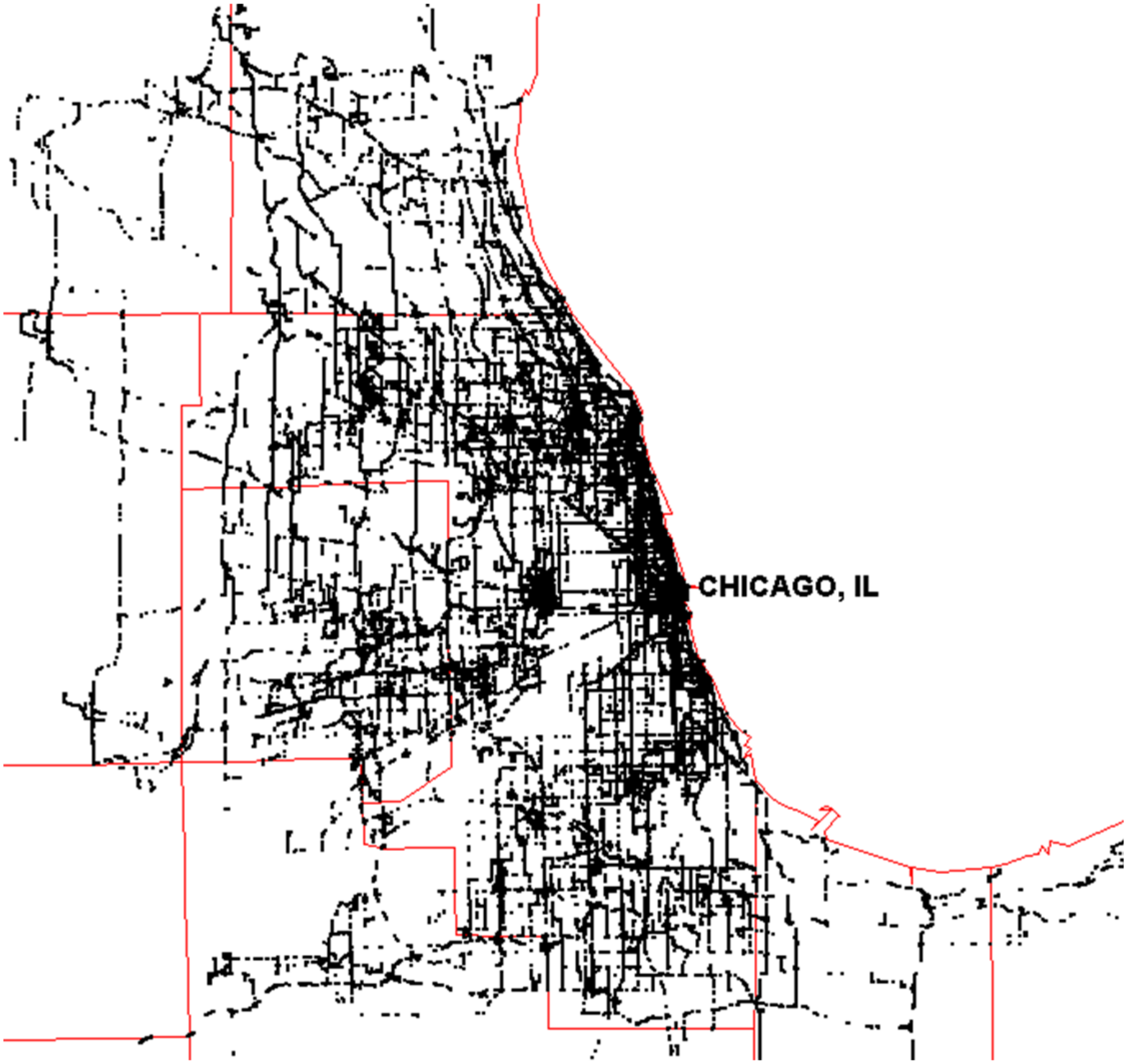


Figure 2.2 Geographic distribution of trips across county borders in the Chicago area.

2.4.1 Response Rate

Response rate is probably the first indicator looked at when assessing survey quality. Different methodologies exist for calculating response rate. The study team respectively used the following method and formula from the National Cooperative Highway Research Program (NCHRP) (Stopher et al. 2008) and the American Association of Public Opinion Research (AAPOR) when they devised this indicator:

$$RR3A = \frac{SR}{(SR + PI) + (RB + O) + e_A(UH + UO + NC)} \tag{2.1}$$

where

RR3A = response rate

SR = complete interview/questionnaire

PI = partial interview/questionnaire

RB = refusal and break-off

NC = noncontact

O = other

UH = unknown whether household is occupied

UO = unknown other

e_A = estimated proportion of cases of unknown eligibility that are eligible

Table 2.1 presents the classification of response types and the number assigned to each label in the response rate formula. The study team estimated the proportion of cases of unknown eligibility who were eligible (eA) at 0.8923. This accounts for the 215 ineligible individuals with health conditions, non-English-speakers, or wrong contacts out of a total 1,996 households contacted.

Table 2.1 Classification of Labels for Response-Rate Calculation

Label in RR3A formula	Classification	Elderly respondents	Non-elderly respondents
SR	One or more days of survey completed	54	58
PI	Only upfront surveys completed	19	20
RB	Refusals and dropouts	670	369
NC	No answers and answering machines	259	289
O	Multiple requests for callback, individual never available after callback request	25	15
UH	Fax lines	3	4
UO	Busy signal	1	2

Using the RR3A formula, the survey team estimated the overall survey response rate at 6.48% for individuals and 5.88% for households. The UTRACS survey response rate is lower than traditional 1- or 2-day, pen-and-paper travel-survey response rates. However, considering the complexity of a 2-week, GPS-based Internet survey and the expected commitment from respondents, the response rate is satisfactory.

The cooperation rate, calculated as the ratio of respondents to eligible individuals contacted, was 10.66%. The survey team calculated response and cooperation rates separately for elderly and non-elderly individuals. For elderly individuals, the calculated response and cooperation rates were respectively 5.37% and 7.91%. For non-elderly individuals, the response and cooperation rates were respectively higher at 8.04% and 15.76%. These results are in line with findings of the study by Kurth et al. (2001), who found that elderly households have a higher refusal survey rate. The main reasons for the elderly's high refusal rate might be the survey's Internet-based nature and the requirement to use a computer. Some elderly people were not familiar with computer technology and did not want to deal with it, even if assisted.

2.4.2 Sampling Bias

The sampling bias measure is another indicator of survey quality. Sampling bias is a systematic error in which the data is collected from an intended population that some members or individuals of the target population are less/more likely to be included in the sample than others. This error results in a nonrandom, or biased, sample in which all instances are not equal. According to the NCHRP (2008) recommendations, household size, vehicle ownership, age, race, gender, household income, and geographical distribution are among variables tested for sampling bias.

The root mean-squared error (RMSE) percentage is calculated for all variables using the following formula to indicate total error resulting from sampling bias:

$$PercentRMSE = \sqrt{\frac{1}{n_i}\sum_{i=1}^{n_i}\frac{1}{n_{ij}}\sum_{j=1}^{n_{ij}}\left(\frac{r_{ij}-s_{ij}}{r_{ij}}\right)^2} \times 100 \qquad (2.2)$$

where:

n_i = number of variables i
n_{ij} = number of categories j in variable i
r_{ij} = reference value of variable i in category j
s_{ij} = sample value of variable i in category j.

The study team estimated each variable's reference values from the American Community Survey (ACS) for Cook, DuPage, Lake, and Will Counties. The reference values and sample values for each variable are shown in Table 2.2.

Table 2.2 Reference and Sample Value for Sampling Bias Variables (Frignani et al. 2010)

Variable	ACS: Elderly	Sample: Elderly	ACS: Non-elderly	Sample: Non-elderly
Geographic Distribution				
Cook County	77.27%	79.63%	71.80%	79.31%
DuPage County	10.88%	12.96%	12.32%	12.07%
Lake County	6.37%	5.56%	8.92%	6.90%
Will County	5.12%	1.85%	6.96%	1.72%
Household Size (Average)	1.91	1.88	2.93	2.88
Vehicle Availability				
No vehicle	21.90%	4.08%	10.83%	3.92%
One or more vehicles	78.10%	95.92%	89.17%	96.08%
Household Income				
$34,999 or less	50.33%	19.51%	24.38%	19.57%
$35,000 to 49,999	14.37%	17.07%	12.92%	15.22%
$50,000 to 74,999	14.97%	21.95%	19.63%	8.70%
$75,000 to 99,999	7.85%	26.83%	14.63%	19.57%
More than $100,000	12.49%	14.63%	28.44%	36.96%
Race				
White	73.55%	81.48%	61.12%	82.46%
Black/African American	17.37%	16.67%	19.12%	10.53%
Other	9.07%	1.85%	19.77%	7.02%
Gender				
Male	39.76%	38.89%	47.31%	34.48%
Female	60.24%	61.11%	52.69%	65.52%
Age				
18 through 44	—	—	61.33%	34.48%
45 through 64	—	—	38.66%	65.52%
65 through 74	51.74%	72.22%	—	—
75 and over	48.26%	27.78%	—	—

The RMSE calculated for elderly respondents was 57.24%. The high value of RMSE for the elderly is due to the over-representation in the sample of households with income between $75,000 and $99,999 per year. The RMSE calculated for non-elderly respondents was 38.25%. The sample variables that caused the most inflation of RMSE for non-elderly respondents were age and race, with few non-white or non-African American individuals.

2.4.3 Trip Rate

Trip rate is another indicator most commonly used for quality assessment of travel surveys. The overall trip rate in the UTRACS data was 3.92 trips per person per day, which is higher than the 3.4 trips per person per day recommended as the reference trip rate for personal trips in NCHRP (2008). This result, along with findings from previous studies, shows that GPS-based surveys have increased the propensity for capturing underreported trips and thus improved data quality. For elderly respondents, the trip rate was 3.77 trips per person per day, compared with 4.06 trips per person per day for non-elderly respondents.

2.4.4 Trip and Activity Attributes Cross Validation

Tables 2.3 and 2.4 respectively summarize the reported trip and activity attributes in the UTRACS data. They also compare the study area's collected data against observed trip and activity attributes collected by the Chicago Metropolitan Agency for Planning (CMAP) 2008 Travel Tracker Survey (CMAP 2009). The Travel Tracker is a major multimodal household travel and activity survey conducted in the Chicago metropolitan area. More than 23,000 individuals participated in the 1- or 2-day survey, of which 4,315 were individuals age 65 years and older. Table 2.3 presents the average number of activities by type per person per day and the percentages of accompanying people. Table 2.4 displays the travel mode, trip duration, daily travel time, trip distance, and automobile and bus speeds for the elderly and non-elderly groups.

Because trip distance is calculated as a straight line from one activity to the next, the study team increased reported trip distances in the Travel Tracker Survey by 20% to obtain the real trip distance and compared it with UTRACS data. They also divided trip distance by travel time to estimate average speed.

As indicated in Table 2.3, UTRACS data presented a higher activity rate per person-day than the Travel Tracker Survey for almost all activities. This difference is more obvious for shopping activities, with a 50% higher rate than in the reference data. This remarkable difference might be due to UTRACS' automated recording and detection of minor shopping activities, such as stopping on the way and buying a drink. People usually think of these minor shopping activities as unimportant; however, given UTRACS' automated recording and detection mode, the data resulted in a much higher rate of this activity type than in the reference data. UTRACS also reported a higher frequency than the Travel Tracker for activities performed with other individuals.

Moreover, UTRACS captured a higher portion of trips with auto-driver mode and reported slightly more short-duration trips. The total daily travel time reported in the UTRACS data is lower than the reference value in the CMAP survey. This difference is remarkable for non-elderly respondents. By contrast, the average automobile and bus speeds are remarkably higher in the UTRACS data. This last result brings up suspicions that self-reported surveys overstate travel time and support possible improvements in activity-travel surveys using GPS technology.

Table 2.3 Summary of Activity Attributes

Attribute	Value	CMAP: Elderly	UTRACS: Elderly	CMAP: Non-elderly	UTRACS: Non-elderly
Average number of activities by type per person per day	Change travel mode	0.0192	0.0851	0.0556	0.0645
	Health care	0.1373	0.1441	0.0691	0.1199
	Social, leisure/recreation	0.3545	0.5365	0.3439	0.5082
	Meal	0.2293	0.2899	0.2269	0.2369
	Other	0.4564	0.5365	0.5535	0.5007
	Personal business	0.1574	0.2240	0.1237	0.1514
	Work	0.1537	0.1059	0.7066	0.6912
	Religious/civic	0.1123	0.1788	0.0578	0.0705
	School	0.0050	0.0139	0.0783	0.0705
	Shopping	0.6137	0.9583	0.4472	0.7466
Share of accompanying people	Alone	65.72%	59.52%	65.28%	64.50%
	With others	34.28%	40.48%	34.72%	35.50%

Table 2.4 Summary of Trip Attributes

Attribute	Value	CMAP: Elderly	This survey: Elderly	CMAP: Non-elderly	This survey: Non-elderly
Share of travel mode	Auto driver	71.38%	75.97%	72.21%	81.01%
	Auto passenger	16.91%	12.45%	10.32%	9.63%
	Bicycle	0.41%	0.33%	1.03%	0.34%
	Bus	1.89%	4.37%	1.93%	1.33%
	Commuter rail	0.38%	0.62%	1.80%	0.88%
	Light rail	0.29%	0.67%	1.57%	0.71%
	Walk	7.29%	5.29%	9.47%	5.24%
	Other	1.46%	0.29%	1.66%	0.85%
Share of trip duration	1 to 15 minutes	64.21%	71.62%	59.66%	67.09%
	16 to 30 minutes	22.30%	17.89%	22.07%	21.05%
	31 to 45 minutes	6.35%	6.70%	8.24%	7.83%
	46 to 60 minutes	3.36%	1.78%	4.88%	2.05%
	More than 60 minutes	3.78%	2.01%	5.15%	1.98%
Share of daily travel time	0 to 30 minutes	37.37%	40.80%	20.03%	32.92%
	31 to 60 minutes	19.57%	26.78%	18.53%	29.00%
	61 to 120 minutes	25.09%	23.13%	33.88%	27.12%
	More than 120 minutes	17.97%	9.29%	27.56%	10.97%
Share of trip distance	0 to 5 kilometers	56.92%	50.86%	48.59%	44.44%
	6 to 10 kilometers	20.46%	21.57%	18.40%	21.70%
	11 to 20 kilometers	13.31%	16.27%	15.92%	17.39%
	21 to 30 kilometers	4.48%	5.59%	6.94%	6.88%
	31 to 50 kilometers	2.88%	3.88%	6.69%	6.26%
	> 51 kilometers	1.94%	1.84%	3.45%	3.32%
Share of average speed for automobile trips	0 to 30 km/h	64.42%	11.83%	56.14%	12.00%
	31 to 60 km/h	29.66%	72.03%	35.73%	66.94%
	61 to 90 km/h	4.58%	13.91%	6.38%	18.11%
	More than 90 km/h	1.34%	2.24%	1.75%	2.95%
Share of average speed for bus trips	0 to 30 km/h	73.69%	60.76%	84.10%	30.00%
	31 to 60 km/h	21.44%	39.24%	14.27%	70.00%

2.5 GIS ANALYSIS

This section briefly analyzes GIS data exploring the distribution of elderly people and their interconnection with the geographic distribution of hospitals, senior centers, parks, and public transit stations. Figure 2.3 shows the distribution of elderly people in Chicago at the census-tract level. It also shows each tract's median age in Chicago for 2011. Figure 2.4 shows the elderly population distribution using a population density indicator. It shows the elderly population density per acre and the elderly population as a percentage of each tract's total population. Figure 2.5 illustrates the connection between the distribution of the elderly population and hospital locations in Chicago. The study team also performed a hot-spot analysis to examine this interconnection statistically, which showed that 12 of 42 hospitals are located in areas with the most elderly people. The same analysis was performed for senior centers, where 50% of the senior centers are in tracts with the most elderly people. The results are shown in Figure 2.6. Figure 2.7 presents results of the GIS analysis for Chicago Transit Authority (CTA) rail stations. This Figure shows the CTA rail system covering only a small area with a high elderly population, aside from the Loop and Streeterville neighborhoods.

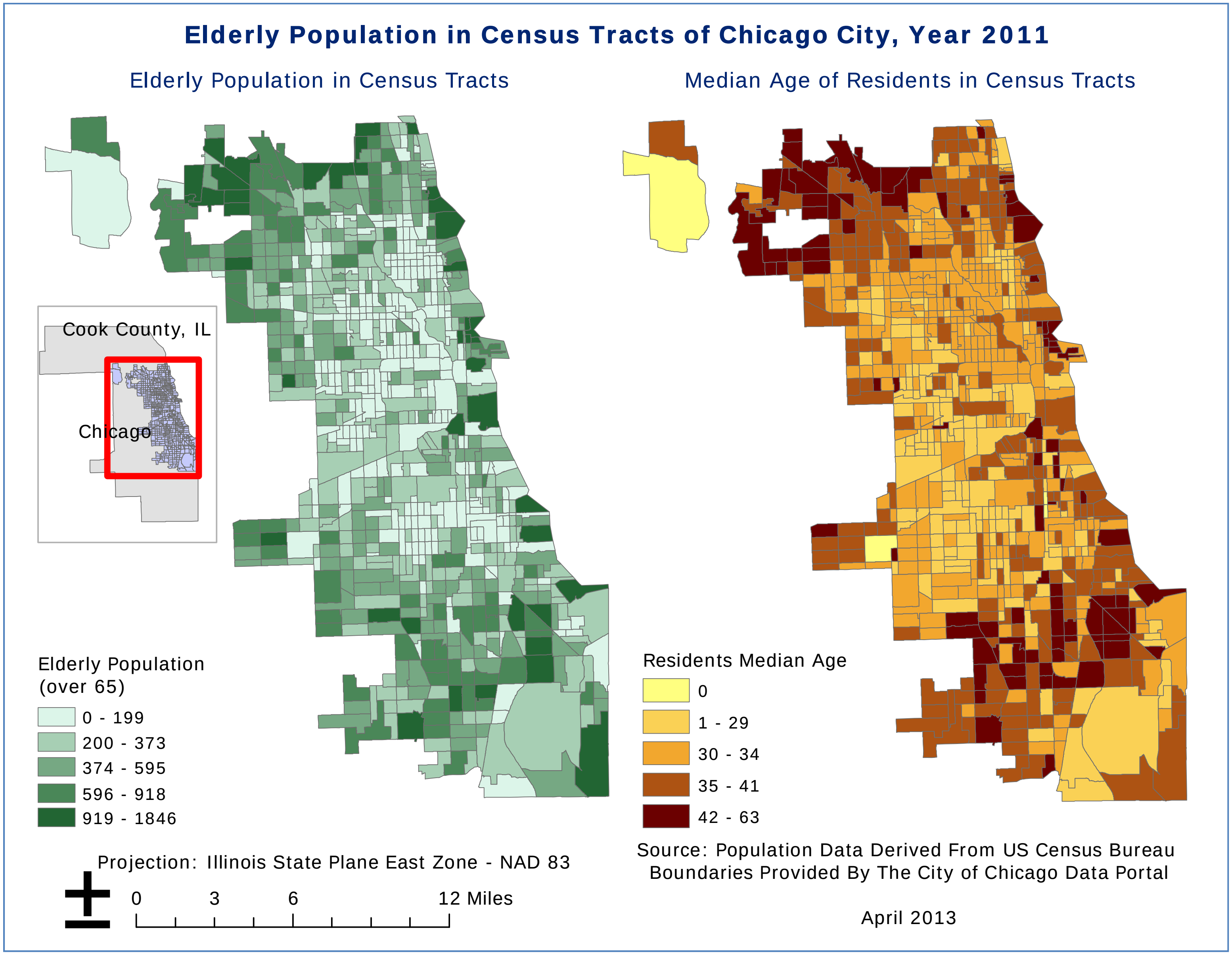


Figure 2.3 Geographic distribution of the elderly population in the Chicago area.

