Understanding Use of Transport Network Companies (TNC) in Virginia

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ABSTRACT

This study deals with a) Understanding familiarity with transportation network companies (TNCs) and their use frequency b) Understanding travel choices in alcohol-related situations in Virginia. Ordered logistic regression models were used to identify factors associated with the respondent's perceived familiarity with transportation network companies (TNCs) and use frequency. Based on the two models, the consistent factors were using a mobile wallet, a cell phone for entertainment, an app for taxi services, or an app for hotel booking/air transport arrangements, living in Northern Virginia, normally using multiple transportation modes for a single trip, higher education levels, and higher household income which were associated with increased TNC familiarity and use frequency. Self-identifying as White/Caucasian was also associated with increased TNC use frequency. Increased age was associated with decreasing TNC familiarity and use frequency.

Subsequently, travel choices in alcohol related situations were studied with the objective of understanding the role of Transportation Network Companies (TNCs) in these situations and whether they have an impact on DUIs. For this objective, this study analyzes travel-choices associated with three scenarios alcohol related situations: (a) the last time the respondent consumed alcohol, (b) when avoiding driving after drinking, and (c) when avoiding riding with a driver who had been drinking. Multinomial Logistic Regression models were developed for all the three scenarios. For model (a), significant factors included use of a personal vehicle to arrive at the location where last consuming alcohol, being comfortable with having a credit card tied to a cell phone app, age, income, travelling alone when leaving the location where last consuming alcohol, having the highest educational attainment of high school graduate (GED), consumption of alcohol at bar/tavern/club, consumption of alcohol at home of friends/acquaintance place, and transportation network company (TNC – e.g., Uber, Lyft) weekly use frequency. For (b), use of a personal vehicle to arrive at the location where last consuming alcohol, consumption of alcohol at a bar/tavern/club, consumption of alcohol at the home of friends/acquaintance place, comfort with tying of credit card to apps, age, gender, income, multi-modal travel for a regular trip, TNC weekly use frequency, and use of an app for hotel reservations and/or air transportation

arrangements are significant factors. For (c), use of a personal vehicle to arrive at the location where last consuming alcohol, walking to the location where last consuming alcohol, consumption of alcohol at a bar/tavern/club, comfort with tying a credit card to apps, age, income, TNC weekly use frequency, previously riding in a car with a driver who may have drunk too much to drive safely, and being employed full time are the significant factors.

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GENERAL AUDIENCE ABSTRACT

The study intends to improve understanding of the characteristics of early adopters of TNC services and contribute towards understanding travel choices made by individuals in alcohol-related situations. Data for this study came from a telephone survey of just over 3000 respondents across three metropolitan regions of Virginia; Northern Virginia, Hampton Roads/Tidewater and the Richmond urban area.

This study deals with a) Understanding familiarity with transportation network companies (TNCs) and their use frequency b) Understanding travel choices in alcohol-related situations in Virginia. Based on the surveys, ordinal logit models were developed to predict the degree of familiarity and use frequency of TNCs. The results showed that income was significantly associated with both increased familiarity and increased use frequency of TNCs. Educational attainment was also significant and positively associated with familiarity and use frequency. Age was significantly and negatively associated with TNC familiarity and use frequency. This may be important in understanding TNC use in locations with older populations. Individuals located in Northern Virginia were associated with increased TNC familiarity and use frequency. Individuals who used multiple modes to commute had a higher likelihood of being familiar with and using TNCs more frequently. Use of an app for sourcing taxi services was associated with increased TNC familiarity and use frequency. Similarly, using an app for hotel reservations and/or air transportation arrangements was associated with increased TNC use frequency. In addition, individuals using their phone for entertainment were more likely to be familiar with and use TNCs. Use of mobile wallet was associated with increased TNC familiarity and use frequency. Employment status “student” was significantly associated with TNC familiarity which suggests that information is easily accessible for this group of people. Also, individuals self-identifying their race as white had a higher probability of using TNCs.

The second part of the research analysis included multinomial logistic regression models which identified factors associated with respondents’ travel choices in alcohol-related situations: (1) the last time the respondent consumed alcohol, (2) when avoiding driving after drinking, and (3) when avoiding riding with a driver who had been drinking. From the model results, it was found

that consumption of alcohol at a bar was statistically associated with use of TNC services in all three alcohol-related situations. TNCs were more likely to be used by younger people in all three alcohol-related situations examined in this study. Older people were more likely to ride with designated drivers than to use TNCs when avoiding driving after drinking and the last instance of consuming alcohol. Familiarity with, and regular use of TNCs increased the likelihood of using TNCs in all three alcohol-related situations in this study.

This thesis is dedicated to my mother and grand-mother, thank you!

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CHAPTER 1: INTRODUCTION

1.1. BACKGROUND

The digitalization of products and services is changing the contemporary landscape of various related business sectors ranging from products to services over the past few decades (1). The widespread use of mobile internet has given rise to a new economy known as the sharing economy. Transportation network companies like Uber and Lyft are two of the biggest firms in the sharing economy. They use information technology (IT systems), typically available via web-based platforms, such as mobile “apps” on Internet-enabled devices, to facilitate peer-to-peer transactions. Research into the impacts of such services has increased in recent years and has led to important conclusions for future research and related to policy implications. However, the willingness to use innovative technologies including the perception, expectation, intention to use and actual use behavior determines user acceptance (2). This study is a step towards understanding the use of technology and other variables affecting the use of TNCs both in general and as an alternative associated with alcohol consumption.

This study focuses on identifying factors associated with (a) familiarity of adults with transportation network companies (TNCs) as well as how often adults use TNCs, and (b) travel choices in three alcohol-related situations: (1) the last time the respondent consumed alcohol, (2) when avoiding driving after drinking, and (3) when avoiding riding with a driver who had been drinking.

Data for this study came from a telephone survey of just over 3000 respondents across three metropolitan regions of Virginia; Northern Virginia, Hampton Roads/Tidewater and the Richmond urban area. Self-reported perceived familiarities with TNCs were measured on a four-factor scale: not familiar at all, somewhat unfamiliar, somewhat familiar, and very familiar; and, similarly, use frequency was measured on a four-factor scale: never used, rarely, sometimes, and often. These perceived familiarities and use measures served as the dependent variables in ordered logit models with demographic characteristics, smartphone use, location of the respondent and transportation mode use as explanatory variables. Understanding the familiarity and use frequency of TNCs is important in understanding information about relatively early adopters of TNC services.

This study incorporates TNC use in alcohol related situations which has been limited in prior studies (3-7). Multinomial logistic (MNL) regression was used to model travel choices including the likelihood of using TNCs.

1.2. OBJECTIVES OF THESIS

Studies in the past have tended to focus on understanding the impact of TNC and DUI crashes using crash or police conviction records, however, limited research have focused on understanding the factors associated with TNC familiarity and use frequency (8-9) and also the specific factors affecting TNC use in alcohol related situations. The role played by these new services in determining travel choices in alcohol related situations is also not understood. However, their availability increases the choice set for an individual to consider, which can possibly have an impact on DUIs.

The study intends to improve understanding of the characteristics of early adopters of TNC services and contribute towards understanding travel choices made by individuals in alcohol-related situations. To the best of the authors' knowledge, no studies have examined the influence of specific factors on TNC use in alcohol-related situations.

The specific objectives of this research include identifying specific factors which are associated with (a) understanding familiarity with transportation network companies (TNCs) and their use frequency, and (b) understanding travel choices in different alcohol-related situations in urban areas in Virginia. Outcomes of this research can provide agencies like the Virginia Department of Motor Vehicles with greater insight into individual TNC familiarity and use and the impact it has on mobility behavior such as use of transportation modes in alcohol related situations.

1.3. CONTRIBUTION OF THESIS

This study helps to bridge the gap in the travel behavior literature, regarding early adopters and the travel behavior in alcohol-related situations with the advent of TNCs. The study identified numerous factors that are associated with early TNC adopters such as younger people who are comfortable with (and users of) technology being more familiar with and more frequent users of TNC services. Understanding these characteristics can provide valuable information to agencies like Virginia Department of Motor Vehicles for use in programming countermeasures to deter driving under influence.