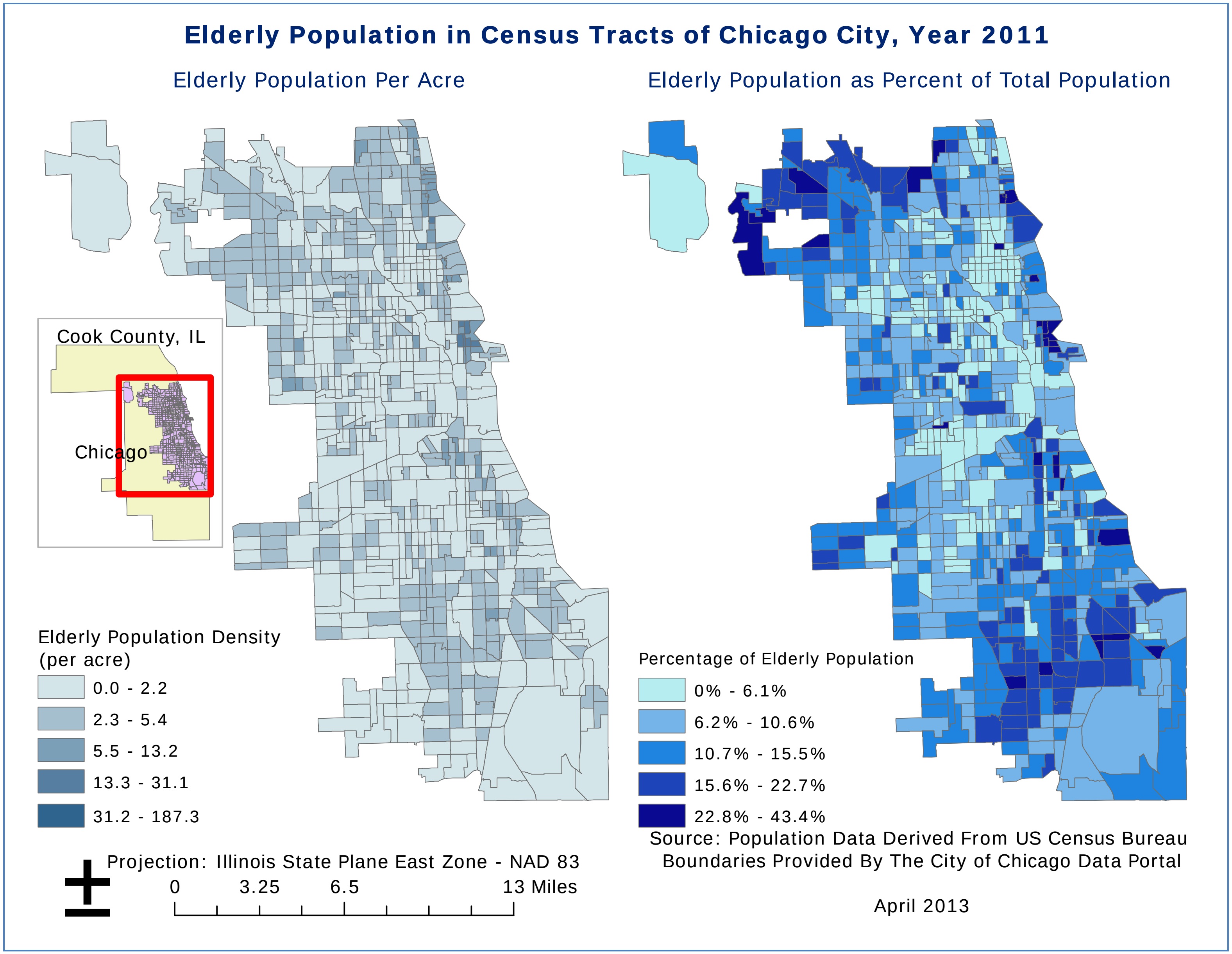


Figure 2.4 Elderly population density in the Chicago area.

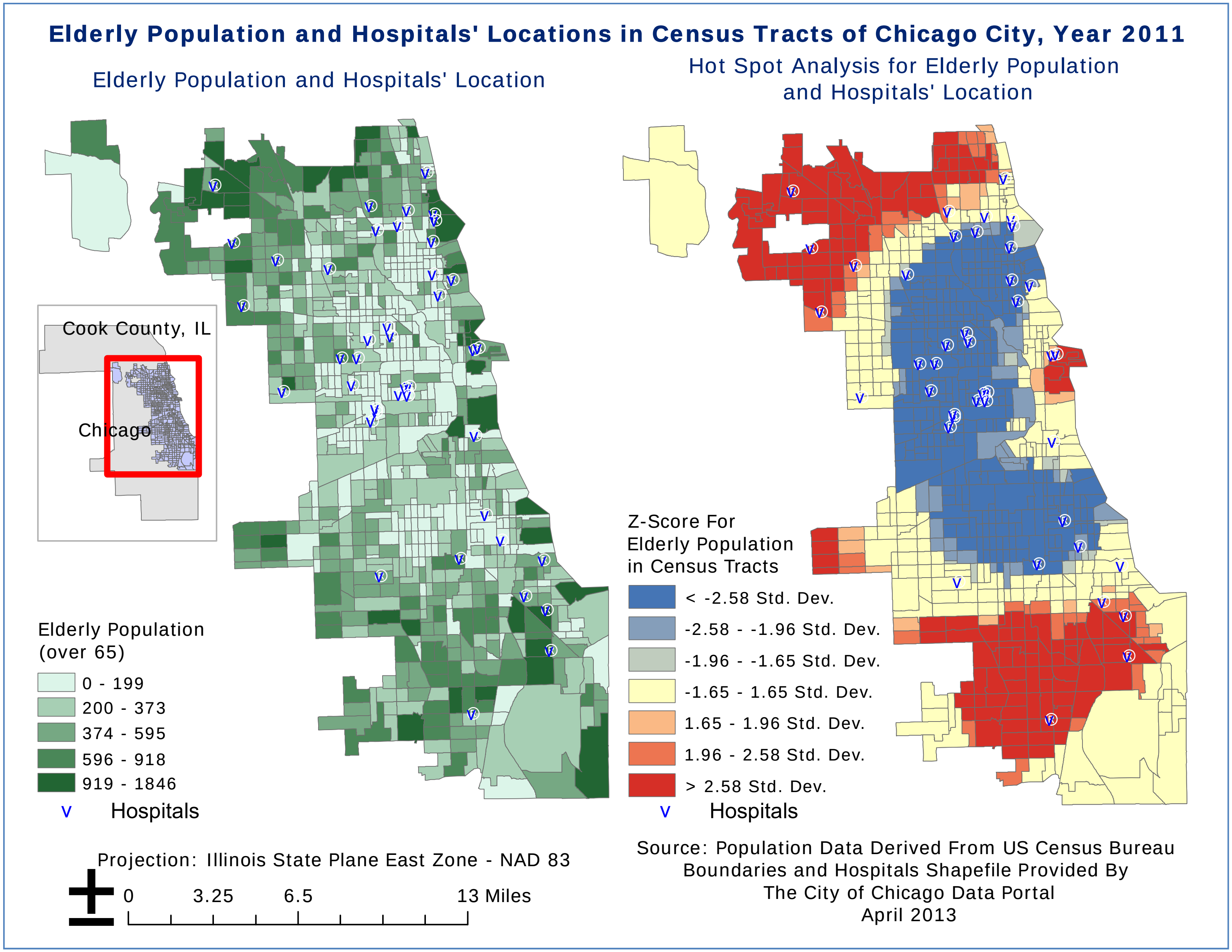


Figure 2.5 Distribution of the elderly population with regard to hospital locations in the Chicago area.

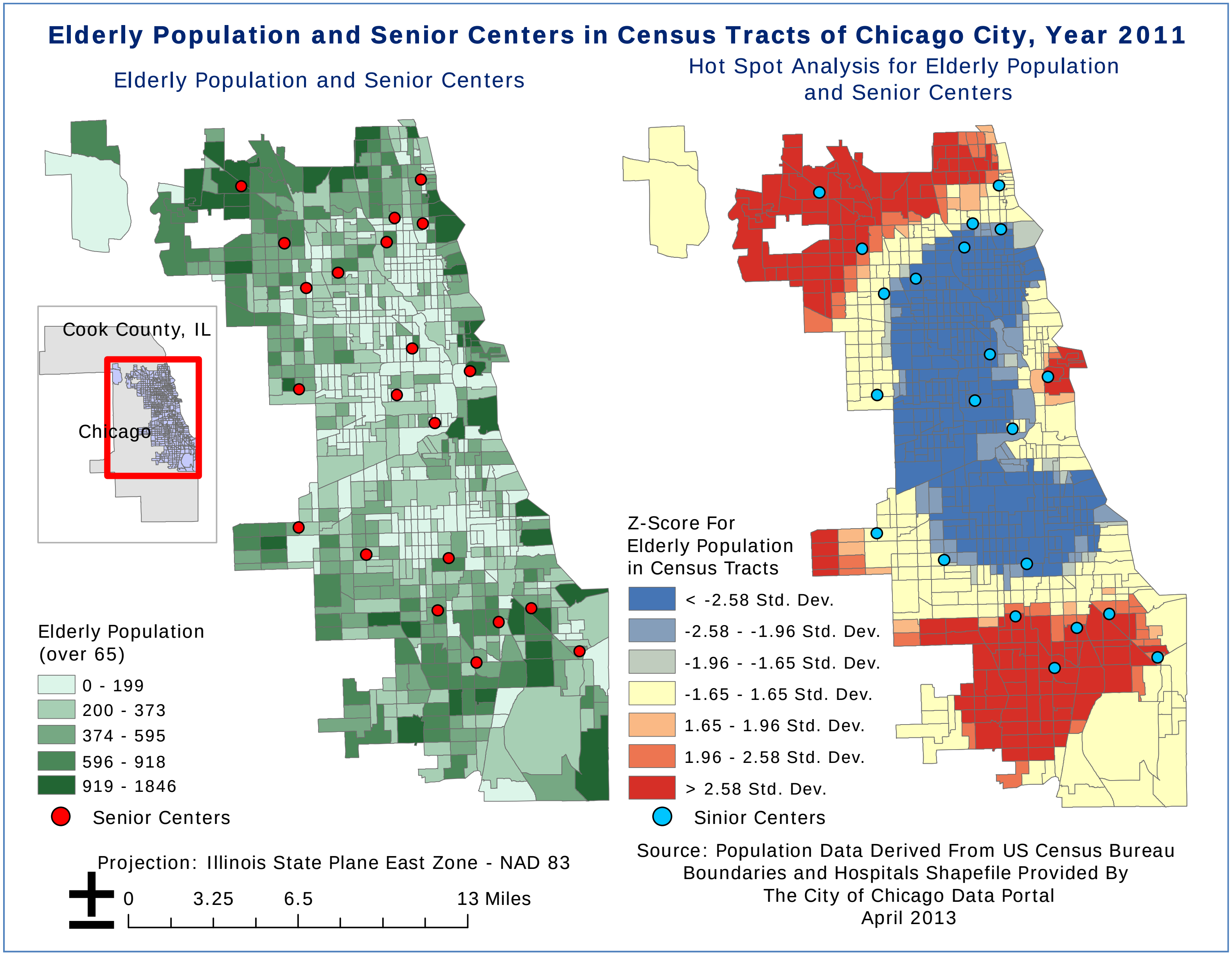


Figure 2.6 Distribution of the elderly population with regard to senior centers in the Chicago area.

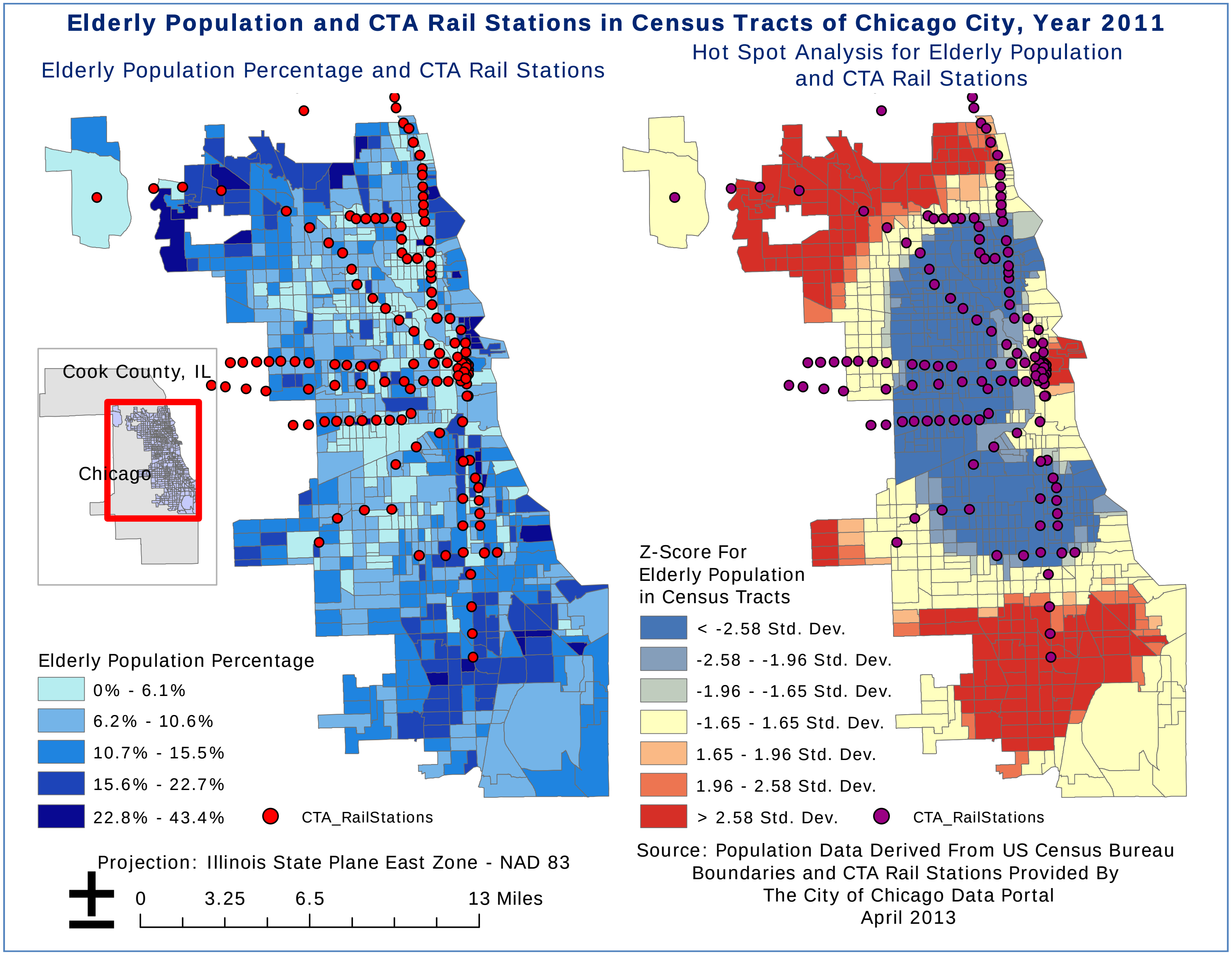


Figure 2.7 Distribution of the elderly population with regard to CTA rail stations in the Chicago area.

CHAPTER 3 DESCRIBING SENIORS' TRAVEL-PLANNING BEHAVIOR

In UTRACS, the research team asked the respondents about their activity-travel planning. The research team asked respondents when their activities started, what kind of trips they took, where each of the activities occurred, how long each of the activities took, and the number of people involved in each of the trips and activities.

3.1 ACTIVITIES

Planning-time horizon is defined as the duration between decision making on an activity and carrying out that activity. Figure 3.1 compares the distribution of the activity-planning horizons of elderly and non-elderly people. For the non-elderly group, routine decisions were the most common, accounting for 35.8% of all decisions to engage in an activity. Following routine activities were the impulsive activities, those decided less than one hour before the start of the activity. This accounted for 24.6% of all activities. Third were the activities that were decided upon the same day as they were performed. Around 46% of the activities conducted had a planning horizon shorter than one full day; that is, the activity was conceived and carried out on the same day.

Routine (25.5%) was the most common planning horizon for the elderly, closely followed by same day. They performed routine tasks 25% less than the non-elderly, probably because many of them were retired. Routine activities, however, are still a significant proportion of the elderly's activities and are more diverse than those of the non-elderly.

For the elderly, work represents 12.8% of all out-of-home routine activities. Forty-eight percent of all routine activities are civic/religious, recreational, leisure/entertainment or other types not specified on the multiple-choice answer. This shows the elderly developing new routines comprised of more diverse activities in the absence of traditional “mandatory” daily activities (e.g. work and school).

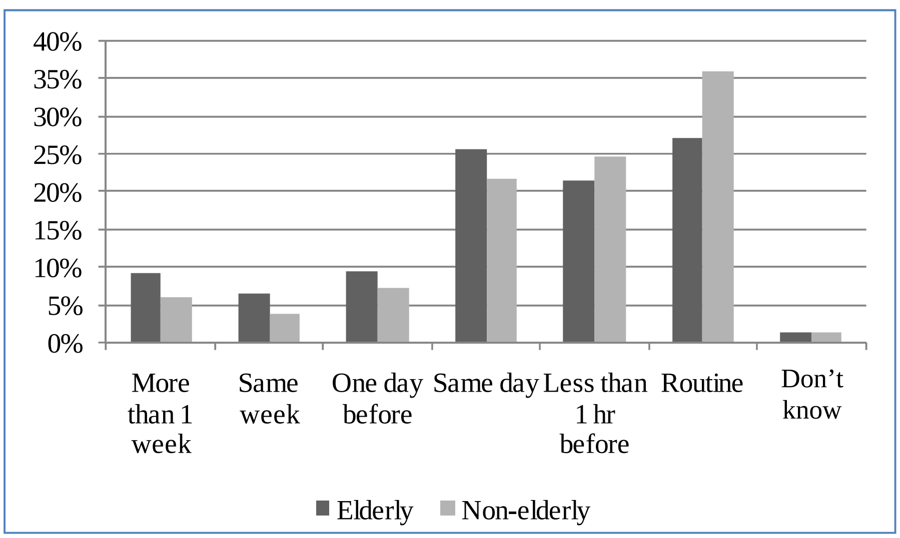


Figure 3.1 Activity-planning horizon.

Impulsive decisions were the third most common type for elderly individuals, accounting for 21.4% of all decisions. These types of decisions were approximately 15% less frequent among the elderly than the non-elderly. For longer-term planning, the difference is even more notable; while 9.1% of the elderly's activities were planned more than one week in advance, only 6.0% of the non-elderly's activities received longer-term planning.

These results reveal that the elderly are less prone to spontaneous decisions and very likely to plan their activities, especially when it comes to longer-term planning. This travel behavior characteristic by the elderly is positive for public transportation use because it facilitates the coordination of activity schedule and travel. It indicates that on-demand services in which users have to schedule service ahead of time will fit more than half of the elderly's travel needs. Transportation planners may take advantage of this characteristic when thinking of transit strategies for the elderly.

3.1.1 Location

Elderly and non-elderly individuals exhibit similar flexibilities when considering activity location choices. Figure 3.2 shows that more than 80% of the time, both groups of respondents indicated that their activities occurred at the only location they considered. Between 10 and 15% of the time, the activities could have occurred in two or three different locations. Only about 2% of the activities could have been performed in more than three different locations. This finding indicates that individuals, regardless of age, perceive themselves to be very inflexible when choosing their activity locations; and most times, people do not consider alternative sites for performing their activities. Most of the time, individuals strongly linked the execution of an activity to a specific location, equating for example the thought "I need to buy groceries" with "I need to go to grocery store X".

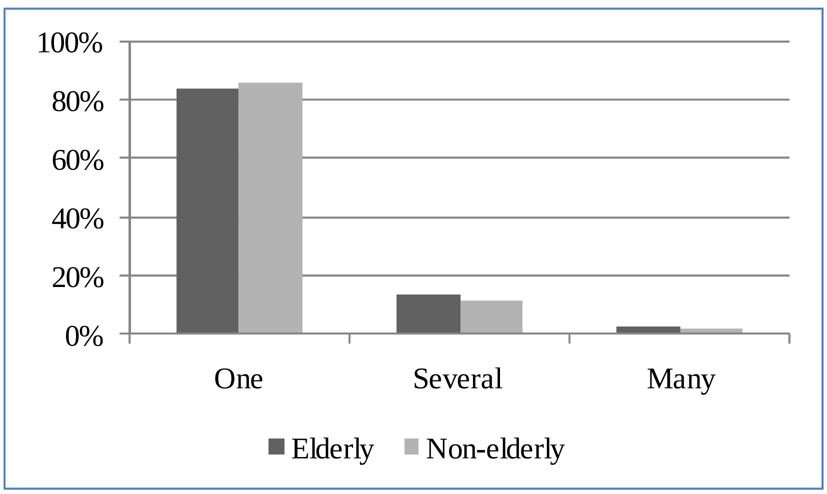


Figure 3.2 Number of activity locations considered.

3.1.2 Timing

The study team then examined activity start time and duration. Contrasting with what was observed for activity location flexibility, the non-elderly appear to be slightly more flexible over activity start time than their older counterparts. Figure 3.3 shows assessed flexibility levels and their frequencies. The frequency of very flexible activities (i.e. those that could happen virtually at any time) was slightly higher for the elderly; but the non-elderly more frequently reported the next flexibility level. The frequency of those activities that could start within a few hours of the actual start time was analogous for both age cohorts; but the most inflexible activities (i.e. those with a specific start time) were nearly 10% more common among the elderly.

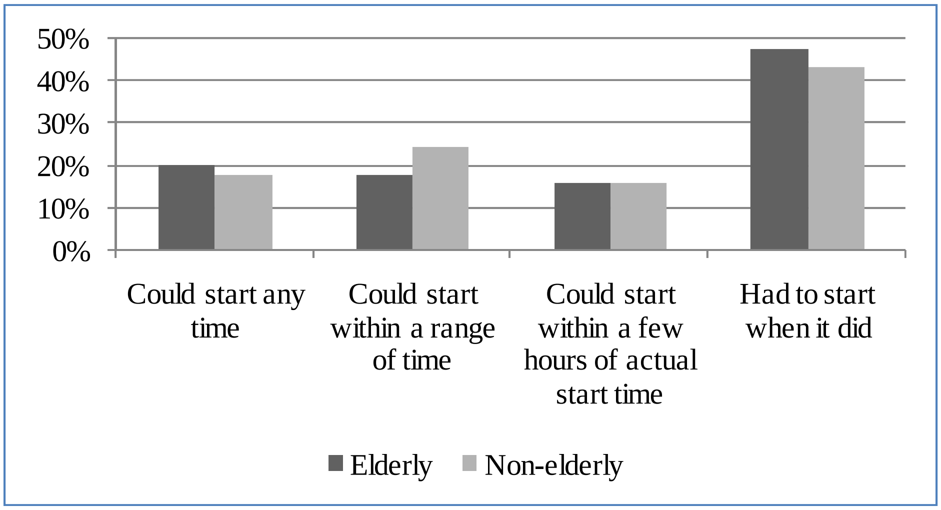


Figure 3.3 Start time flexibility.

For activity-duration planning, the non-elderly group appears once again to be more flexible. Nevertheless, the overall result is that 40 to 45% of the activity durations had to last as long as they did. The remaining 55 to 60% had some or plenty of room for accommodating schedule adjustments (Figure 3.4). About one-fifth of all activities could have had a very different duration than they actually did.

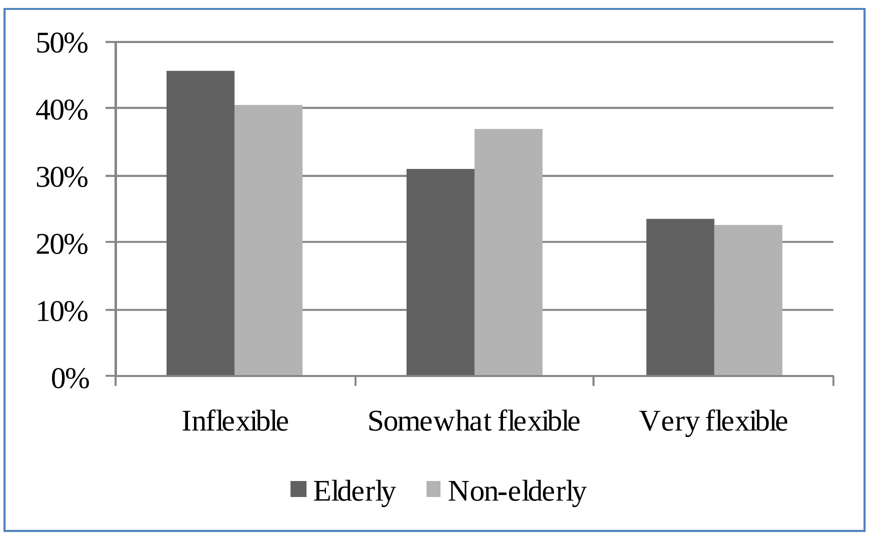


Figure 3.4 Activity-duration flexibility.

3.1.3 People Involved

Figure 3.5 shows the distribution of people accompanying elderly and non-elderly respondents. When other people were present during the activity, the requirement of involvement for these people is shown through different shades in the columns. Elderly individuals perform activities alone less frequently, partly because they spend significantly less time in activities that are usually performed alone, such as work and school. The elderly perform more activities with family and friends and especially family members only.

The types of activities that are usually engaged in with family members differ between the elderly and the non-elderly. The elderly have more of their changes in transportation, health care, meals out-of-home, and some of their shopping activities accompanied by family members, while younger people have more of their religious/civic, pick-up/drop-off, household errands, services, and social activities with family members. Non-elderly people have more activities with co-workers. This is expected because 72% of the elderly respondents were retired.

The elderly run 71% of their household errands and have 63% of their service activities alone. Non-elderly individuals perform more changes in transportation and took more out-of-home meals, leisure/entertainment, and recreational activities alone than the elderly do.

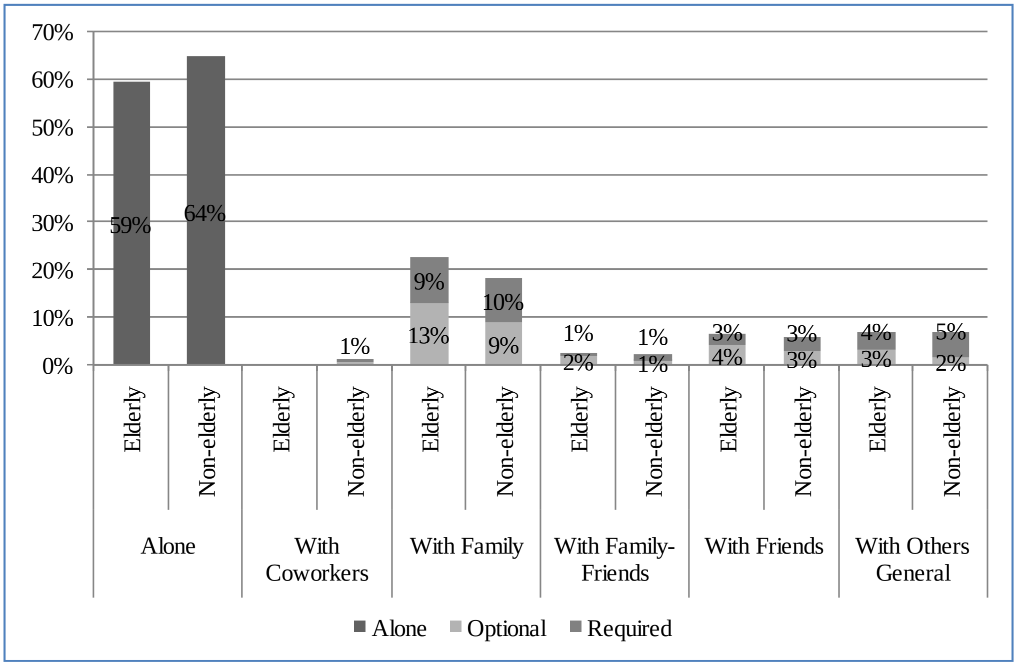


Figure 3.5 People involved in the activity episodes and flexibilities.

3.2 TRIPS

The trip-related decision-making process captured in this survey regards the travel mode and route choices. For travel mode, respondents were asked about the planning horizon and reasons for mode choice. This second question, about travel mode, allows the inference of mode flexibility. The exploration of results regarding the mode and route choice is presented in the two following subsections.

3.2.1 Mode

The single most important factor affecting respondents' mode choice was whether they previously used a particular mode for a trip in the same tour. In 65% of the trips, respondents chose their mode this way, primarily because they were already driving. There was no return mode choice. It was previously made for the whole tour, not for this individual trip.

Respondents drove 79% of the time because they were using a car. The other 12% of the time, respondents were auto passengers, resulting in only 9% of the trips being constrained when the mode in use was not a car.

Convenience was the most important factor on mode choice in more than half the cases when respondents were not driving. This factor is frequently used to explain why driving is so popular. After convenience, respondents cited the lack of alternatives as the second most popular reason for mode choice. This accounts for almost one-third of the decisions. Figure 3.6, shows the motivations for mode choice.

Safety and cost were minor concerns in mode choice for both elderly and non-elderly people. Overall, travel time was not as major a concern as assumed. It accounted for less than 15% of non-elderly trips. Speed was even less important for elderly people. The elderly only made 7% of their mode choices based on travel time. By contrast, the elderly valued convenience to a higher degree than younger people did. The elderly chose to drive 58% of the time because it was convenient. This was 21% more than for the non-elderly. They chose to drive approximately 7% of the time because it was quicker. Meanwhile, the non-elderly chose to drive 17% of the time for the same reason. A number of these choice factors such as speed, traffic, and convenience are related. This finding likely explains why convenience was often chosen. Cost, speed, and time are likely subsets of convenience.

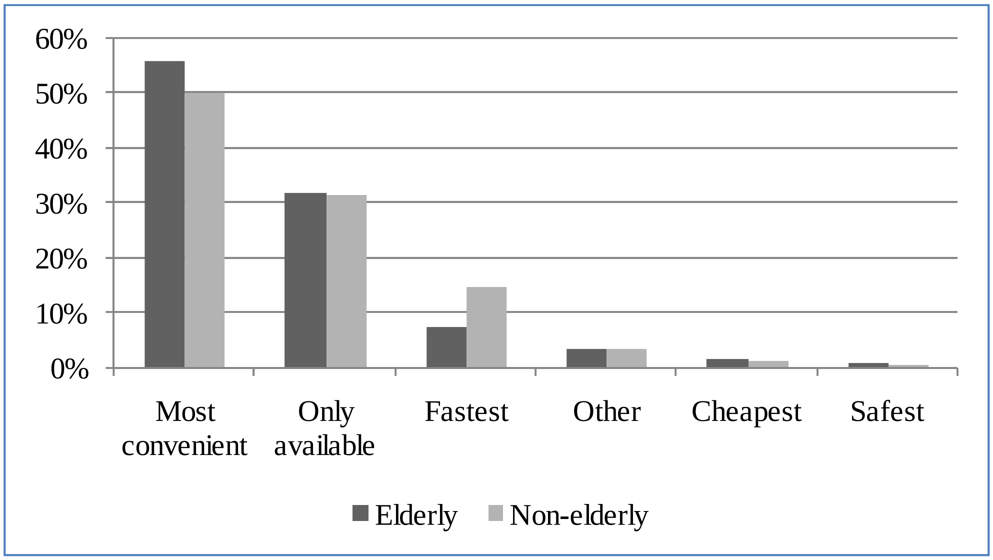


Figure 3.6 Motivation for mode choice.

The motivation for using the auto-passenger mode differs between elderly and non-elderly people. For the elderly, the lack of options was responsible for 42% of auto-passenger choices. For the non-elderly, the lack of options was the reason for only 36% of auto-passenger mode choices. When elderly people chose transit, 63% of the time they did it because it was the most convenient mode. For the non-elderly, however, they chose transit 87% of the time for convenience. Speed and cost motivated older people to take transit far more than it motivated younger people.

People chose travel-mode with the activity-execution decision about 40% of the time. More than one-third of travel mode choices were based on routine. This result indicates that, as with location choice and people involved, the choice of travel mode is strongly related to activity execution. In many cases, when an individual thinks about performing an activity, he or she already knows where to go, how, and with whom. Routine is also an important factor influencing the travel mode. However, it is 35% less decisive for the elderly than for younger people.

3.2.2 Route

Once a travel mode is selected, travelers decide what route to take. Figure 3.7 shows people choosing travel time as their primary deciding factor for route choice nearly 60% of the time. Routine was the second most frequent decision factor, selected for approximately 25% of the time.

For the elderly, cost had a larger weight on decisions than traffic, while for the non-elderly it was the opposite. It was an unexpected observation that traffic was more relevant to the non-elderly than to the elderly because the literature suggests the opposite. Despite its low power ultimately to influence a choice in daily travel, aesthetical qualities appear to be far more appealing to the elderly than the non-elderly. Scenery was three times more of a factor for older individuals. Safety and the quantity of traffic control devices, such as lights and stop signs, did not play a major role in route choice.

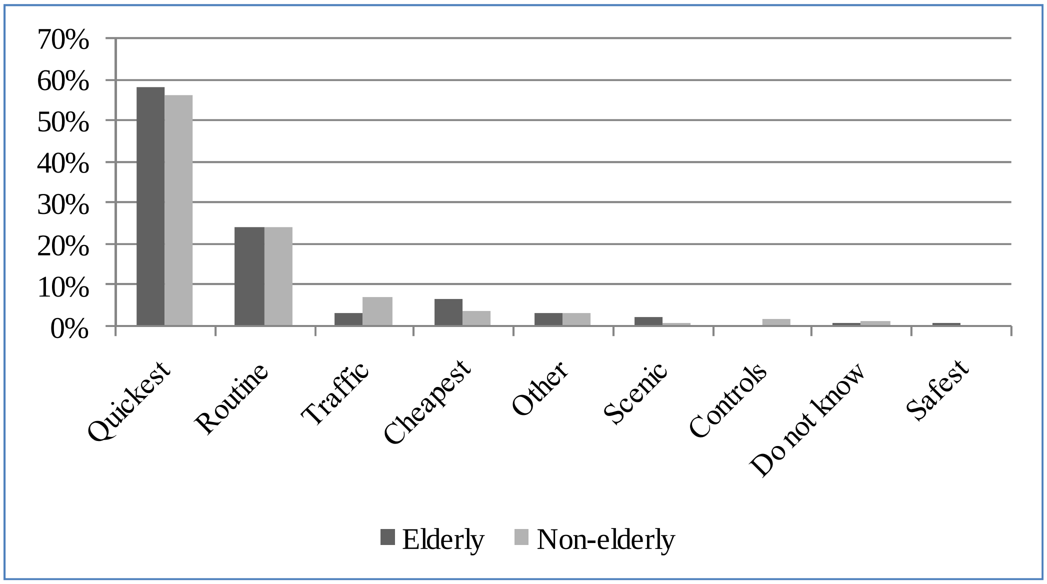


Figure 3.7 Motivation for route choice.

3.3 YOUNG-OLD ELDERLY VS. BABY BOOMERS

The Department of Health and Human Services projects that there will be 72.1 million people older than 65 in 2030, which is twice the amount in 2000. The elderly population has already increased considerably, as the baby boomers turned 65 in 2011. Baby boomers, born between 1946 and 1965 represent the peak rate of U.S. births dating back to 1930 (National Center for Health Statistics 1994). They have experienced major social transformations and will behave differently than previous generations. As they age, they will require services that have never been provided before (Buckley 2008; Rowland 1991).

Studying the present senior population can provide information about the nature of their travel behavior and reveal information about future elderly populations (Rashidi and Mohammadian 2008). Some surveys reveal that approximately 80% of pre-retirement baby boomers (ages 55 through 64 years) will tend to work at the same capacity past their retirement age (Roper 2004; Miringoff et al. 2010). If baby boomers do work after retirement age, the travel behavior of this next young-old elderly group (ages 65 through 74 years) is similar to the observed behavior of pre-retirement (ages 55 through 64 years) baby boomers.

This huge demographic change and its impact on metropolitan area travel patterns is still a mystery that requires substantial research. Mohammadian and Bekhor (2008) emphasized that the travel patterns of special population groups, including seniors, need to be closely studied. Hilderbrand (2003) addressed "the current lack of a detailed description of elderly travel characteristics and behaviors" as a deficiency in the area of transportation planning.

The 55- to 64-year-old baby boomers lived in the industrial and technological era of the early 21st century and have grown accustomed to high mobility and accessibility. People in this generation are considerably dependent on driving, especially compared with previous generations. But the demand for multiple types of transportation modes increases as they age. This demographic surge in the total number of seniors necessitates serious attention to maintain equity, welfare, and quality-of-life at desirable levels. If the new generation (ages 55 through 64) of seniors decides to keep its current traveling habits, then a significant change is expected in older citizens' (ages 65 through 74) behavior as boomers join their ranks.

The research team attempts to fill this gap by investigating some lifestyle aspects of seniors 65 through 74 years old in this section. These aspects include travel behaviors not adequately addressed so far and a comparison between travel behaviors of young-old seniors (ages 65 through 74 years) and non-senior baby boomers (ages 55 through 64). Table 3.1 shows a sample description of both young-old elderly (ages 65 through 74 years) and pre-retirement baby boomers (ages 55 through 64 years).

Table 3.1 Sample Description of Young-Old Elderly and Preretirement Baby Boomer Cohorts

Variable	Young-old elderly (65–74)	Baby boomers (55–64)
Household Size (Average)	1.91	2.35
Vehicle Availability		
No vehicle	2.94%	0.00%
1 or more vehicles	97.06%	100.00%
Household Income		
$34,999 or less	19.23%	18.75%
$35,000 to 49,999	15.38%	31.25%
$50,000 to 74,999	15.38%	18.75%
$75,000 to 99,999	30.77%	12.50%
More than $100,000	19.23%	18.75%
Race		
White	86.11%	77.27%
Black/African American	11.11%	22.73%
Other	2.78%	0.00%
Gender		
Male	38.89%	22.73%
Female	61.11%	77.27%
Total Number of Respondents	34	22

Elderly individuals performed 2,706 of the 6,041 total activities. The young-old elderly performed 1,656 of these activities. Females, who constituted 60% of all respondents, performed 52% of the young-old elderly activities.

Non-elderly individuals performed 3,335 activities. Baby boomers 55 through 64 years old performed 893 of these activities. Females, who constituted 75% of all respondents, performed 72% of the baby boomers' activities.

3.3.1 Methodology

The study team conducted an explanatory analysis on young-old seniors' and baby boomers' travel activities. They initially focused on time-of-day choice, activity duration, and planning-time horizons to see how young-old seniors and baby boomers behaved differently. The comparison between these two groups opens avenues to understanding their behavioral differences. Different nonparametric probability density plots of activity duration, time-of-day choice, activity type, and planning-time horizons schematically show how travel behaviors evolve as middle-aged people become seniors.

The unpaired t-test and the Fisher test (F-test) show how corresponding plots differ statistically from each other. These two tests assume that population is Gaussian (a normal distribution). The null hypothesis of the F-test assumes that the two samples' variances are statistically equal. Similarly, the null hypothesis in a two-sample t-test considers that the means of the two samples are statistically identical.

3.3.2 Activity Duration vs. Activity Type

Table 3.2 shows eleven activity classifications bundled into five aggregate categories based on their similarities. Henceforth, all analyses will be constructed across these five activity categories. In Table 3.2, older people are less involved in mandatory activities, but they are busy with other types of activities. This finding supports that as people reach retirement, they become engaged in more flexible and non-mandatory activities. This switch in activity type significantly impacts other activity attributes, such as mode choice, activity duration, time-of-day, etc. Although a relatively small portion of activities is related to personal, religious, health care, service, errands, and pick-up and drop-off activities, over time their importance in day-to-day life remains unchanged as middle-aged individuals become seniors.

Table 3.2 Share and Definition of Activity Types for Young-Old Seniors and Baby Boomers

Definition	**Young-old seniors**	**Baby boomers**
Work/school/volunteer	8.0%	29.9%
Personal/religious/health care	16.9%	14.3%
Services (barbershop, auto service etc.), errands, pick-up or drop-off	9.6%	7.1%
Discretionary	30.7%	23.9%
Shopping	34.8%	24.9%

The schematic analysis shows activity duration across different activity types for the weekend and weekdays, and for young-old seniors and baby boomers. Figure 3.8 illustrates the nonparametric probability density functions of activity duration. This is calculated by dividing the total number of executed instances of a specific activity type in a 30-minute batch by the total number of all executed activity types during weekdays or weekends.

The general pattern of all four diagrams in Figure 3.8 shows that as the duration increases up to 30 minutes, the probability of activity execution also increases. After that, the probability steadily decreases. However, mandatory trips do not follow this pattern and have a smoother shape with very small peaks, especially for young-old seniors on weekends. The probability of activity execution is very high during the first hour and declines over time. Further, the probability of performing an activity with short duration is very high on weekdays, while on weekends, people have more time to do longer activities. Activity types included in the service-activity category are more important for seniors. Baby boomers meanwhile view mandatory activities as more critical.

Table 3.3 presents statistical tests on Figure 3.8's corresponding plots. Numbers in the table represent the p-value for the null hypothesis. Except for elderly weekdays vs. baby boomers weekdays, personal/religious/health care and services/errands/pick-up and drop-off activity types are mixed and then compared with each other because of the low number of observations.

Accordingly, there are five rows for the third column in which elderly and baby boomers' weekday activities are compared, while other categories have four rows. As explained before, the null hypothesis for the t-test assumes that both sample means are equal. Similarly, for the F-test, the null hypothesis considers whether both samples' variances are the same. For example, these tests reveal that baby boomers' shopping activity duration is statistically the same over weekdays and weekends.