1.4. ORGANIZATION OF THE THESIS

The remainder of this thesis is organized into five additional chapters. Chapter 2 presents the literature review conducted on TNCs, and discusses its impact, users and alcohol related studies; and finally discusses the gaps that we aim to address in our study. Chapter 3 describes the overall methodology, a discussion of the survey and summary of the survey results, and the need for Chapter 4 and 6. Chapter 4 presents the statistical modeling of the TNC familiarity and use in Virginia and Chapter 6 includes the statistical modeling of the travel choices in alcohol-related situations in Virginia. Both Chapters 4 and 6 have a paper format; the paper "Familiarity and Use of Transportation Network Company (TNC) Services in Virginia" (chapter 4) has been accepted for a poster presentation and presented at Transportation Research Board 98th Annual Meeting and the paper "Factors Influencing Choice of Travel Mode in Alcohol-Related Situations in Virginia" (chapter 6) has been submitted to Transportation journal and is under review. Chapter 5 discusses the benefits of the Mixed Multinomial logistic regression models over General multinomial logistic regression which was suggested by reviewers of Transportation journal. Finally, Chapter 7 presents the conclusions and directions for future studies along with recommendations.

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CHAPTER 2: LITERATURE REVIEW

Transportation Network Companies represent new services that provide real-time and demand-responsive trips by using advances in smart-phone-based technology. According to the California Public Utilities Commission, which is the California regulator of infrastructure and transportation services including privately owned passenger transportation companies, TNCs are companies that "provide prearranged transportation services for compensation using an online enabled application or platform (such as smartphone applications) to connect drivers using their personal vehicles with passengers" (1). Well-known TNCs in the United States include Uber and Lyft. These services have grown exponentially (2,3) over the years. Lyft reported 2.8 million unique riders in May 2016 across their various markets, as well as 25% increase in year-over-year ride per active passenger (2). In mid-July 2016 Uber announced that it had completed 2 billion rides (3). These numbers demonstrate that these companies are growing at an exponential rate. Factors that might have led to the extraordinary growth include aggressive market entry; and their convenient, on-demand, door-to-door service. However, with the introduction of TNCs there might have been substitution of public transit trips and researchers are working towards understanding this impact. According to a study by UC Davis researchers, after using ride-hailing, the average net change in transit use is a 6% reduction among Americans in major cities (4).

2.1. REGULATIONS

The emergence of TNCs has generated uncertainty about the legal status of TNC services, criticism from the taxicab industry, and concerns about public safety. TNCs have faced criticism and protests from opponents and taxicab representatives who argue that TNCs are operating illegally outside otherwise highly regulated markets. Studies have been done to understand TNC regulations in major cities (5,6). Since this study focuses on regions in Virginia, the general operational requirements for transportation network companies and TNC partner in Virginia are listed below

a) "TNCs would provide passenger transportation only on a prearranged basis and only by means of a digital platform and not through ride hailing at streets." (7)
b) "Payment for ride would be collected only through the digital platform." (7)
c) "TNC partners or drivers who violate the provision of a and b, would be removed from the transportation network company's digital platform for at least one year." (7)

d) “A TNC partner shall carry at all times while operating a TNC partner vehicle proof of coverage under each in-force TNC insurance policy, which may be displayed as part of the digital platform, and each in-force personal automobile insurance policy covering the vehicle.” (7)
e) “The transportation network company shall adopt and enforce a policy of nondiscrimination based on a passenger's points of departure and destination and shall notify TNC partners of such policy.” (7)
f) “No TNC partner shall operate a motor vehicle for more than 13 hours in any 24-hour period.” (7)

It is important to understand the operational requirements for transportation network companies and TNC partner in Virginia, especially in the cities where they are operating, so that everyone with a smartphone and electronic payment methods can have equitable access TNCs in general and alcohol related situations and is not discriminated based on their locations. Also, to ensure the safety of the passengers using the platform to meet their travel needs, it is important to have requirements regarding the working hours and appropriate insurance coverage in case of accidents.

2.2. IMPACT

There is a growing body of research exploring the potential benefits of Transportation Network Companies. A study by Transportation Research Board TRB (8), found that new, innovative mobility services are expanding travel choices and are being widely embraced by millions of travelers. Another study by the Transportation Sustainability Research Center at UC Berkeley found that ride sourcing trips are spatially and temporally not well served by public transit, suggesting a complementary relationship with transit, at least for some trips. It also found that ride sourcing users also appear to be less likely to own an automobile (9).