Table 3.3 Statistical Tests on Plots Presented in Figure 3.8 (p-values for the null hypothesis)

<table>
<tr><th rowspan="2">Group of Activity Types</th><th colspan="2">Elderly (weekends vs. weekdays)</th><th colspan="2">Baby Boomers (weekends vs. weekdays)</th><th colspan="2">Weekdays (elderly vs. baby boomers)</th><th colspan="2">Weekends (elderly vs. baby boomers)</th></tr>
<tr><th>F-test</th><th>t-test</th><th>F-test</th><th>t-test</th><th>F-test</th><th>t-test</th><th>F-test</th><th>t-test</th></tr>
<tr><td>Work/School/Volunteer</td><td>*</td><td>*</td><td>*</td><td>*</td><td>0.30</td><td>0.54</td><td>*</td><td>*</td></tr>
<tr><td>Personal/Religious/Health Care</td><td rowspan="2">0.01</td><td rowspan="2">0.04</td><td rowspan="2">0.00</td><td rowspan="2">0.01</td><td>0.02</td><td>0.86</td><td rowspan="2">0.08</td><td rowspan="2">0.06</td></tr>
<tr><td>Services/Errands/Pick-Up and Drop-Off</td><td>0.12</td><td>0.75</td></tr>
<tr><td>Discretionary</td><td>0.51</td><td>0.70</td><td>0.48</td><td>0.85</td><td>0.02</td><td>0.96</td><td>0.12</td><td>0.93</td></tr>
<tr><td>Shopping</td><td>0.01</td><td>0.42</td><td>0.00</td><td>0.05</td><td>0.01</td><td>0.29</td><td>0.00</td><td>0.15</td></tr>
</table>

*Number of activities are smaller than 30

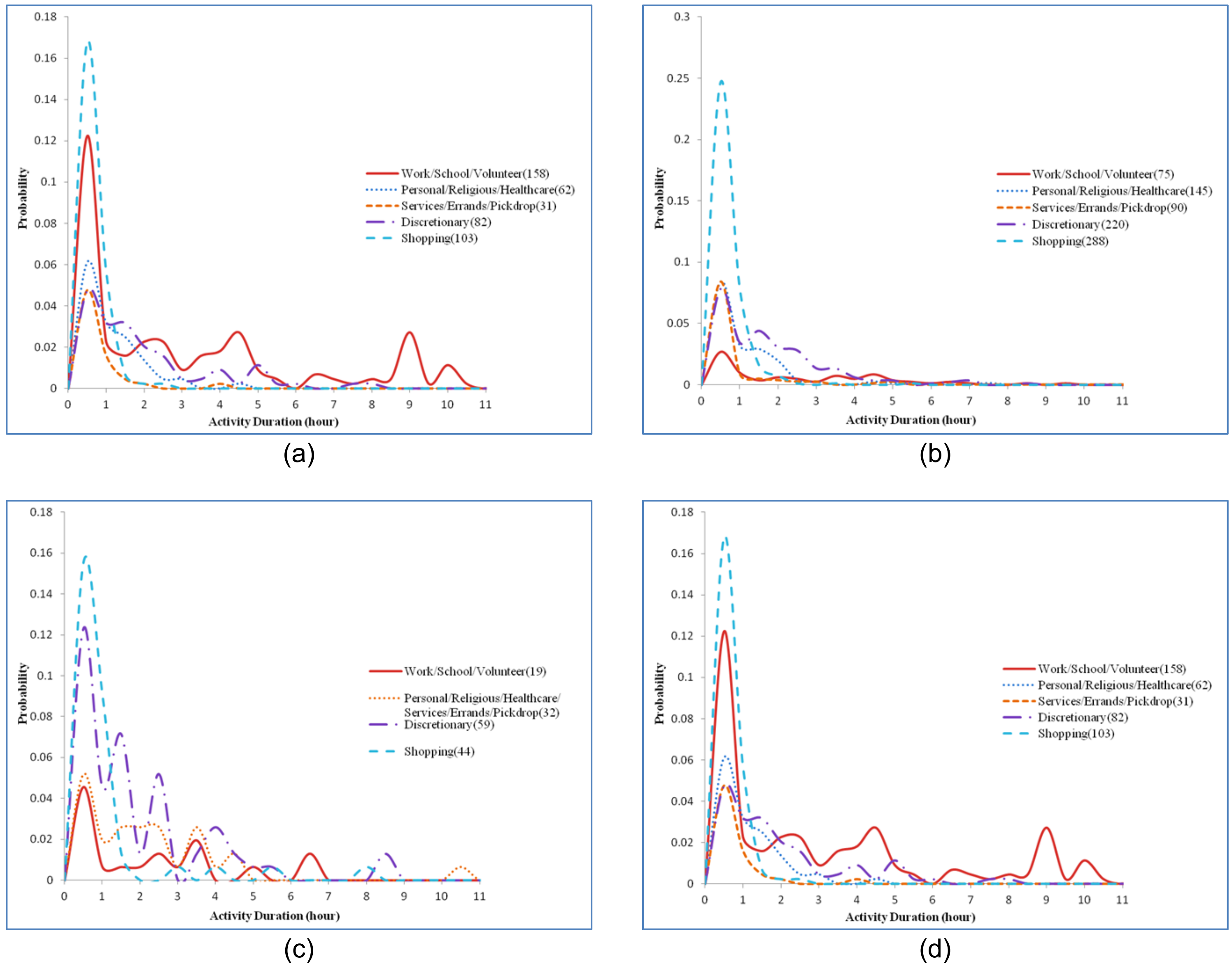


Figure 3.8 Activity-duration probability plots for different activity types: (a) young-old seniors on weekends (b) young-old seniors on weekdays (c) baby boomers on weekends (d) baby boomers on weekdays.

3.3.3 Time-of-Day Choice vs. Activity Type

Activity start time is important in activity-based models and even in conventional four-step models (Committee for Determination of the State of the Practice in Metropolitan Area Travel Forecasting 2007; Hensher and Button 2000). The study team thus examined time-of-day choice behavior between young-old seniors and pre-retirement baby boomers for differences. Figure 3.9 depicts probability density plots of different activity types across a range of activity start times for both young-old seniors and baby boomers, separately for weekends and weekdays. Two-hour bins calculate the probabilities. In Figure 3.8, young-old seniors and baby boomers have similar behavior regarding activity duration, but in Figure 3.9, these two groups choose different times of day for their activities.

Figure 3.9(b) shows time-of-day choice behavior of young-old seniors during weekdays. The general pattern of some activities is very similar to one another, meaning that young-old seniors consecutively perform these activities. The probability density function (pdf) curve of services/errands/pick-up and drop-off activities almost matches with the pdf curve of work/school/volunteer activities. Meanwhile the pdf curve of personal/religious/health care activities stands very close to the pdf curve of discretionary activity. Only shopping activity stands alone above all the other four curves.

Before 10:00 a.m., the probability of doing a discretionary activity is higher than for other activities for seniors, but from 10:00 a.m. to 6:00 p.m., shopping is dominant over other activities. If all plots in Figure 3.9(b) are summed together, roughly morning and afternoon peak hours for young-old seniors are at noon and 4:00 p.m. Therefore, seniors are more likely to be out around these two peak periods. This finding should be of interest to firms providing services to this specific age group,

In Figure 3.9(d), which displays time-of-day choice behavior for baby boomers on weekdays, the pdf curve of work/school/volunteer activities, especially in the morning, stands above the other activity types. After 12 noon, the likelihood of a shopping activity being performed increases steadily until 4:00 p.m., while work/school/volunteer remains the dominant activity. After 6:00 p.m., the probability of shopping and discretionary activities stays higher than that of other activities. Except for the shopping and work/school/volunteer activities, other activities do not show a prominent peak point.

During weekends, for both age ranges, plots of discretionary and shopping activities remain on top. The shapes of the curves for these two activity types are similar indicating that people consecutively do those (Figures 3.9 (a) and (c).

Table 3.4 presents statistical tests on corresponding plots in Figure 3.9. In most cases, the null hypothesis of the F-test is rejected (the p-value greater than 0.05). It indicates that the young-old elderly and baby boomers display very dissimilar behavior in time-of-day choice.

Table 3.4 Statistical Tests on Plots Presented in Figure 3.9 (p-values for the null hypothesis)

Group of Activity Type	Elderly (weekends vs. weekdays)		Baby boomers (weekends vs. weekdays)		Weekdays (elderly vs. baby boomers)		Weekends (elderly vs. baby boomers)	
	F-test	t-test	F-test	t-test	F-test	t-test	F-test	t-test
Work/school/volunteer	*	*	*	*	0.02	0.01	*	*
Personal/religious/health care	0.56	0.85	0.12	0.37	0.66	0.01	0.29	0.28
Services/errands/pick-drop					0.79	0.12		
Discretionary	0.10	0.01	0.51	0.28	0.50	0.10	0.28	0.73
Shopping	0.53	0.96	0.04	0.37	0.01	0.01	0.45	0.06

*Number of observations is less than 30

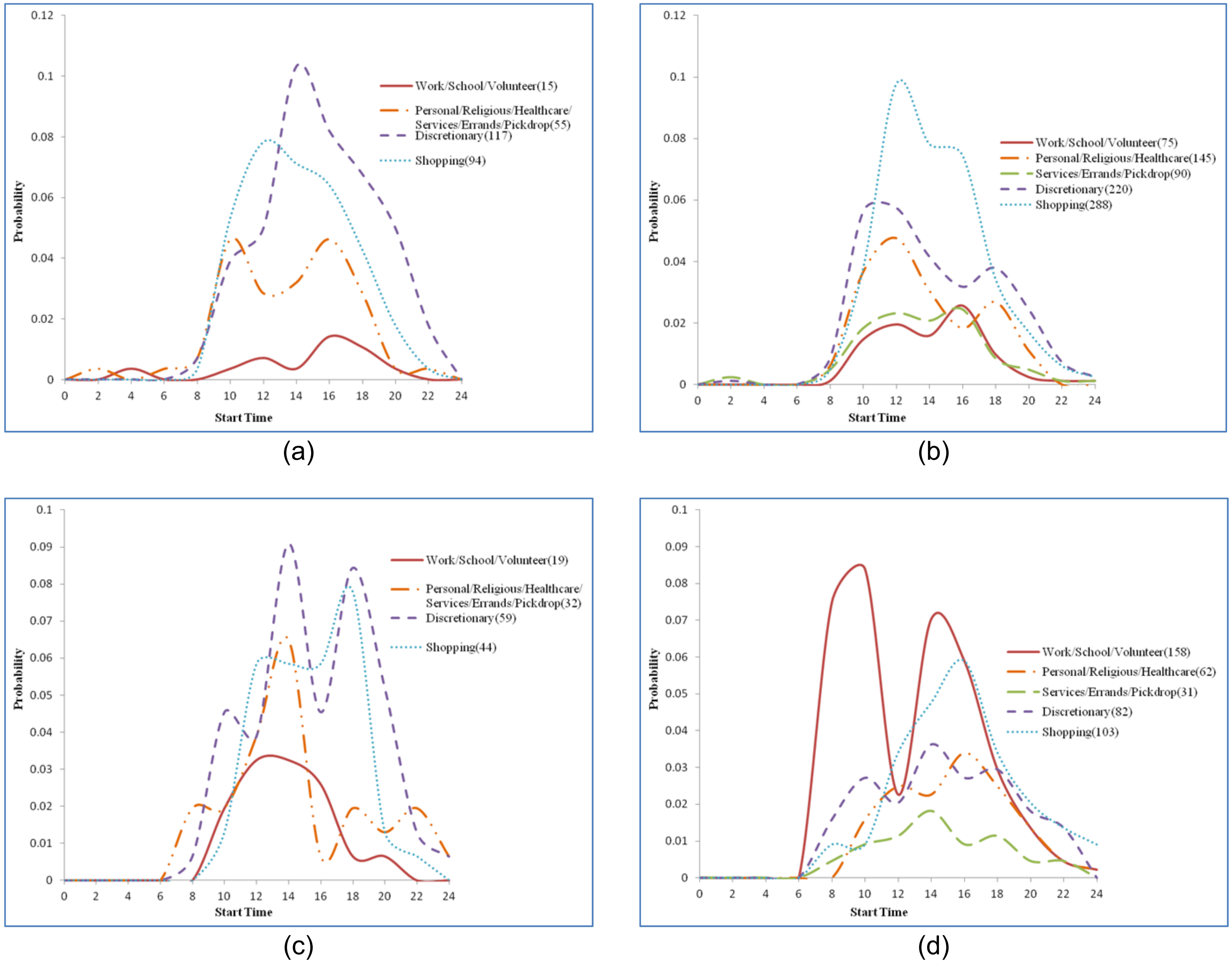


Figure 3.9 Probability plots of chosen time of day for different activity types: (a) young-old seniors on weekends, (b) young-old seniors on weekdays, (c) baby boomers on weekends, (d) baby boomers on weekdays.

3.3.4 Activity Duration vs. Planning-Time Horizons

Planning-time horizon is important when modeling activity scheduling of pre-planned activities (Mohammadian and Doherty 2006; Akar et al. 2009). It is the time between deciding to join in and the activity's actual performance. During this period, the person may resolve possible conflicts with other activities and evaluate the activity's importance compared to other potential activities. Table 3.5 shows classifications used to analyze planning-time horizons and the main difference in planning-time horizons between young-old seniors and baby boomers' routine activities. Baby boomers are more involved in mandatory activities than young-old seniors are.

Table 3.5 Share and Definition of Planning-Time Horizons for Young-Old Seniors and Baby Boomers

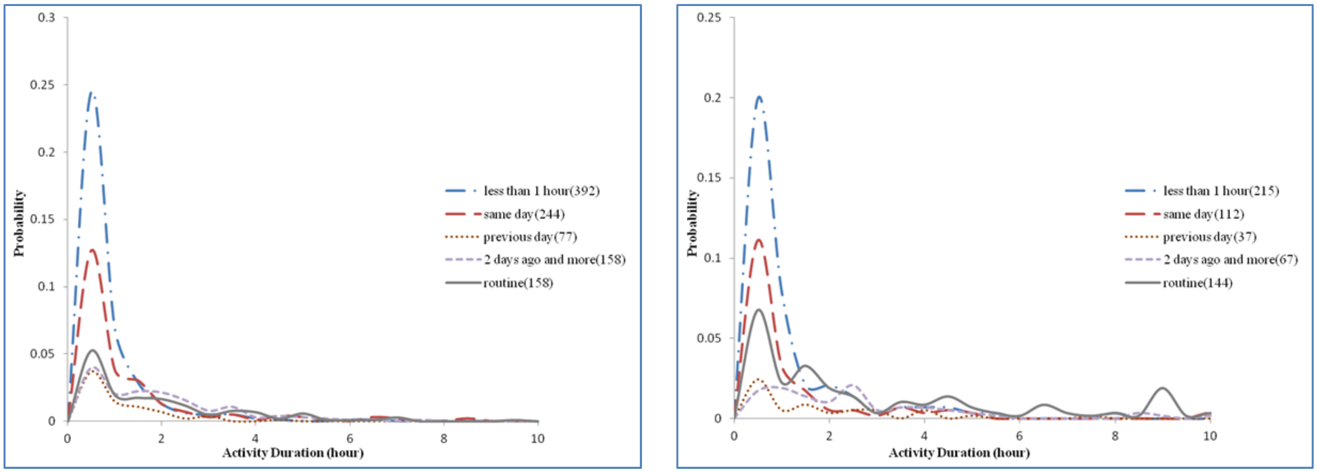
Definition	Young-old seniors	Baby boomers
Planned less than 1 hour before the activity performance	37.9%	37.3%
Planned same day of the activity performance	23.7%	19.6%
Planned previous day of the activity performance	7.6%	6.1%
Planned 2 days ago or more of the activity performance	15.4%	11.8%
Routine activity	15.4%	25.2%

Planning-time horizon has a very close connection with activity duration. To see how activity duration can affect planning-time horizons, Figure 3.10 displays the probabilities of different planning-time horizons versus activity duration.

If "less than 1 hour" and "same day" planning-time horizons are indicative of impulsive activities, then people appear to impulsively plan their short activities.

In each of Figure 3.10's curves, a curve's steeper slope should represent the planning-time horizon's greater sensitivity to activity duration. They do not show much sensitivity to activity duration for activities that last longer than 1.5 hours. Shorter activities on the other hand show high sensitivity to activity duration.

In figures (a) and (b), routine activities show major differences between young-old seniors and baby boomer time horizons. For other time horizons, the curves show a close relationship in the travel behavior of young-old seniors and baby boomers.



(a) (b)

Figure 3.10. Probability plots of activity duration for different planning-time horizons: (a) young-old seniors, (b) baby boomers.

Table 3.6 shows statistical tests on the corresponding plots in Figure 3.9. The p-values of the null hypothesis (equality of means and variances) are small for activities that are pre-planned the previous day or earlier and that are routine. Both the young-old elderly and the pre-retirement baby boomers thus display similar behavior in their pre-planning processes. For impulsive activities, disparity is significant on variance or mean.

Table 3.6 Statistical Tests on Plots Presented in Figure 3.10 (p-values for the null hypothesis)

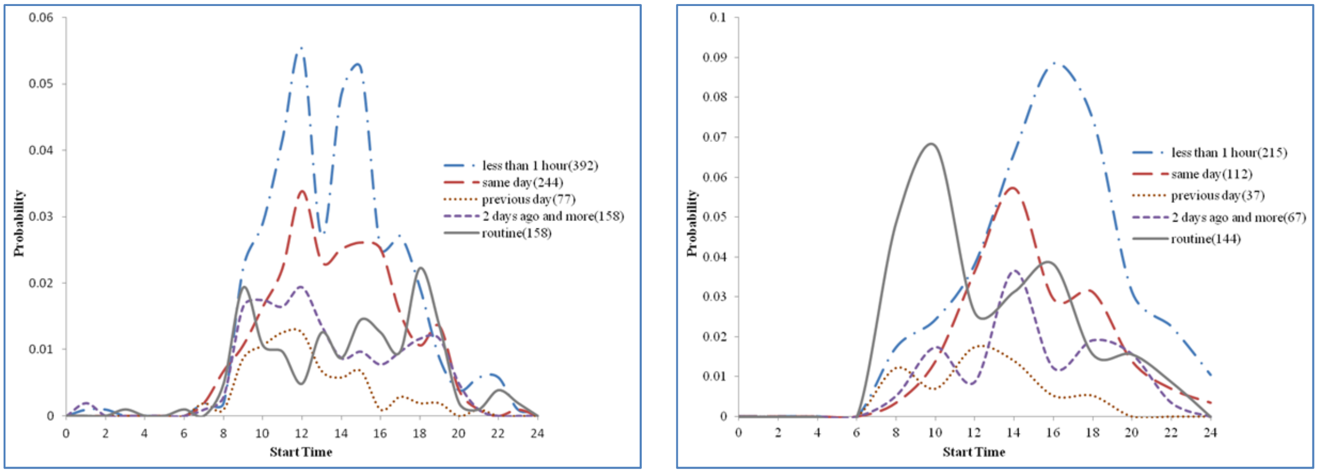
Planning-time horizon	F-test	t-test
Planned less than 1 hour before the activity performance	0.79	0.06
Planned same day of the activity performance	0.08	0.96
Planned previous day of the activity performance	0.01	0.03
Planned 2 days ago or more of the activity performance	0.29	0.10
Routine activity	0.01	0.01

3.3.5 Time-of-Day Choice vs. Planning-Time Horizons

As with activity duration, activity start-time and planning-time horizons are close. If an activity is planned in the early morning at rush hour, it is treated differently than a similar activity completed during off-peak hours. Figure 3.11 plots the probability density function curves of different planning-time horizons versus chosen time-of-day.

Young-old seniors, shown in Figure 3.11(a), do not show as much sensitivity to time-of-day choice for their pre-planned activities (previous day or earlier). Their impulsive activities are time-of-day sensitive. They tend to carry out these activities from 11:00 a.m. to 1:00 p.m. and from 2:00 p.m. to 4:00 p.m.

Figure 3.11(b) shows that baby boomers' morning activities are connected to routine activities. They impulsively perform a major part of their activities between 1:00 p.m. and 7:00 p.m.



(a) (b)

Figure 3.11. Probability Plots of Chosen Time of Day for Different Planning-Time Horizons: (a) Young-Old Seniors, (b) Baby Boomers.

Statistical tests presented in Table 3.7 show the statistical equality of the means of the corresponding plots (except for planned previous-day horizon). The plots' dispersions, however, are statistically different, based on F-test results. In contrast to the previous section, both age groups display similar behavior in time-of-day choices for their impulsive activities.

Table 3.7 Statistical Tests on Plots Presented in Figure 3.11. (p-values for the null hypothesis)

Planning-time horizon	**F-test**	**t-test**
Planned less than 1 hour before the activity performance	0.02	0.01
Planned same day of the activity performance	0.39	0.03
Planned previous day of the activity performance	0.45	0.62
Planned 2 days ago or more of the activity performance	0.69	0.03
Routine activity	0.92	0.01

CHAPTER 4 TRIP AND TOUR FORMATION

Chapter 4 discusses trip and tour formation differences between elderly and non-elderly people. The first part of this chapter is a descriptive analysis. The second part presents a model for interactivities (with a focus on shopping activities) that form 30% of seniors' out-of-home activities. The intershopping model determines how often a person shops.

4.1 DESCRIPTIVE ANALYSIS

A tour is defined as a sequence of trips that starts and ends at the same place (Ortuzar and Willumsen 2011). Characteristics of tours depend on the order, number, and specifications of executed trips and activities, such as activity types, travel mode, time-of-day choice, trip and activity duration, and party size. Tours can be categorized into simple (one activity) and complex (more than one activity). Home–work–home is an example of a simple tour and home–work–shopping–home is an example of a complex tour. Providing better understanding for travel behavior, analysis of trip chaining patterns in complex tours has been an attractive subject in recent years (Bhat 1997; Kuppam and Pendyala 2001; Ye et al. 2007).

4.1.1 Quantity of Tours and Stops within Tours

The research team identified 1,682 tours in the data set. The elderly took 744 tours and the non-elderly took 938 tours.

The elderly make fewer tours per day than the non-elderly. They make an average of 1.29 tours per day, while the non-elderly make an average of 1.38 tours per day.

The columns in Figure 4.1 show the elderly and non-elderly's stops-per-tour distributions, while the line shows the cumulative distribution of the number of stops per tour. The average number of stops per tour (all the activities done during the tour), was 2.41 for elderly people and 2.25 for non-elderly people. This 7% difference in the average number of stops per tour supports the theory that the elderly trip chain more than the non-elderly.

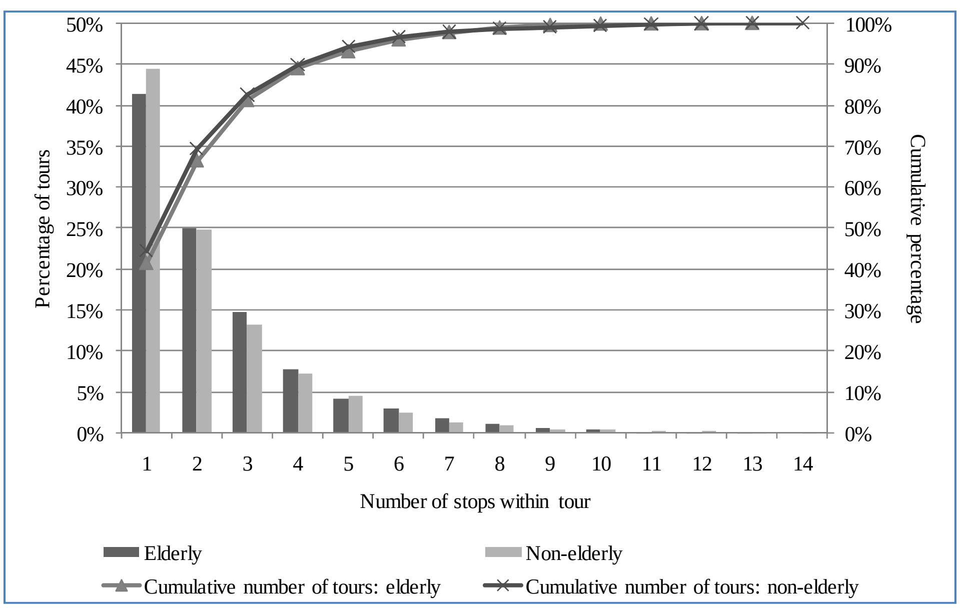


Figure 4.1 Distribution of the number of stops within tours

Non-elderly people have more simple tours (i.e. tours with only one stop). Simple tours represent 40 to 45% of all tours in both age groups. Elderly people make 12% more tours with three stops and 8% more tours with four stops, compared to non-elderly people. Approximately 90% of all tours have four stops or fewer. Nevertheless, when it comes to complex tours (i.e., tours in which more than one stop take place), the elderly average slightly more complex tours than the non-elderly.

Table 4.1 shows the average number of stops per tour and the average number of tours per day by age group and gender. Without considering gender, the elderly make more complex tours. Their complex tours have a slightly higher number of stops on average and their proportion of complex tours to all tours is higher (60% for the elderly versus 55% for younger people).

Considering gender, elderly males typically make fewer complex tours per person per day than non-elderly males. They also typically make a higher number of stops per complex tour. Elderly females typically make slightly less complex tours per person per day than non-elderly females. They also typically make a higher number of stops per complex tour than their non-elderly counterparts.

Table 4.1 Characteristics of Complex Tours by Age Group

Subset		**Average number of stops per complex tour**	**Average number of complex tours per person per day**
Elderly	Male	3.42	0.77
	Female	3.29	0.78
	Total	3.34	0.78
Non-elderly	Male	3.45	0.72
	Female	3.13	0.79
	Total	3.23	0.77

Some activity types tend to be performed more frequently on simple tours or earlier in more complex tours. Recreational activities and approximately 80% of religious/civic activities occur in simple tours or as first stops in complex tours for both age groups. Primary work is another activity that typically occurs early in the tour. Nevertheless, it is more common to find a previous stop before going to work than before going to church.

Some other activities are unlikely to occur on simple tours or are very likely to be chained with others. For both age groups, less than 11% of household errands are conducted as the sole tour activity. Pick-ups and drop-offs are also seldom the single activity in a tour.

Although shopping activities are usually simple tours, the elderly more consistently chain all variants of this activity with other activities. The greatest disparity is found for major item shopping. Although the non-elderly made a specific tour for major item shopping 33.3% of the time, the elderly did so only 7.7% of the time. Along with the observation that major item shopping is the only sort of shopping when the elderly make more impulsive decisions than the non-elderly, this finding indicates that major item shopping is intrinsically different than other types of shopping.

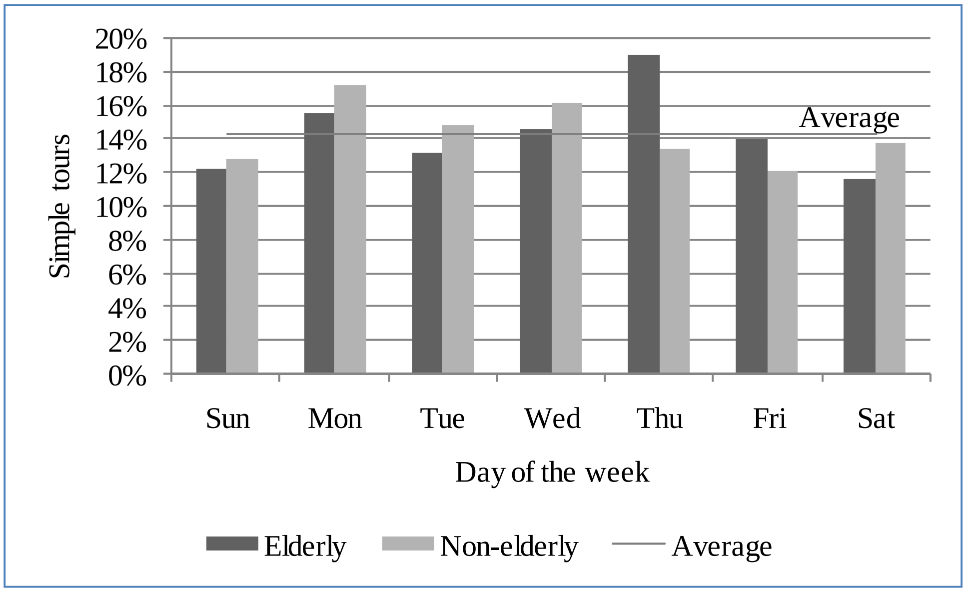
4.1.2 Temporal Distribution of Tours

Besides differing in quantity and in average number of stops, elderly tours also differ in temporal distribution from that of the non-elderly. Figure 4.2 shows the tour distribution by day-of-the-week. Part A relates to simple tours, those with only one stop; and part B relates to complex tours. The line indicates a uniform distribution along which the tours would be equally distributed across the week. Overall, the non-elderly performed more complex tours during the week (Monday through Friday). By contrast, the elderly consistently performed more complex tours on the weekends than younger individuals. The opposite occurs with simple tours. The non-elderly concentrate their simple tours at the beginning of the week (Monday, Tuesday, and Wednesday) and Saturdays; and the elderly have a higher number of simple tours at the end of the week (Thursday and Friday).

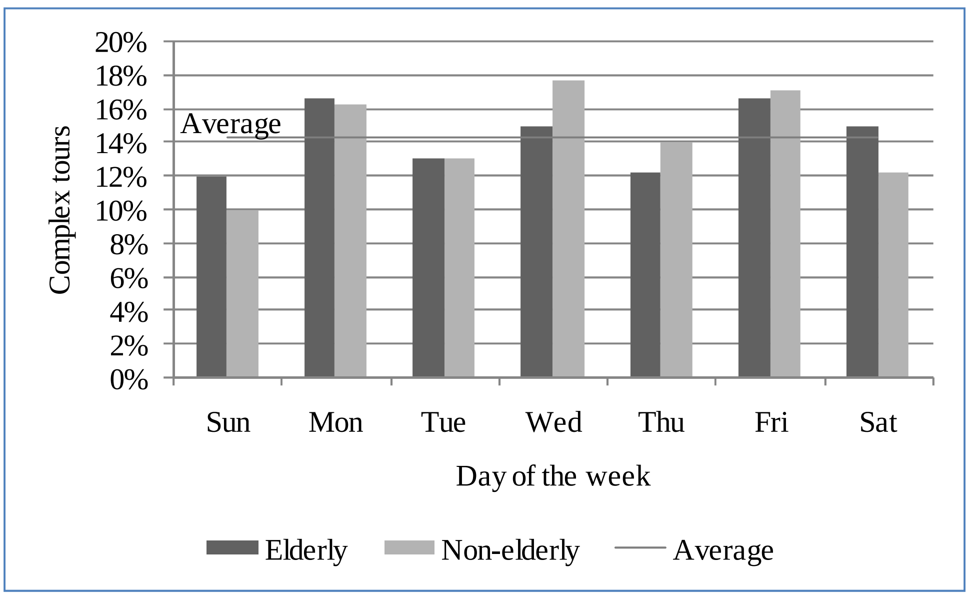
The peak of complex tours for the non-elderly happens on Wednesdays and Fridays, but the peak of complex tours for the elderly happens on Fridays and Mondays. These results contrast somewhat with a previous study (Noland and Thomas 2007), in which the elderly's complex tours peaked on Mondays, while the non-elderly's complex tours peaked on Fridays.

The peak pattern for simple tours is the opposite. The elderly conducted most of their simple tours on Thursdays, while the non-elderly conducted most of their simple tours on Mondays.

The discrepancy between the relative number of simple tours performed by the elderly and the non-elderly on these peak days is very large. The elderly had 42% more simple tours on Thursdays than the non-elderly and the least amount of simple tours on Tuesdays. The non-elderly had 10% more simple tours on Mondays than the elderly and an above average number of simple tours on Tuesdays. Overall, simple and complex tours show a complementary pattern, suggesting that these two travel types are intrinsically different. The behavior of the elderly and non-elderly in both instances of tours is also diverse, indicating advanced age plays a noteworthy role in tour formation.



(a)



(b)

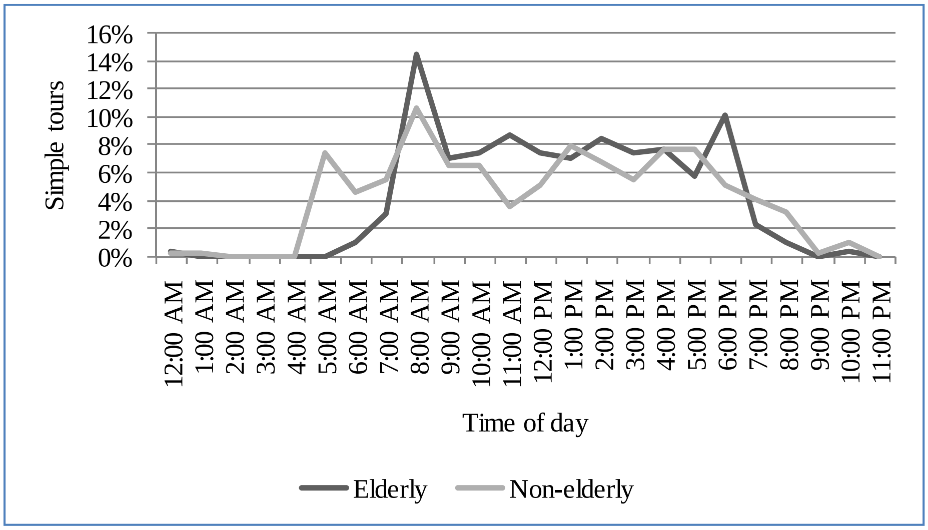
Figure 4.2 Tour distribution by day of the week: (a) simple and (b) complex Tours

The simple and complex tour distribution within the day also suggests these two tour types have different natures. Elderly behavior fundamentally differs from non-elderly behavior.

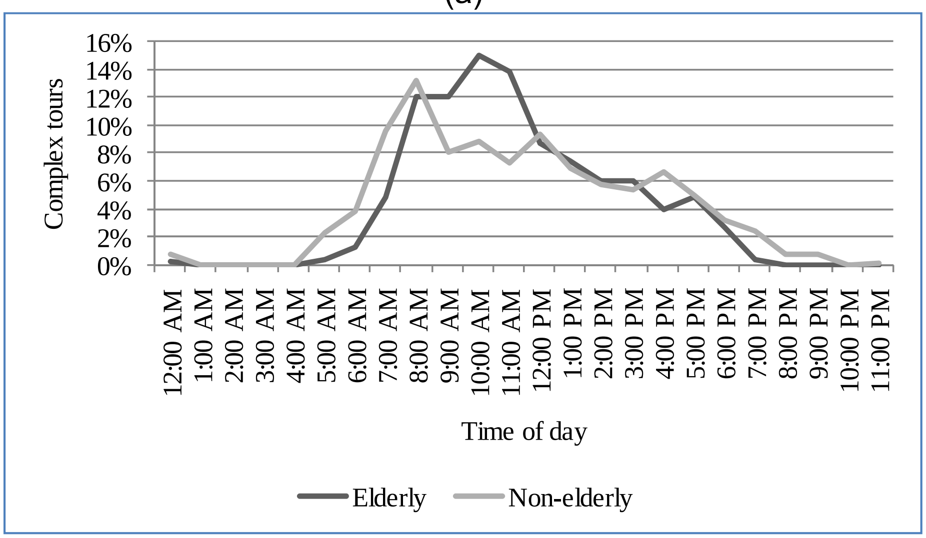
Figure 4.3 shows the tour distribution start-time for (a) simple tours and (b) complex tours. These tour distributions are very dissimilar for both age groups. The elderly started their tours as early as 6:00 a.m. They began most of their simple tours between 8:00 a.m. and 9:00 a.m. and most of their complex tours at 10:00 a.m. Although they generally engaged in more midday tours, their simple and complex tours peaked in the early afternoon, possibly to avoid rush hour congestion.

The non-elderly began their tours as early as 5:00 a.m. They began most of their simple tours between 7:00 a.m. and 9:00 a.m. and most of their complex tours around 7:30 a.m. They still began tours when the elderly were already at home.

Especially for the elderly, simple tours had their start time relatively spread out over the day with peaks occurring in the morning and evening. Complex tours had a more defined peak in the morning since these tours are longer and require more time.



(a)



(b)

Figure 4.3 Start Time Distribution by Time-of-Day for (a) Simple and (b) Complex Tours

4.2 A LATENT SEGMENTATION MODEL FOR INTERSHOPPING DURATIONS

The *Transportation Charter of 2001* depicts a desirable transportation system as one that allows “every American to participate fully in society whether or not they own a car and regardless of age, ability, ethnicity, or income” (STPP 2001). A huge gap remains, however, between this ideal and what is currently in operation, especially for particular age groups and people with disabilities. It emphasizes the need for serious attention to seniors' mobility needs as an important part of American society (Karimi et al. 2012; Mohammadian and Bekhor 2008 and Hilderband 2003).

The elderly population is expected to double between 2000 and 2030. In fact, 2011 was a milestone because the oldest baby boomers turned 65, which is the first year a middle-aged person is classified as a senior (Wan et al. 2005). Baby boomers are people born between 1946 and 1965. That era's birth rate was the highest in the United States since1930 (Jones and Hoffmann 2003; National Center for Health Statistics 1994).

Seniors spend approximately one-third of their time away from home shopping. This is 1.5 times more than that of non-seniors (Frignani et al. 2010). Despite the importance of these activities, researchers have not sufficiently addressed these travel patterns in the literature from the perspective of travel attributes, especially for the elderly cohort.

One of activity/travel modeling's least studied areas is the time between shopping activities ("intershopping duration"). Studies that have analyzed this parameter have typically modeled the time between shopping activities using Proportional Hazard (PH) models. Proportional hazard models are often applied to survival analysis and are estimated using restrictive assumptions subject to validation. Proportional Hazard models assume proportionality (i.e. the hazard ratio of two individuals does not depend on time). Bhat et al. (2004), Schönfelder and Axhausen (2001), and Kim and Park (1997) have applicable models when the proportionality assumption is valid.

In this study, the study team presents a model of intershopping duration for cases where the proportionality assumption is invalid. To release the proportionality assumption, the research team used an Accelerated Failure Time (AFT) model that does not assume proportionality.

Similar to Bhat et al.'s (2004) method, the research team used latent segmentation to endogenously distinguish erratic shoppers from regular shoppers. Regular shoppers do their shopping in relatively fixed intershopping durations. Their limited schedules result in more regular shopping patterns (Kim and Park 1997). The research team thus assumed that their baseline hazard was time-dependent and the erratic shoppers' hazard function was time-sensitive and not fixed.

The study team used UTRACS, a multi-day GPS-based, activity-travel survey collected in the Greater Chicago area (Frignani et al. 2010 and Auld et al. 2009). They tested the proportionality assumption and discovered it does not hold within the data set. They ran the proposed model for the elderly (65 years and older) and non-elderly to compare their rhythmic patterns and examined the time between successfully executed maintenance shopping activities.

In addition to dealing with non-proportional data, Accelerated Failure Time models can directly measure covariate effects on survival time and not on conditional probability, which makes interpreting results much easier.

In the remaining sections, the study team reviews the existing literature and discusses how this paper contributes to the literature, presents the UTRACS database and its specifications, tests the proportionality assumption, develops an Accelerated Failure Time-based model and its results, and provides conclusions and discusses future research directions.

4.2.1 Literature Review and Contributions

Activity-based models provide platforms that can show daily travel behavior of different homogenous groups at a disaggregate level. Usually, the survival analysis or the time-to-event analysis is used in activity-based models to model rhythms of interactivity durations. Hazard-based models, including Proportional Hazard and Accelerated Failure Time models show an event's duration or the time between events in activity-based models. Duration models provide a dynamic basis when time is significant, thus improving activity-based models' prediction potential.

Hazard-based models were developed mainly to handle datasets that contain censored observations (right, interval, and left censorship) and their complexities. They can be categorized into nonparametric and parametric groups. Nonparametric hazard-based models make no assumptions about the distribution of survival time. Parametric hazard-based models assume that survival time is distributed according to a well-known distribution (e.g., Weibull, exponential, Gompertz).

Cox's (1972) Proportional Hazard model is the most famous hazard-based model and is used in various research fields. The Proportional Hazard model makes no assumption concerning the distribution form of survival time and is estimated based on a partial likelihood approach. This approach becomes cumbersome, however, when there are many tied failure times. Accommodating unobserved heterogeneity within the Cox partial likelihood structure requires enough multiple integrals to match the number of observations.

Previous attempts for modeling intershopping duration used Cox's Proportional Hazard model, a fully parametric Proportional Hazard model, and a nonparametric Proportional Hazard model (see Bhat et al. 2004; Schönfelder and Axhausen 2001; and Kim and Park 1997). Bhat et al. (2004) and Kim and Park (1997) used a latent variable or latent segmentation approach in their mixed Proportional Hazard structure to endogenously distinguish between erratic and regular shoppers. These studies showed that endogenously dividing shoppers into two groups can significantly improve a model's performance.