In addition to service synergies, researchers have found that there is a role for policy makers to ensure public benefit. TRB found that without public-sector intervention, TNCs could exacerbate the digital divide, which is the divide between those who have access to technologies like smartphones and have the digital literacy to capitalize on these services and those who do not (10). Similarly, Shared-Use Mobility Center (SUMC) recommended that “public entities should identify opportunities to engage with [technology-enabled mobility companies] to ensure that benefits are widely and equitably shared". Through thoughtful partnerships, these services could enhance mobility for low-income and older adults. Some of the cited benefits of TNC's include:

- A study sponsored by Uber found that UberX service in low-income areas was better than that of taxis, with taxi riders waiting twice as long and paying twice as much compared to a comparable UberX ride (11).
- The San Francisco Late Night Transportation Working Group found that ride sourcing services are quicker and more reliable during late night periods (9 pm to 5 am), which is important for late-night workers, residents, and visitors (12).
- One study found that Uber has an average wait time of 3.35 minutes, compared to 4.62 for a flag-down taxi (38% faster) and 9.39 minutes for a dispatch taxi (180% faster) (13).
- The average occupancy for ride sourcing trips was 1.8 passengers compared to 1.1 passengers for taxis, suggesting ride sourcing trips are more efficient and reduce unnecessary travel (9).
- Uber both substitutes for and complements public transit. If Uber were not available, many ride sourcing users would have otherwise used transit for long trips. However, most of the trips began/ended near a transit location (9).

However, in contrast, Uber is reducing average travel speeds, and increasing overall congestion in Manhattan according to a transportation blogger who analyzed Uber's data (14). Another study found that part-time and full-time TNC drivers are likely to deadhead to pick-up passengers, thus increasing vehicle miles travelled and pollution (15).

2.2.1. DRIVING UNDER INFLUENCE

In America, someone is injured in an alcohol related crash every two minutes and 28 people die every day because of drunken driving accidents. DUIs cost the U.S. economy nearly $200 billion every year. In an effort to reduce drunk driving, TNCs have been promoted as an alternative option; however, there have been limited studies towards understanding the impact of TNCs on driving under the influence.

Using data from the Federal Bureau of Investigation Uniform Crime Reports (UCR), a 2016 study which looked at 150 cities and counties where Uber operated between 2010 and 2013, found a 6 percent decline in fatal crashes in cities after Uber becomes available, however, the effect on drunken-driving deaths was insignificant (16). Similarly, examining the relationship between traffic fatalities and Uber entry using negative binomial regression models in the 100 most populated metropolitan areas in the United States between 2005 and 2014, Brazil and Kirk (2016) found that deployment of Uber services in a given metropolitan county had no association with the number of subsequent traffic fatalities(17).

However, another study by Greenwood and Wattal (2015), using the California Highway Patrol (CHP) safety and crash dataset, found that low cost Uber X services were associated with a significant reduction in traffic fatalities (18). This study however looked at only cities in California and did not include comparable data from the other cities where Uber operated in the same time period. So, it is difficult to understand its impacts. Peck (2017), in her study based on alcohol-related collision data maintained by the New York State Department of Motor Vehicles, found a 25 to 35% decrease in alcohol related collision rates after the introduction of Uber in four boroughs of New York City, excluding Staten Island (19). A study examining the number of monthly alcohol-related crashes before and after the entry of Uber in California, conducted by Mothers Against Drunk Driving (MADD) and supported by Uber indicated that an estimated 1,800 alcohol-related crashes had been prevented in California since the entry of UberX in July 2012(20).

The various studies discussed above that tried to understand the impact of TNCs on DUIs shows that the results are mixed. Also, all the studies have focused on the overall change in DUI related incidents using crash or police conviction records and none have focused on the individual which may provide greater understanding towards understanding the impacts.

2.3. USERS

According to a study by the Pew Research Center (22) that looked at TNC users in America, just 15% of American adults have used a ride-hailing service such as Uber or Lyft. Half of all Americans (51%) are familiar with these services but have not actually used them, while one-third (33%) have never heard of these services. Ride-hailing usage varies significantly by age. Roughly one-quarter of 18- to 29-year-olds (28%) and one-in-five 30- to 49-year-olds (19%) have used ride-hailing, but just 4% of Americans 65 and older have done so. The median age of adult ride-hailing users in the United States is 33. Along with young adults, ride-hailing usage (as well as awareness) is particularly high among college graduates and the relatively affluent. Among the college graduates, 29% have used ride-hailing services and just 13% are unfamiliar with the term. Among those who have not attended college, just 6% have used these services and half (51%) have never heard of them before. There are no substantial differences in ride-hailing usage across gender or racial lines. Pew's study also found that 26% of survey respondents who earned more than $75,000 had used TNC services before, whereas only 10% of those who earn less than $30,000 had used the service. The above findings suggest that without government intervention, there may be a continued divergence based on income level for those who can and those who cannot access TNCs as a mobility services. Hence, it is important for research studies to understand the users of such services in different cities and under different situations, both general and alcohol related so that these services cannot exclude a large swath of the population.