Kim and Park (1997) divided shoppers into two homogenous groups: random (or erratic) shoppers and routine (or regular) shoppers. They maximized the log-likelihood of two conditional likelihoods weighted by a latent variable to estimate the parameters. The latent variable was used to balance the weight of erratic and regular shoppers in the final likelihood function. They found that erratic shoppers constitute 68% of total shoppers.

Later, Bhat et al. (2004) improved the model presented by Kim and Park (1997). They implemented a nonparametric baseline hazard instead of a parametric function. They also used a latent segmentation approach based on a binary logit structure to endogenously categorize individuals as erratic or regular shoppers, based on the individuals' socioeconomic characteristics.

The models used in these studies have a major drawback. They do not account for cases where the proportionality assumption is invalid. Some tests are available that can be used to check this assumption. If this assumption is invalid, non-proportional models (e.g. Accelerated Failure Time models) can be used as alternative approaches. Therefore, one of this study's main contributions is to develop a latent segmentation Accelerated Failure Time-based model for intershopping durations when the proportionality assumption does not hold within the data set.

4.2.2 Checking of the Proportionality Assumption

The proportionality assumption is a critical assumption in Proportional Hazard models. It means that the hazard ratio of two individuals is constant over time. The proportionality assumption is valid only if covariates used in the model are time-independent. Generally, there are two tests developed by Grammsch and Therneau to check the proportionality assumption (Grammsch and Therneau 1994).

The first method suggests adding time-dependent variables to the original model. If these new variables are statistically significant, then the proportionality assumption is not satisfied for the given covariate with the given data. Time-dependent variables can be obtained from the product of a variable of interest and the logarithm of survival time. Also, Grammsch and Therneau used the absolute value of the summed Schoenfeld residuals and designed a global test for the proportionality assumption (Grammsch and Therneau 1994). To run these two tests, the study team developed a Cox's Proportional Hazard model on the UTRACS data set. As an advantage, there is no need to make an assumption for the baseline hazard when a Cox's Proportional Hazard model is developed. In other words, Cox's Proportional Hazard proportionality assumption test is independent of the form of the baseline hazard function.

Table 4.2 shows the results of the modeling exercise to find the best-fitted Cox Proportional Hazard using the UTRACS data. Table 4.3 displays the results of the validation analysis on the proportionality assumption. Part A of Table 4, re-estimates the Proportional Hazard model with time-dependent variables. Four variables, "Total activities", "HHSIZE", "HHTYPE_MC", and "HHTYPE_MNC"—were statistically significant, meaning that they are time-dependent. Therefore, if a Proportional Hazard model is developed with this set of variables, it violates the proportionality assumption; and the coefficients might be spurious. Also, in Part B of Table 4.3, the proportionality assumption for all defined time-dependent covariates is tested all at once (i.e., general test). A significant result indicates that the proportionality assumption is violated. Therefore, the proportional assumption is not valid for the data set that is used in this study, unless the set of explanatory variables is shrunk to a small set.

Table 4.2 Cox Proportional Hazard Model Results on Intershopping Duration of Non-Routine Shoppers

Variable	**Definition**	**Estimate**	**Hazard ratio**	**Mean**	**Standard deviation**
Total activities	Average of total activities performed on two previous intershopping episodes	–0.266***	0.767	2.828	2.907
Jointactivity	1 if shopping activity is performed jointly by other person(s), 0 otherwise	0.245***	1.278	0.409	0.492
Flexible_Start	1 if start time of shopping activity is flexible, 0 otherwise	–0.170***	0.844	0.425	0.495
HHSIZE	Household size	–0.084***	0.919	2.456	1.240
HHTYPE_MC	1 if household type is married with children, 0 otherwise	0.186*	1.205	0.358	0.480
HHTYPE_MNC	1 if household type is married without children, 0 otherwise	0.229***	1.257	0.357	0.479
Employed	1 if a person is employed, 0 otherwise	0.223***	1.25	0.882	0.323

*Level of confidence greater than 85% ** Level of confidence greater than 90% ***Level of confidence greater than 95%

Table 4.3 Proportionality Assumption Checking on Covariates

Part A: Checking covariates separately		
Variable	**Estimate**	**Level of confidence**
Total activities	–0.951	<.0001
Jointactivity	0.206	0.0131
Flexible _Start	–0.135	0.1017
HHSIZE	–0.315	<.0001
HHTYPE_MC	0.694	<.0001
HHTYPE_MNC	0.598	<.0001
Employed	0.229	0.0888
Total activities_time	0.192	**<.0001**
Jointactivity_time	0.004	0.8918
Flexible _Start_time	0.001	0.9608
HHSIZE_time	0.096	**<.0001**
HHTYPE_MC_time	–0.205	**<.0001**
HHTYPE_MNC_time	–0.114	**0.0018**
Employed_time	0.011	0.7867

Part B: Checking covariates all at once				
Label	**Level of confidence**	**DF**	**Level of confidence**	**Wald chi-square**
Proportionality_test	<.0001	7	<.0001	383.2

4.2.3 Proposed Model

This study's proposed model is a latent segmentation, Accelerated Failure Time-based duration model. Because no information was available to show whether a shopper was regular or erratic, the research team used a latent segmentation approach to endogenously distinguish regular shoppers from erratic shoppers. Through this approach, the probability of being a regular or an erratic shopper was obtained from a binary logit model developed from individual-related characteristics.

We first provide a brief introduction to Accelerated Failure Time models and then respectively present each segment of these models for regular and erratic shoppers. We conclude this chapter with a discussion of the latent segmentation approach and model estimation.

4.2.3.1 AFT Models

Accelerated failure time has the following formula for each observation *i,* according to Kalbfleisch (1980):

$$ln(T_i) = \mu + \beta' x_i + \sigma\, \varepsilon_i \tag{4.1}$$

where T_i is the observation *i*'s survival time, ε is the error term; x is the vector of covariates, β' is the transposed vector of the corresponding coefficients to be estimated, σ is the scale parameter, μ is the shape parameter, and *ln(.)* is the natural logarithm function.

In an Accelerated Failure Time model, however, the covariates' effects are directly measured on survival time t and not on a conditional probability. This approach would make interpretation of the results much easier.

For each distribution of error term ε, there is a related distribution of survival times T. So far, there are five parametric Accelerated Failure Time models: exponential, Weibull, log-logistic, log-normal, and gamma Accelerated Failure Time models. These models are named after the distribution of their survival times not error terms. A nonparametric estimate of vector β is possible (i.e., without assuming the error term's distribution) with Han's maximum rank correlation estimator; however, this approach does not provide information about the hazard function.

The survival function of T_i can be expressed from survival function of ε_i :

$$S_i(t) = Prob(T_i > t) = Prob(\ln(T_i) > \ln(t)) = Prob\ (\mu + \beta' x_i + \sigma\ \varepsilon_i > \ln(t))$$
$$= Prob\left(\ \varepsilon_i > \frac{\ln(t)-\mu-\beta' x_i}{\sigma}\right) = S_{\varepsilon_i}\left(\frac{\ln(t)-\mu-\beta' x_i}{\sigma}\right) \tag{4.2}$$

Therefore, $\lambda_i(t)$, the hazard function of AFT model, can be obtained from $S_i(t)$:

$$\lambda_i(t) = \frac{-S'_i(t)}{S_i(t)} \tag{4.3}$$

where $S'_i(t)$ is the first derivative of $S_i(t)$.

The hazard function of the exponential Accelerated Failure Time model is independent from time, and its baseline hazard is a constant number. Other types of Accelerated Failure Time models have a time-dependent hazard function; however, their hazard function shapes differ from each other. The shape of Weibull model's hazard function is monotone; but for the log-normal, log-logistic, and gamma models, it is variable. In other words, the Weibull model holds the proportionality property; but the log-normal, log-logistic, and gamma models are non-proportional models.

4.3.2.2 Regular Shoppers' Model

Regular shoppers, unlike erratic shoppers, are time-pressed and have a limited schedule that forces them to choose an almost fixed intershopping duration. Therefore, a time-dependent baseline hazard is assumed for this group of shoppers. All Accelerated Failure Time models have time-dependent hazard functions, except the exponential model.

Because the study team was developing a model for cases where proportionality was not a valid assumption, they excluded the Weibull model. They also assumed intershopping durations would follow a log-logistic distribution. The log-logistic Accelerated Failure Time model with scale parameter σ has the following survivor and probability density functions for person *i*:

$$S(t_i|x_i) = \left[1 + {t_i}^{1/\sigma}\ e^{\left(\frac{-\mu-\beta' x_i}{\sigma}\right)}\right]^{-1} \tag{4.4}$$

$$f(t_i|x_i) = \frac{{t_i}^{\left(\frac{1}{\sigma}-1\right)} e^{\left(\frac{-\mu-\beta' x_i}{\sigma}\right)}}{\sigma\left[1+{t_i}^{1/\sigma}\ e^{\left(\frac{-\mu-\beta' x_i}{\sigma}\right)}\right]^2} \tag{4.5}$$

The likelihood function conditional on the person *i* being a regular shopper with m_i durations, where the last observation is right censored is:

$$L_{i,regular} = \left[\prod_{j=1}^{m_i-1} f(t_j|x_j)_{regular}\right] S(t_{m_i}|x_{m_i})_{regular} \quad (4.6)$$

4.3.2.3 Erratic Shoppers' Model

As noted earlier, erratic shoppers are individuals who irregularly shop. The hazard function for this group of shoppers is assumed to be constant over time (i.e., independent from time). Among all Accelerated Failure Time models, only the exponential Accelerated Failure Time model represents this condition:

$$S(t_i|x_i) = e^{\left\{-t_i\, e^{(-\alpha' x_i - \rho)}\right\}} \quad (4.7)$$

$$f(t_i|x_i) \;=\; e^{(-\alpha' x_i - \rho)} e^{\left\{-t_i\, e^{(-\alpha' x_i - \rho)}\right\}} \quad (4.8)$$

where ρ is the shape parameter in an Accelerated Failure Time model, and α is the vector of coefficients to be estimated.

The likelihood function conditional on person *i* being an erratic shopper with m_i durations in which the last observation is right censored is:

$$L_{i,erratic} = \left[\prod_{j=1}^{m_i-1} f(t_j|x_j)_{erratic}\right] S(t_{m_i}|x_{m_i})_{erratic} \quad (4.9)$$

4.3.2.4 Latent Segmentation

Since no information can show whether shopper *i* is regular or erratic, the study team used the latent segmentation approach similar to Bhat et al. (2004) to endogenously distinguish erratic from regular shoppers. They estimated the probability of shopper *i* being a regular shopper with the following binary logit model:

$$Prob_{\ i,regular} = \frac{e^{\gamma' z_i}}{1+e^{\gamma' z_i}} \quad (4.10)$$

where z_i is a vector of related characteristics to shopper *i,* and γ is vector of the coefficients to be estimated. The likelihood function of shopper *i* to choose intershopping duration t_i unconditional on being a regular or erratic shopper can be obtained by combining $L_{i,erratic}$ and $L_{i,regular}$:

$$L_i = \left(1 - Prob_{i,regular}\right) * L_{i,erratic} + Prob_{i,regular} * L_{i,regular} \quad (4.11)$$

Where,

L_i: Unconditional likelihood function of person *i*

$L_{i,erratic}$: Conditional likelihood function of person *i* being erratic shopper

$L_{it,regular}$: Conditional likelihood function of person *i* being regular shopper

$Prob_{i,regular}$: Probability that person *i* is a regular shopper; and $\left(1 - P_{i,regular}\right)$ shows the probability that person *i* is an erratic shopper.

4.2.4 Model Estimation

The proposed model's parameters are estimated with the maximum likelihood estimator (MLE) method. The log-likelihood function to be maximized is

$$LL = \sum_{i=1}^{N} \log L_i \qquad (4.12)$$

where *N* is the total number of individuals. The research team used SAS software's interactive matrix language (IML) to estimate the log-likelihood function. The vector of parameters β, μ, and σ from the duration model of regular shoppers; the vector of α and ρ from the duration model of erratic shoppers; and the vector of γ from the latent segmentation model are parameters that need to be estimated.

4.2.4.1 Overall Results

For the non-elderly group, the log-likelihood value of the proposed model is –800.53. Also, the likelihood value for the case that all shoppers are regular ones is –864.03, and for the case that all shoppers are erratic is –866.34. Running the likelihood ratio test on both a purely regular model and a purely erratic model with a latent segmentation model indicates that not all shoppers are either erratic or regular shoppers (p-value for both cases is smaller than 0.00).

For the elderly group, the log-likelihood value of the proposed model is –860.32. Also, the likelihood value for the case that all shoppers are regular ones is –926.41, and for the case that all shoppers are erratic is –864.91. Running the likelihood ratio test of a purely regular model with a latent segmentation model indicates that not all shoppers are regular shoppers (p-value for this case is smaller than 0.00).

Running this test on a pure erratic model with a latent segmentation model shows that all elderly shoppers are statistically erratic shoppers (p-value for this case is 0.515). In other words, elderly people's intershopping duration can be modeled with a purely erratic model since they include people with fewer shares of mandatory activities (work/school activities). Therefore, shoppers in this group are less time-pressed and have a more flexible schedule.

As discussed earlier, intershopping durations are direct results of Accelerated Failure Time model formulation. Employing Equation (4.1), the study team calculated the average intershopping duration for each age group. For the non-elderly group, the average intershopping duration of the regular segment is equal to 9.86 days, and for the erratic segment it is equal to 1.70 days. For the non-elderly group, these values are equal to 1.72 days and 1.89 days, respectively, for the regular and erratic segments.

The study team can conclude that the average value of the intershopping durations for the regular and erratic segments is almost the same for the elderly group. Unlike the elderly group, non-elderly regular shoppers typically choose an intershopping duration 5.8 times that of erratic shoppers.

The next section discusses the effects of covariates in both age groups. As discussed above, all elderly people are statistically erratic shoppers. The purely erratic model thus represents them. For the non-elderly group, the study team will discuss the result of the latent segmentation model.

4.2.4.2 Covariate Effects

The study team used a combination of variables representing household, personal, and activity characteristics in their models. Table 4.4 displays the definitions of the variables and their mean and standard deviation values in the sample.

Table 4.4 Variables Used in the Model

Variable	Definition	Non-elderly group		Elderly group	
		Mean value	**Standard deviation**	**Mean value**	**Standard deviation**
Total Activities	Average of the total activities performed on two previous intershopping episodes	2.74	3.35	2.91	2.44
Joint Activity	1 if shopping activity is performed jointly with other person(s), 0 otherwise	0.39	0.49	0.43	0.50
Education	1 if shopper holds a college degree or higher, 0 otherwise	0.66	0.48	0.64	0.48
LogHHINCperSize	Ln (annual household income per household size)	3.13	0.53	3.56	0.59
HHSIZE	Household size	3.08	1.43	1.82	0.58
HHTYPE_MC	1 if household type is married with children, 0 otherwise	0.52	0.50	0.24	0.43
HHTYPE_LA	1 if person lives alone, 0 otherwise	0.14	0.35	0.13	0.34
HHTYPE_SC	1 if household type is single with children, 0 otherwise	0.10	0.30	0.02	0.15
Female	1 if a person is female, 0 otherwise	0.60	0.50	0.58	0.50
INTERNET_Frequently	1 if a person uses the Internet frequently, 0 otherwise	0.92	0.27	—	—

Tables 4.5 and 4.6 represent the results of the intershopping duration models developed for non-elderly and elderly shoppers. The Accelerated Failure Time model formulation allows for easier interpretation of covariate effects. Intershopping duration is the direct output of Equation (4.1). It should be noted that positive coefficients increase an intershopping duration (i.e., decrease the frequency of shopping activities).

For non-senior shoppers, higher income and bigger household size result in smaller, regular intershopping durations and bigger random-shopping durations. Families with these characteristics may have limited schedules and more items in their shopping baskets. Therefore, they prefer small, regular intershopping durations. Their limited schedule does not allow them to frequently participate in random shopping.

People with a higher educational level tend to choose longer, regular intershopping durations and do more random shopping activities. “HHtype_LA” has the same effect on both segments, possibly because shopping activity for people who live alone is more recreational. The estimated coefficient for the erratic segment is much bigger than that of the regular segment, meaning that people who live alone tend to pick small, random intershopping durations.

“Total activities” between two shopping activities can increase the intershopping duration in the regular and erratic segments. The “Total Activities” covariate is an example of what a person’s schedule might look like. The bigger this covariate’s value, the busier the schedule a person has and the likelier he or she will postpone shopping.

For the elderly group, a negative sign of “Joint Activity” indicates that participating in shopping activities with companions decreases intershopping duration, perhaps since seniors seize each opportunity to socialize with other people. Higher-income seniors perform shopping activities more frequently. Also, “HHtype_SC” and “HHtype_MC” indicate that seniors with children perform more shopping activities. “Total activities” has the same effect as it has for the non-elderly group.

Table 4.5 Intershopping Duration Model Results for Non-Elderly People

	Regular shopper segment		**Erratic shopper segment**	
Variable	**Parameter**	**t-stat**	**Parameter**	**t-stat**
Total activities	0.280	13.32	0.109	4.94
Education	0.221	2.54	–0.296	–1.63
logHHINCperSize	–0.435	–5.48	0.292	0.95
HHsize	–0.279	–6.18	0.151	2.31
HHtype_LA	–0.294	–2.28	–0.884	–1.58
Constant	–0.316	–0.28	2.431	6.98
Scale Parameter	0.561	20.63	—	—

Table 4.6 Intershopping Duration Model Results for Elderly People

	Pure erratic shopper model	
Variable	**Parameter**	**t-stat**
Total activities	0.263	9.68
Joint Activity	–0.324	–2.94
logHHINCperSize	–0.251	–3.00
HHtype_SC	–0.336	–0.82
HHtype_MC	–0.205	–1.82
Constant	1.310	4.36

4.2.4.3 Segmentation Model

As discussed earlier, all elderly shoppers are essentially erratic shoppers. Therefore, the study team only presents the segmentation model results of the non-elderly group in this section. Table 4.7 provides the results of the binary logit model that was used to endogenously divide shoppers in two groups of regular and erratic shoppers. The base category for the binary logit model is the erratic shopper group. Being female, having a higher education level, and frequently using the Internet increase one’s likelihood of being a regular shopper, while living in a bigger household increases the likelihood of being an erratic shopper.

Table 4.7 Segmentation Model for Non-Elderly People

Variable	**Parameter**	**t-stat**
HHsize	–0.703	–2.11
Female	0.766	0.89
Education	0.882	0.97
INTERNET_Frequently	1.986	1.23
Constant	–0.103	–0.06

The size of the erratic and regular segments can be calculated as follows:

$$S_{i,regular} = \frac{\sum_{i=1}^{N} Prob_{\ i,regular}}{\sum_{i=1}^{N} Prob_{\ i,regular} + \sum_{i=1}^{N} Prob_{\ i,erratic}} = \frac{\sum_{i=1}^{N} Prob_{\ i,regular}}{N} \tag{4.13}$$

$$S_{i,erratic} = \frac{\sum_{i=1}^{N} Prob_{\ i,erratic}}{N} \tag{4.14}$$

Sixty-two percent of non-elderly people are regular shoppers, while 38% of them are erratic shoppers. This result differs from that of elderly shoppers who are 100% erratic shoppers.

CHAPTER 5 MODE CHOICE

5.1 INTRODUCTION

The United States' transition to an aging country has made seniors an interesting social group to study (Karimi et al. 2012). Analysis of seniors' travel and activity patterns goes back more than 30 years to Wachs (1979). He collected senior travel and activity pattern data over two years to predict senior travel patterns in the year 2000. Since that time, several studies have primarily sought to show how seniors travel using statistical and econometric approaches (Hilderband 2003; Chang and Wu 2005; Su et al. 2009; Van den Berg et al. 2010) and how senior travel behavior differs from that of non-seniors (Karimi et al. 2012; Frignani et al. 2011; Mercado and Páez 2009; Páez et al. 2007; Giuliano et al. 2003).

The approaches previously used were not advanced enough to reveal complexities in the decision-making process of elderly people compared to non-elderly people. Tour-based models can be very helpful for understanding how decisions are related to each other (Ye et al. 2007). A tour is a trip sequence that starts and ends at the same place (Ortuzar and Willumsen 2011). Thus tour characteristics depend on the order, number, and specifications of executed trips and activities, such as activity types, travel mode, time-of-day choice, trip and activity duration, party size, etc.

Depending on the number of activities executed in a tour, tours can be categorized into simple (one activity) and complex (more than one activity) tours. Home–work–home is an example of a simple tour, and home–work–shopping–home is an example of a complex tour.

Analyzing trip-chaining patterns in complex tours has been an attractive subject in recent years (Bhat 1997; Kupram and Pendyala 2001; Ye et al. 2007). Researchers have used advanced econometric tools to explore the decision-making process in complex tours to see how the different decisions are interlinked to better understand travel behavior (Pendyala and Bhat; Habib et al. 2008 and 2009; Konduri et al. 2011).

To fulfill this gap, this study presents a copula-based joint model of main mode choice and main activity type for non-work complex tours of elderly and non-elderly people. Main mode is the travel mode used for the longest trip and main activity is the longest activity. The study team developed models for the elderly and non-elderly cohorts. Finally, a copula is a function that generates joint probability of random variables with (any) predefined marginal distributions (Nelsen 2006).

To the authors' best knowledge, this study is the first attempt to compare the travel behavior of elderly and non-elderly people using a tour-based joint model. GPS-based surveys have recently provided much more accurate and rich information on tour formation and have made tour-based analysis more accurate and trustworthy than before. The study team used the UTRACS dataset as the data source. It provided precise temporal and spatial information about trips and activities already completed for elderly and non-elderly individuals (Frignani et al. 2010; Auld et al. 2009).

The study team also looked at three travel modes (auto, transit, and non-motorized) and three non-work activity types (shopping, socializing, and personal) in the choice sets. They estimated the copola-based joint model using an Archimedean class of copula, including the Frank, Clayton, and Gumbel copulas and compared the joint model's results with independent multinomial logit (MNL) models of main mode choice and main activity type choice.

In this section, the study team discusses the methodology and data set used, the joint model's results, and comparisons with the independent models.

5.2 METHODOLOGY

Krishnamurthi and Raj's (1988) marketing study was among the earliest studies using joint models to analyze interlinked decisions. Researchers since then have developed and described three main approaches in the joint modeling literature. In the first approach, researchers have considered a suitable econometric model for each random variable. An example is a multinomial logit model for the discrete variable and a hazard-based model for the continuous one.

Researchers transform each model's random component into a standard normally distributed random variable form to build a joint probability function since the joint distribution of two normally distributed random variables is also normal (Lee 1983). This transformation seeks to accommodate a possible correlation between two random variables.

Bhat (1997) presented a joint model with a number of stops (ordered structure with a normally distributed random component) and work-mode choice (multinomial logit) during work commutes. Habib et al. (2008) examined the relationship among "with whom" (multinomial logit model), start time, and activity duration (continuous hazard model) of social activities to develop a discrete–continuous model. Habib et al. (2009) applied the same structure to examine trip-timing (continuous hazard model) and mode-choice (multinomial logit model) decisions.

In the second approach, researchers use the simultaneous equation model system. Similar to the previous approach, error terms are usually considered normally distributed or transformed into a normal distribution.

Pendyala and Bhat (2004) developed a discrete–continuous, simultaneous equations system for timing and duration of maintenance activities. Konduri et al. (2011) presented a joint discrete–continuous model to analyze the relationship between vehicle type choice and tour length using simultaneous equation systems. Imposing a restrictive distribution assumption on the error terms (as discussed, usually a normal distribution) can be considered the main drawback of these approaches.

To deal with this deficiency, Bhat and Eluru (2009) opened the third approach to joint-modeling. They developed a copula-based model for residential neighborhood choice and daily household traveled vehicle miles. A copula is a function that generates joint probability of random variables with (any) predefined marginal distributions (Nelsen 2006). In short, a copula is a connector. A variety of copula classes are available that let researchers examine different dependency structures between random variables. Unlike the previously mentioned approaches, a copula provides a flexible structure.

Spissu et al. (2009) developed a copula-based joint discrete–continuous model to examine the relationship between choice of vehicle type and distance traveled. A comparison of the results obtained with previous joint-modeling approaches showed a better goodness-of-fit for the copula-based model. Studies presented by Portoghese et al. (2011), Sener et al. (2010), Sener and Bhat (2011 and 2012), Eluru et al. (2010a), Bhat et al. (2010), Bhat and Sener (2009), and Eluru et al. (2010b) show diverse applications of copula for travel-behavior analysis. All these studies have emphasized the flexibilities of copula-based models.

A copula in short is a connector that can provide a dependence structure among random variables with a pre-specified marginal distribution (Nelsen 2006; Trivedi and Zimmer 2007). Consider a uniformly distributed random vector $(U_1, U_2, \dots, U_m)$ over [0, 1]. Then,

$$C_\theta(u_1, u_2, \dots, u_m) = \Pr(U_1 < u_1, U_2 < u_2, \dots, U_m < u_m) \quad (5.1)$$

is the *m*-dimensional copula of random variables U_1, U_2, ..., and U_m. θ is the copula parameter that shows how random variables are interrelated. Employing copula, one can generate joint multivariate distribution functions with predefined margins. Consider a random vector (V_1, V_2, …, V_m) with predefined margins of ($F_1(\vartheta_1)$, $F_2(\vartheta_2)$, …, $F_m(\vartheta_m)$). Then a joint multivariate distribution can be generated as (Sklar 1973):

$$J(\vartheta_1, \vartheta_2, \dots, \vartheta_m) = \Pr(V_1 < \vartheta_1, V_2 < \vartheta_2, \dots, V_m < \vartheta_m) =$$

$$\Pr(U_1 < F_1(\vartheta_1), U_2 < F_2(\vartheta_2), \dots, U_m < F_m(\vartheta_m)) = C_\theta(F_1(\vartheta_1), F_2(\vartheta_2), \dots, F_m(\vartheta_m)) \quad (5.2)$$

Let *i* be the index for individual, m be the index for main mode choice, and *a* be the index for main activity type choice. Consider the following bivariate copula, which is the case of this study.

$$J(\vartheta_{im}, \mu_{ia}) = C_\theta(F(\vartheta), G(\mu)) \quad (5.3)$$

where ϑ_{im} and μ_{ia} are random variables of main mode choice and main activity type choice models with the following indirect utility functions:

$$k_{im} = \beta' x_{im} + \vartheta_{im} \quad (5.4)$$

$$l_{ia} = \gamma' y_{ia} + \mu_{ia} \quad (5.5)$$

where x_{im} and y_{ia} are vectors of independent variables; and β and γ are corresponding coefficients to be estimated. Assume that ϑ_{im} and μ_{ia} are identically and independently extreme value type I distributed across individuals *i* and their choice set (*m* or *a*) with a location parameter equal to 0 and a scale parameter equal to 1. Therefore, the cumulative distribution functions for ϑ_{im} and μ_{ia} will result in the famous multinomial logit model (Train 2003):

$$\Pr_{im} = \Pr(\vartheta_{in} < \beta' x_{im} + \vartheta_{im} - \beta' x_{in}, \forall n \neq m) = \frac{e^{\beta' x_{im}}}{\sum_n e^{\beta' x_{in}}}, \; i = 1, 2, \dots, I \quad (5.6)$$

$$\Pr_{ia} = \Pr(\mu_{ib} < \gamma' y_{ia} + \mu_{ia} - \gamma' y_{ib}, \forall b \neq a) = \frac{e^{\gamma' y_{ia}}}{\sum_b e^{\gamma' y_{ib}}}, \; i = 1, 2, \dots, I \quad (5.7)$$

where $\Pr_{im}$ and $\Pr_{ia}$ are probabilities of choosing main mode m and main activity type a by individual i, respectively.

Let r_{im} and s_{ia} be dichotomous variables; $r_{im} = 1$ if individual *i* chooses main mode *m,* and $r_{im} = 0$ otherwise. $s_{ia} = 1$, if individual *i* chooses main activity type *a,* and $s_{ia} = 0$ otherwise. Then, the joint probability of choosing travel mode *m* and activity type *a* can be formulated as below:

$$\Pr(r_{im} = 1, s_{ia} = 1) = \Pr((\vartheta_{in} < \beta' x_{im} + \vartheta_{im} - \beta' x_{in}, \forall n \neq m), (\mu_{ib} < \gamma' y_{ia} + \mu_{ia} - \gamma' y_{ib}, \forall b \neq a)) = C_\theta(\Pr_{im}, \Pr_{ia}) \quad (5.8)$$

Let O_{ima} be dichotomous variables; $O_{ima} = 1$ if individual *i* chooses mode *m* as the main mode and activity type *a* as the main activity type, and $O_{ima} = 0$ otherwise. Then, the likelihood function for Equation (5.8) takes the following form:

$$L_i = \prod_{m=1}^{M} \prod_{a=1}^{A} [\Pr(r_{im} = 1, s_{ia} = 1)]^{O_{ima}} \quad (5.9)$$

5.3 DATA

UTRACS has captured a significant amount of data on the respondents' activity-travel planning process (Frignani et al. 2010; Auld et al. 2009). One important survey aspect was focused on using GPS traces to identify the respondents' tour formation behavior.

The core component of the tour formation process is the within-tour mode-choice modeling component. Factors that influence the choice of a specific mode (e.g. transit) are identified within this component.

In total, elderly and non-elderly respondents registered 625 and 788 tours respectively. Out of these numbers, elderly and non-elderly people completed 276 and 224 non-work complex tours, respectively. Table 5.1 shows the distribution of the main activity type and the main mode of non-work complex tours. This table shows that the elderly are less auto-dependent than non-elderly people for non-work tours. The distribution of the main activity type provides a totally different pattern. Elderly people perform more social/recreational and shopping activities, compared with the younger cohort.

Table 5.1 Distribution of Main Activity Type and Main Travel Mode

		Elderly	**Non-elderly**
Main Mode	Auto	87%	93%
	Transit	7%	3%
	Non-motorized	6%	4%
Main Activity	Personal	47%	17%
	Socializing	37%	49%
	Shopping	16%	35%

5.4 MODEL ESTIMATION

A wide range of bivariate copulas allow researchers to test different dependency structures between two random variables, including the Archimedean class, the Gaussian copula, and the Farlie-Gumbel-Morgenstern (FGM). The Archimedean class includes different types of copulas. Nelsen (2006) lists 14 one-parameter Archimedean copulas. In addition to this variety, the class of Archimedean copulas can generate an asymmetric dependence structure in contrast to FGM and Gaussian copulas, which assume a radially symmetric dependence relationship about the center point.

In this study, three famous copulas from the Archimedean class are employed: Gumbel, Clayton, and Frank. In contrast to the Frank copula, the Clayton and Gumbel copulas are asymmetric. The Clayton copula displays greater dependence in the negative (lower) tail, and the Gumbel copula shows greater dependence in the positive (upper) tail.

Parameters of the proposed model are determined with the maximum likelihood estimator (MLE). Log-likelihood to be maximized is

$$LL = \sum_{i=1}^{N} \log L_i \qquad (5.10)$$

where *N* is the total number of individuals. SAS software's interactive matrix language (IML) estimated this log-likelihood function. The vectors β and γ and the copula parameter θ are parameters to be estimated. Table 5.2 presents a descriptive analysis of the variables used in the utility functions.

5.4.1 Overall Results

Tables 5.3 and 5.4 respectively show model estimation results for the non-elderly and elderly groups. Because the copula models are non-nested, the traditional likelihood ratio test cannot be used to compare them. The study team instead used the Bayesian information criterion (BIC) to find the best copula model (Trivedi and Zimmer 2007). Because the number of observations and the number of parameters are equal, log-likelihood value can directly be used to compare the models. For both age groups, the Frank model represents the biggest log-likelihood value at convergence. For non-elderly people, the Frank model's log-likelihood value at convergence is –205.45. This is bigger than that of the Clayton model (–208.14) and the Gumbel model (–208.86). The story is the same for the elderly group. The Frank model's log-likelihood value at convergence is –265.38. This outperforms the Clayton model (–273.59) and the Gumbel model (–275.81).

Also, a nested likelihood ratio test between the independent model and the Frank model showed that the copula model outperforms the independent model. The independent model's likelihood can be calculated by multiplying the probability of choosing the main mode by the probability of choosing the main activity. For the case of the Frank copula, restricting the dependence parameter to almost zero can yield the independent model. The log-likelihood of the independent model at convergence was –228.95 and –322.21 for the non-elderly and elderly groups, respectively. The nested likelihood ratio test resulted in a test value of 47.00 for the non-elderly group and 113.66 for the elderly group, which is higher than the chi-squared value with one degree of freedom and any level of significance.

The Kendall's τ is a "measure of association" that can be used to interpret concordance between random variables. Concordance is a form dependency. Two random variables are directly concordant when there is a tendency of association between large values and a tendency of association between small values of those random variables. The random variables are inversely concordant when there is a tendency of association between large values for one variable and small values for the other.

The τ lies between –1 and 1. When tau is zero, there is no association between random variables. When τ is equal to 1, there is a perfectly direct concordance between variables. When τ is equal to –1, there is a perfectly inverse concordance between variables. For the case of the Frank copula, τ can be calculated from the estimated dependence parameter θ as follows:

$$\tau_\theta = 1 - \frac{4}{\theta}[1 - D_1(\theta)] \tag{5.11}$$

where $D_1(\theta)$ is the Debye function:

$$D_1(\theta) = \frac{4}{\theta}\int_0^\theta \frac{t}{e^t - 1}\,dt. \tag{5.12}$$

The calculated Kendall's τ for each pair of main travel modes and main activity types is shown in the bottom of Table 5.3 for the non-elderly group and Table 5.4 for the elderly group. The tau values for both age groups are pretty close to +1, meaning there is a strong direct concordance between the choice of the main mode and the choice of the main activity type. The corresponding tau values of the non-elderly group are higher than those of the elderly group. The concordance of the main mode choice and the main activity type is thus stronger among non-elderly people than among the elderly.

5.4.2 Covariate Effects

Key findings of the joint model are summarized as follows.

For the non-elderly group, it was found that

- Individuals within the same household and having similar personal characteristics opt for non-motorized transportation as their first choice, auto as their second choice, and transit as their least probable choice for short trips.
- A higher number of cars reduces the propensity for using a non-motorized mode.
- Individuals with an average income level of $50,000 to $100,000 are more likely to choose a non-motorized mode.
- Being alone increases the likelihood of selecting the transit mode, perhaps because people who live alone have more free time.
- The likelihood of participating in shopping activities increases in the early afternoon.
- The likelihood of socializing decreases in late morning and late afternoon.
- A higher number of cars would increase the likelihood of socializing.
- Individuals who live alone do more socializing.
- Individuals within the lower-income range (under $50,000) do less socializing.

For the elderly group, is was found that

- Individuals within the same household and having similar personal characteristics opt for non-motorized transportation as their first choice, transit as their second choice, and auto as their least probable choice for short trips.
- A higher number of cars reduces the propensity for choosing transit.
- Bigger households are less likely to choose non-motorized modes.
- Holding a college degree decreases the propensity for choosing transit.
- Traveling alone increases the likelihood of choosing a non-motorized mode.
- The likelihood of undertaking shopping activities increases in late morning and in early afternoon.
- Individuals with an average income level of $50,000 to $100,000 participate in more social activities.
- Married individuals without children tend to participate in fewer social activities.
- Elderly individuals who are alone tend to engage in more social activities.

Table 5.2 Descriptive Analysis of Variables Used in the Model

Variable	Type	Definition	Lower value		Upper value		Average		Standard deviation	
			Seniors	Non-seniors	Seniors	Non-seniors	Seniors	Non-seniors	Seniors	Non-seniors
Cost	continuous	Travel costs in U.S. dollars	$0.1	—	$18.75	—	$2.17	—	$2.10	—
TravelTime	continuous	Travel time in hours	0.05	0.06	2.50	1.91	0.39	0.31	0.37	0.27
NCar	discrete	Number of available cars in the household	0	0	4	2	2.24	1.42	1.03	0.62
HHSize	discrete	Household size	1	—	5	—	1.83	—	0.63	—
Alone	binary	1, if person is traveling alone; 0, otherwise	0	0	1	1	0.44	0.42	0.50	0.49
Ave_Income	binary	1, if the household income is between $50,000 and $100,000; 0, otherwise	0	0	1	1	0.44	0.32	0.50	0.46
NoFamily	binary	1, if the person lives alone; 0, otherwise	0	0	1	1	0.10	0.12	0.32	0.32
Married_NoChildr	binary	1, if the household is married without children; 0, otherwise	0	0	1	1	0.13	0.48	0.34	0.50
early_afternoon	binary	1, if the person executed his or her activity between 12 noon and 3 p.m.; 0, otherwise	0	0	1	1	0.32	0.30	0.47	0.46
Married_Children	binary	1, if the household is married with children; 0, otherwise	0	—	1	—	0.53	—	0.50	—
late_morning	binary	1, if the person executed his or her activity between 9 a.m. and12 noon; 0, otherwise	0	0	1	1	0.17	0.34	0.38	0.47
late_afternoon	binary	1, if the person executed his or her activity between 3 and 6 p.m.; 0, otherwise	0	0	1	1	0.28	0.20	0.45	0.40
Low_Income	binary	1, if the household income is under $50,000; 0, otherwise	0	—	1	—	0.26	—	0.44	—
Degree	binary	1, if the person holds a college degree; 0, otherwise	0	—	1	—	.068	—	0.47	—

Table 5.3 Results of Independent and Joint Models for Non-Elderly People

Variable	MNL (Main Travel Mode)			MNL (Main Activity Type)		
	Auto	**Transit**	**Non-motorized**	**Personal**	**Socializing**	**Shopping**
Constant	0.273 (0.273)	— —	1.103 (1.310)	— —	0.854 (6.735)	0.375 (2.895)
$Cost$	–0.253 (–1.119)	–0.253 (–1.119)	— —	— —	— —	— —
$TravelTime$	–4.442 (–3.609)	–2.839 (–2.317)	–2.593 (–1.840)	— —	— —	— —
$NCar$	— —	— —	–0.441 (–0.743)	— —	0.389 (1.963)	— —
$Alone$	0.357 (0.620)	— —	— —	— —	— —	— —
$Average\_HHincome$	— —	— —	0.724 (0.449)	— —	— —	— —
$NoFamily$	— —	0.600 (9.917)	— —	— —	1.984 (8.831)	— —
$Married\_NoChildren$	— —	— —	— —	1.113 (3.077)	— —	— —
$early\_afternoon$	— —	— —	— —	— —	— —	0.776 (3.824)
$Married\_Children$	— —	— —	— —	— —	— —	0.706 (2.995)
$late\_morning$	— —	— —	— —	— —	–0.853 (–3.438)	— —
$late\_afternoon$	— —	— —	— —	— —	–0.951 (–4.967)	— —
$Low\_HHincome$	— —	— —	— —	— —	–1.051 (–2.436)	— —
Copula dependence parameter						
Personal	0.852 (0.502)	*	0.815 (0.278)			
Socializing	0.838 (18.055)	0.841 (2.000)	0.871 (0.682)			
Shopping	0.858 (2.797)	*	0.904 (0.346)			

*There were not enough observations for personal/transit and shopping/transit pairs

Table 5.4 Results of Independent and Joint Models for Elderly People

Variable	MNL (Main Travel Mode)			MNL (Main Activity Type)		
	Auto	Transit	Non-motorized	Personal	Socializing	Shopping
Constant	— —	0.277 (3.682)	0.347 (0.562)	— —	1.189 (12.526)	0.380 (2.207)
$TravelTime$	–0.552 (–8.393)	–0.356 (–4.351)	–0.313 (–3.405)	— —	— —	— —
$NCar$	— —	–0.514 (–5.917)	— —	— —	— —	— —
$Alone$	— —	— —	0.168 (0.250)	— —	— —	— —
$HHSize$	— —	— —	–0.418 (–0.951)	— —	— —	— —
$NoFamily$	— —	— —	— —	— —	0.216 (1.220)	— —
$Married\_NoChildren$	— —	— —	— —	— —	–0.384 (–1.645)	— —
$early\_afternoon$	— —	— —	— —	— —	— —	0.869 (5.097)
$Married\_Children$	–0.358 (–3.593)	— —	— —	— —	— —	— —
$late\_morning$	— —	— —	— —	— —	— —	0.542 (3.049)
$late\_afternoon$	— —	— —	— —	— —	–0.628 (–2.329)	— —
$Average\_HHincome$	— —	— —	— —	— —	0.374 (1.934)	— —
$Degree$	— —	–0.201 (–4.970)	— —	— —	— —	— —
Copula dependence parameter						
Personal	0.747 (1.454)	0.660 (0.583)	0.703 (0.866)			
Socializing	0.879 (22.355)	0.776 (1.299)	0.787 (1.090)			
Shopping	0.822 (1.913)	0.783 (0.769)	0.779 (0.717)			

REFERENCES

Akar, G., K.J. Clifton, and S.T. Doherty (2009). How Travel Attributes Affect Planning Time Horizon of Activities. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2132, pp. 33–41.

Alsnih, R., and D.A. Hensher (2003). The mobility and accessibility expectations of seniors in an aging population. *Transportation Research Part A*, Vol.37, Elsevier, Oxford, pp.903–916.

Arentze, T., and H. Timmermans (2003). A learning-based transportation oriented simulation system. *Transportation Research Part B: Methodological*, Vol.38, Elsevier, Oxford, pp.613–633.

Arentze, T., H. Timmermans, P. Jorritsma, M.J.O. Kalter, and A. Schoemakers (2008). More grey hair—but for whom? Scenario-based simulations of elderly activity-travel patterns in 2020. *Transportation*, 35, Springer Netherlands, Dordrecht, pp.613–627.

Auld, J., C. Williams, A. K. Mohammadian, and P. Nelson (2009). An Automated GPS-Based Prompted-Recall Survey with Learning Algorithms. *Transportation Letters: The International Journal of Transportation Research,* Vol. 1, No. 1, pp. 59–79.

Bachu, P. K., T. Dudala, and S. Kothuri (2001). Prompted Recall in Global Positioning System Survey: Proof-of-Concept Study. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1768,* TRB, National Research Council, Washington, D.C., pp. 106–113.

Bell, W., and W. Olsen (1974). An Overview of Public Transportation and the Elderly: New Directions for Social Policy. *The Gerontologist*, Vol.14, No.4, Oxford Journals, Oxford, pp.324–330.

Bhat, C.R. (1997). Work Travel Mode Choice and Number of Nonwork Commute Stops, *Transportation Research Part B*, Vol. 31, No. 1, pp. 41–54.

Bhat, C.R., and I.N. Sener (2009). A Copula-Based Closed-Form Binary Logit Choice Model for Accommodating Spatial Correlation Across Observational Units, *Journal of Geographical Systems,* Vol. 11, No. 3, pp. 243–272

Bhat, C.R., and N. Eluru (2009). A Copula-Based Approach to Accommodate Residential Self-Selection Effects in Travel Behavior Modeling, *Transportation Research Part B*, Vol. 43, No. 7, pp. 749–765.

Bhat, C.R., I.N. Sener, and N. Eluru (2010). A Flexible Spatially Dependent Discrete Choice Model: Formulation and Application to Teenagers' Weekday Recreational Activity Participation, Transportation Research Part B, Vol. 44, No. 8–9, pp. 903–921.

Bhat, C.R., T. Frusti, H. Zhao, S. Schonfelder, and K.W. Axhausen (2004). Inter-shopping Duration: An Analysis Using Multiweek Data*, Transportation Research Part B*, 38 (1), pp. 39–60.

Buckley, J. (2008). Baby boomers, obesity, and social change, *Obesity Research & Clinical Practice*, Volume 2, Issue 2, July 2008, pp. 73–82.

Chang, H., and S. Wu (2005). Exploring the mode choice in daily travel behavior of the elderly in Taiwan. *Journal of the Eastern Asia Society for Transportation Studies*, Vol. 6, pp. 1818–1832.

Clark, A. F., and S. T. Doherty (2008). Examining the Nature and Extent of the Activity-Travel Preplanning Decision Process. In *Transportation Research Record: Journal of the*

Transportation Research Board, No. 2054, Transportation Research Board of the National Academies, Washington, D.C., pp. 83–92.

Clark, A. F., and S. T. Doherty (2009). Activity Rescheduling Strategies and Decision Processes in Day-to-Day Life. Presented at 88th Annual Meeting of the Transportation Research Board, Washington, D.C.

CMAP (2009). Household travel and activity inventory: Travel Tracker Survey. Chicago Metropolitan Agency for Planning. <http://www.cmap.illinois.gov/TravelTrackerData.aspx?ekmensel=c580fa7b_8_16_8798_6>. Accessed Dec. 7, 2009.

Collia, D.V., J. Sharp, and L.Giesbrecht (2003). The 2001 national household travel survey: a look in the travel patterns of older Americans. *Journal of Safety Research*, 34, National Safety Council, Washington, D.C., pp.461–470.

Committee for Determination of the State of the Practice in Metropolitan Area Travel Forecasting (2007). Metropolitan Travel Forecasting: Current Practice and Future Direction. *Transportation Research Board Special Report 28.*

Cox, D.R. (1972). Regression Models and Life-Tables, *Journal of the Royal Statistical Society*, 26 (B), pp. 186–220.

Dobbs, B.M. (2005). *Medical conditions and driving: a review of the literature (1960–2000)*. National Highway Safety Administration, Washington, D.C.

Eluru, N., C.R. Bhat, R.M. Pendyala, and K.C. Konduri (2010a). A Joint Flexible Econometric Model System of Household Residential Location and Vehicle Fleet Composition/Usage Choices, *Transportation*, 2010 TRB Special Issue, Vol. 37, No. 4, pp. 603–626.

Eluru, N., Paleti R., Pendyala R.M., and Bhat C.R., (2010b), Modeling Injury Severity of Multiple Occupants of Vehicles: Copula-Based Multivariate Approach, *Transportation Research Record,* Vol. 2165, pp. 1–11.

Frignani, M., J. Auld, and A. Mohammadian (2011). Empirical Analysis of the Decision-Making and Tour Formation Process: Comparison between Seniors and Younger Individuals, *Transportation Research Record: Journal of the Transportation Research Board*, No. 2231, pp. 27–34.

Frignani, M. Z., J. Auld, C. Williams, A. Mohammadian, and P. Nelson (2010). Urban Travel Route and Activity Choice Survey (UTRACS): An Internet-based prompted recall activity travel survey using GPS data. *Transportation Research Record: Journal of the Transportation Research Board*, 2010, pp. 19–28.

Giuliano, G., H. Hu, K. Lee, and METRANS Transportation Center (2003). Travel patterns of the elderly: the role of land use. *METRANS project 00-8.*

Golob, T.F., and D.A. Hensher (2007). The trip chaining activity of Sydney residents: a cross-section assessment by age group with a focus on seniors. *Journal of Transport Geography*, 15, Elsevier, Oxford, pp.298–312.

Grammsch, P.M. and T.M. Therneau (1994). Proportional hazards tests and diagnostics based on weighted residuals. *Biometrika,* 81, pp. 515–526.

Habib, K.M.N., J.A. Carrasco, and E.J. Miller (2008). Social Context of Activity Scheduling Discrete–Continuous Model of Relationship Between “with Whom” and Episode Start Time and Duration, *Transportation Research Record: Journal of the Transportation Research Board*, No. 2076, Transportation Research Board of the National Academies, Washington, D.C., pp. 81–87.

Habib, K.M.N., N. Day, E.J. Miller (2009). An investigation of commuting trip timing and mode choice in the Greater Toronto Area: Application of a joint discrete-continuous model *Transportation Research Part A* (43), pp. 639–653.

Hanson, P. (1977). The activity patterns of elderly households. *Geografiska Annaler, Series B, Human Geography*, Vol.59, No.2, Swedish Society for Anthropology and Geography, Stockholm, pp.109-124.

Hanson, S., and J.O. Huff (1988). Systematic variability in repetitious travel. *Transportation*, 15, Springer Netherlands, Dordrecht, pp. 111–135.

Hensher, D. A., and K. J. Button (2000). Handbook of Transport Modelling. *Elsevier Ltd.* Volume I, pp. 53–58.

Hibino, N., A. Okada, K. Ohno (2007). Urban Transportation Demand Based on Travel Behavior of Elderly People in Japan. *Proceedings of the 11th World Conference on Transport Research*, June 2007, Berkeley.

Hilderband, E. D. (2003). Dimensions in elderly travel behavior: A simplified activity-based model using lifestyle clusters, *Transportation 30*: pp. 285–306.

Hough, J.A., C. Xinyu, and S.L. Handy (2008). Exploring Travel Behavior of Elderly Women in Rural and Small Urban North Dakota: An Ecological Modeling Approach. *Transportation Research Record: Journal of the Transportation Research Board*, No.2082, Transportation Research Board of the National Academies, Washington, D.C., pp.125–131.

Jones, S., K. Hoffmann, Australian Bureau of Statistics (ABS), and South Australian State Statistical Priorities Committee (SASSPC) (2003). South Australia’s baby boomers: a profile. Canberra, Australian Capital Territory.

Kalbfleisch, J.D., and R.L. Prentice (1980). *Statistical Analysis of Failure Time Data*. New York: Wiley.

Karimi, B., T.H. Rashidi, A. Mohammadian, and K. Sturm (2012). Young-Old Elderly and Baby Boomers: Explanatory Analysis of Activity Duration, Time-of-Day Choice, and Planning Time Horizons. *Transportation Research Record: Journal of the Transportation Research Board,* Vol. 2322, pp. 51–59.

Kim, B., and K. Park (1997). Studying Patterns of Consumer’s Grocery Shopping Trip. *Journal of Retailing*, 73 (4), pp. 501–517.

Konduri, K.C., X. Ye, B. Sana, and R.M. Pendyala (2011). Joint Model of Vehicle Type Choice and Tour Length, *Transportation Research Record: Journal of the Transportation Research Board*, No. 2255, Transportation Research Board of the National Academies, Washington, D.C., pp. 28–37.

Krishnamurthi, L. and S.P. Raj (1988). A model of brand choice and purchase quantity price sensitivity. *Marketing Science* 7, pp. 1–20.

Kuppam, A.R., and R.M. Pendyala (2001). A Structural Equations Analysis of Commuter Activity and Travel Patterns. *Transportation* 28(1), pp. 33-54.

Kurth, D. L., J. L. Coin, and M. J. Brown (2001). Assessment of Quick-Refusal and No-Contact Nonresponse in Household Travel Surveys. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1768,* TRB, National Research Council, Washington, D.C., pp. 114–124.

Lee, L.F. (1983). Generalized econometric models with selectivity. *Econometrica*, 51(2), pp. 507–512.

Lyman, J.M., G. McGwin, and R.V. Sims (2001). Factors related to driving difficulty and habits in older drivers: high-risk conditions and locations. *Accident Analysis and Prevention*, 33, Elsevier, Oxford, pp.413–421.

Mercado, R., and A. Páez (2009). Determinants of distance traveled with a focus on the elderly: a multilevel analysis in Hamilton CMA, Canada. *Journal of Transport Geography*, 17, Elsevier, Oxford, pp.65–76.

Mercado, R., and B.K. Newbold (2009). Car Driving and Public Transit Use in Canadian Metropolitan Areas: Focus on Elderly and Role of Health and Social Network Factors. *Proceedings of the 88th Annual Meeting of the Transportation Research Board*, January 2009, Washington, D.C.

McGwin, G., R. Sims, L. Pulley, and J.M. Roseman (2000). Relations among chronic medical conditions, medications, and automobile crashes in the elderly: a population-based case-control study. *American Journal of Epidemiology*, 152 (5), Oxford Journals, Oxford, pp.424–431.

McLarry, J.J., A. Ståhl, and S. Persich (1993). Implementation of service routes in the United States. *Transportation Research Record*, No.1378, Transportation Research Board of the National Academies, Washington, D.C., pp.21–27.

Meyer, J. W. (1981). Elderly activity patterns and demand for transportation in a small city setting*, Socio. Econ. Plan. Sci*., Vol. 15, pp. 9–17.

Miringoff, L. M., B. L. Carvalho, and S. K. McCulloch (2010). The new reality of 2011: baby boomers at 65, prepared for Home Instead Senior Care.

Mohammadian, A., and S. T. Doherty (2006). Modeling activity scheduling time horizon: Duration of time between planning and execution of pre-planned activities. *Transportation Research Part A 40*, pp. 475–490.

Mohammadian, A., T.H. Rashidi, and P. Takuriah (2007). Effectiveness of Transit Strategies Targeting Elderly People: Survey Results and Preliminary Data Analysis. Report prepared for Illinois Center for Transportation (ICT), Illinois Department of Transportation (IDOT), ICT project R27. Chicago: University of Illinois at Chicago.

Mohammadian, A., S. Bekhor (2008). Travel behavior of special population groups, *Transportation* 35: pp. 579–583.

National Center for Health Statistics (1994). Vital Statistics of the United States, Volume I: Natality. Hyattsville, Maryland.

National Center for Health Statistics, (2012), National Vital Statistics Reports. <Web:www.cdc.gov/nchs.> Accessed on March 12 2013.

NCHRP (2008). Standardized Procedures for Personal Travel Surveys. National Cooperative Highway Research Program Report 571. Transportation Research Board of the National Academies, Washington, D.C.

Nelsen, R. B. (2006). *An Introduction to Copulas* (2nd ed.), Springer-Verlag, New York.

Newbold, K. B., D. M. Scott, S. E. L. Spinney, P. Kanaroglou, and A. Paez (2005). Travel behavior within Canada's older population: a cohort analysis, *Journal of Transport Geography*, Vol. 13, pp. 340–351.

NHTSA (2012). Traffic Safety Facts: Older Population. Traffic Safety Fact Sheet DOT HS 811 640. National Highway's Traffic Safety Administration, Washington, D.C.

Noland, R.B, and J.V. Thomas (2007). Multivariate analysis of trip-chaining behavior. *Environment and Planning B*: Planning and Design, Vol.34, Pion, London, pp.953-970.

Ortuzar, J.de D., and L.G. Willumsen (2011). *Modeling Transport, 4th Edition*, Wiley, New Delhi, India.

Páez, A., D. Scott, D. Potoglou, P. Kanaroglou, and K. B. Newbold (2007). Elderly Mobility: Demographic and Spatial Analysis of Trip Making in the Hamilton CMA, Canada, *Urban Studies*, Vol. 44, No. 1, 123–146.

Pendyala, R.M., and C.R. Bhat (2004). An Exploration of the Relationship Between Timing and Duration of Maintenance Activities, *Transportation*, Vol. 31, No. 4, pp. 429–456.

Pisarki, A.E. (2003). Prescription for research: reviewing the history of TRB's critical issues in transportation. *TR News*, No.226, Transportation Research Board of the National Academies, Washington, D.C., pp.31–35.

Portoghese, A., E. Spissu, C.R. Bhat, N. Eluru, and I. Meloni (2011). A Copula-Based Joint Model of Commute Mode Choice and Number of Non-Work Stops during the Commute, *International Journal of Transport Economics*, Volume: 38, No.3, pp. 337–362.

Rashidi, T.H. and A. Mohammadian (2008). Effectiveness of transit strategies targeting elderly people, Canadian Journal of Transportation, Vol. 2, No. 1, pp. 61–76

Robertson, R., W. Vanlaar (2008). Elderly drivers: future challenges? *Accident Analysis and Prevention*, 40, Elsevier, Oxford, pp.1982–1986.

Roorda, M., A. Páez, C. Morency, R. Mercado, and S. Farber (2009). Trip Generation of Vulnerable Populations in Three Canadian Cities: Spatial Ordered Probit Approach. *Proceedings of the 88th Annual Meeting of the Transportation Research Board*, January 2009, Washington, D.C.

Roper ASW (2004). Baby boomers envision retirement II: survey of baby boomers' expectations for retirement, prepared for AARP Environmental Analysis.

Rosenbloom, S. (2001). Sustainability and automobility among the elderly: an international assessment. *Transportation*, 28, Springer Netherlands, Dordrecht, pp.375–408.

Rosenbloom, S. (2003). The mobility needs of older Americans: implications for transportation reauthorization. The Brookings Institution, Washington, D.C.

Rowland, D.T. (1991). Ageing in Australia, *Longman Cheshire*, Australia.

SAS software, Version 9.2 of the SAS System for Windows. Copyright © 2002–2008 by SAS Institute Inc., Cary, NC, USA.

Schönfelder, S., and K.W. Axhausen (2001). Modeling the Rhythms of Travel Using Survival Analysis. Paper presented to the 80th Annual Meeting of the Transportation Research Board, Washington, D.C., January 2001.

Sener, I.N., and C.R. Bhat (2011). A Copula-Based Sample Selection Model of Telecommuting Choice and Frequency, *Environment and Planning A*, Vol. 43, No. 1, pp. 126–145.

Sener, I.N., and C.R. Bhat (2012). Flexible Spatial Dependence Structures for Unordered Multinomial Choice Models: Formulation and Application to Teenagers' Activity Participation, *Transportation*, Vol. 39, No. 3, pp. 657–683

Sener, I.N., N. Eluru, and C.R. Bhat (2010). On Jointly Analyzing the Physical Activity Participation Levels of Individuals in a Family Unit Using a Multivariate Copula Framework, *Journal of Choice Modelling*, Vol. 3, No. 3, pp. 1–38.

Sklar, A. (1973). Random Variables, Joint Distribution Functions, and Copulas. *Kybernetika*, Vol. 9, pp. 449–460.

Spissu, E., A.R. Pinjari, R.M. Pendyala, and C.R. Bhat (2009). A Copula-Based Joint Multinomial Discrete-Continuous Model of Vehicle Type Choice and Miles of Travel, *Transportation*, Vol. 36, No. 4, pp. 403–422.

Stahl, A. (1992). Mobility and accessibility for elderly and disabled people in Sweden. *IATSS Research*, Vol.16, No.2, International Association of Traffic and Safety Sciences, Suzuka, pp.96–97.

Stirner, F. (1978). Transportation: The Transportation Needs of the Elderly In a Large Urban Environment. *The Gerontologist*, Vol.18, No.2, Oxford Journals, Oxford, pp.207–211.

Stopher, P. R., R. Alsnih, C. G. Wilmot, C. Stecher, J. Pratt, J. Zmud, W. Mix, M. Freedman, K. W. Axhausen, M. Lee-Gosslein, A. E. Pisarski, and W. Brög (2008). *NCHRP Report 571: Standardized Procedures for Personal Travel Surveys.* Transportation Research Board of the National Academies, Washington, D.C.

Su, F., J. D. Schmöcker, and M. G. H. Bell (2009). Mode Choice of Older People Before and After Shopping, *Journal of Transport and Land Use* 2, pp. 29–46

Surface Transportation Policy Project-STPP (2001). New Transportation Charter, adopted on December 11, 2001 with over 700 endorsements of September 2003.

Train, K. (2003). *Discrete Choice Methods with Simulation*. Cambridge University Press, Cambridge.

Trivedi, P.K., and D.M. Zimmer (2007). Copula Modeling: An Introduction for Practitioners, Foundations and Trends in Econometrics Vol. 1, Issue 1, Now Publishers.

Turner, D., C. Giorno, A. De Serres, A. Vourc'h, and P. Richardson (1998). The Macroeconomic Implications of Ageing in a Global Context, *OECD Economics Department Working Papers*, No. 193, OECD publishing, Paris.

U.S. Census Bureau (2004). *State interim population projections by age and sex: 2004–2030*. Table 4: Interim Projections: Change in Total Population and Population 65 and Older, by State: 2000 to 2030. U.S. Census Bureau, Washington D.C.

U.S. Census Bureau (2009). *Aging in the United States–Present, Past, and Future.* Wall chart. U.S. Census Bureau, Washington, D.C. <http://www.census.gov/population/international/files/97agewc.pdf>. Accessed on March 17, 2013.

U.S. Census Bureau (2011). National Characteristics: Vintage 2011, Annual Estimates of the Resident Population by Sex and Five-Year Age Groups for the United States: April 1, 2010 to July 1, 2011, http://www.census.gov/popest/data/national/asrh/2011/index.html, Accessed on March 20, 2013.

Van den Berg, P., T. Arentze, and H. Timmermans (2011). Estimating social travel demand of senior citizens in the Netherlands. *Journal of Transport Geography,* Volume 19 (2), pp. 323–331.

Wachs, M. (1979). Transportation needs for the elderly: Changing lifestyles, changing needs. *University of California Press, Berkley.*

Wan, H., M. Sengupta, V. A. Velkoff, K. A. DeBarros, and U.S. Census Bureau (2005). 65+ in the United States: 2005*, Current Population Reports*, P23–209.

Wolf, J. (2006). Applications of New Technologies in Travel Surveys. In *Travel Survey Methods: Quality and Future Directions* (P. R. Stopher and C. Stecher, eds.), Elsevier Science Ltd., Oxford, United Kingdom, pp. 531–544.

Wolf, J., R. Guensler, and W. Bachman (2001). Elimination of the Travel Diary: An Experiment to Derive Trip Purpose from GPS Travel Data. Presented at 80th Annual Meeting of the Transportation Research Board, Washington, D.C.

Xinyu, C., P.L. Mokhtarian, S.L. Handy (2008). Neighborhood Design and the Accessibility of the Elderly: Empirical Analysis in Northern California. *Proceedings of the 87th Annual Meeting of the Transportation Research Board*, January 2008, Washington, D.C.

Yaffe, K., D. Barnes, M. Nevitt, L.Y. Lui, K. Covinsky (2001). A prospective study of physical activity and cognitive decline in elderly women. Archives of Internal Medicine, Vol.161, No.14, American Medical Association, Chicago, pp.1703–1708.

Ye, X., R.M. Pendyala, G. Giovanni (2007). An exploration of the relationship between mode choice and complexity of trip chaining patterns. *Transportation Research Part B* 41 (1), 96-113.

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