2.4. RESEARCH GAPS

In general, there has been limited peer reviewed, scholarly literature available regarding the impacts of Uber. In particular, empirical studies are very limited. This makes it difficult to develop informed policy decisions and countermeasures by the relevant agencies. All the past studies which tried to understand the impact of TNCs on alcohol related crashes and fatalities tried to analyze it using crash or police conviction records and did not focus on the user of TNC services. This is one of the major research gap that needs to be addressed. These can help to better understand the impact of TNCs in such situations. One of the first comprehensive study which tried to analyze the awareness and frequency of use of the ride sourcing services and its users in general situations (21), however, did not model the degree of familiarity and use frequency and the variables that affect it. As policy makers continue to seek out ways to ensure TNCs have positive benefits on society, our study aims to address the limitations of the previous studies, by trying to understand the users and what influences their travel choice in alcohol related situation, so that better informed decision can be made. The first part of the study improves understanding of the characteristics of early adopters of TNC services, while the second part of the study contributes towards understanding travel choices made by individuals in alcohol-related situations.

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CHAPTER 3: DATA

This chapter discussed the methodology of the survey, the data that pertain to the respondent's familiarity and use of TNCs in general situation and their mode choice behavior in alcohol related situations. The data were collected through cellphone surveys and captured normal travel behaviors, socio-demographic and economic characteristics, as well as the travel behaviors in alcohol related situations. This cellphone survey dataset was used to develop the statistical models in Chapter 4 and 6.

3.1. DATA COLLECTION

To obtain information about the use of alternate modes of transportation including transportation network companies (TNCs), public transportation, taxis, and possible other modes in general and in alcohol related situations, familiarity with TNCs and their use frequency, a cell-phone survey conducted by Virginia Tech's Center for Survey Research. The cellphone telephone survey was based on 45 questions and respondents had the option to refuse to answer any questions at any time during the survey. The VT Center for Survey Research purchased 100,295 cell phone numbers from a vendor, of which 84,165 were eligible for the survey. The survey was conducted during the summer and fall of 2016 and generated 3,004 completions The cellphone survey was conducted in Northern Virginia(Arlington, Alexandria, Fairfax ,Fairfax City, Falls Church, Loudoun, Manassas, Manassas Park, Prince William), Hampton Roads/Tidewater(Chesapeake, Hampton, James City, Newport News, Norfolk, Poquoson, Portsmouth, Suffolk, Virginia Beach, Williamsburg, York), and Richmond(Chesterfield, Colonial Heights ,Hanover, Henrico, Hopewell ,Petersburg, Richmond). Because the study included questions about alcohol consumption, the survey was restricted to the legal drinking age in Virginia (21 and above).

Survey questions pertained to TNC familiarity and qualitative use frequency in general situations; weekly travel frequency by different modes; whether multiple modes were used for a single trip; possession of a driver's license; access to a personal vehicle; technology ownership, use, and comfort; consumption of alcohol in the past year; being a designated driver in the last 30 days; type of establishment where an individual consumed alcohol; qualitative preference of mode in alcohol-related situations; the modes used in the most recent situation to leave the location where an individual last consumed alcohol, when an individual avoided driving after consuming alcohol, and when an individual avoided driving with a driver who consumed alcohol; and basic socio-demographic characteristics.

3.2. SURVEY RESULTS

More of the respondents were from Northern Virginia (38.2%) followed by Hampton Roads/Tidewater (31.7%) and Richmond (30.01%). To put the sample into context, Table 3.1 shows the comparison of the survey dataset with demographic information from the American Community Survey 2011-15. Males were slightly oversampled in the study survey in Northern Virginia and Richmond but under sampled in Hampton Roads. In Northern Virginia, race was well captured while the Hispanic ethnicity was under sampled. In Hampton Roads and Richmond, African Americans were under sampled and Whites were somewhat over sampled. The mean income of our Northern Virginia respondents was lower than the mean from the Census while for the other two regions, the mean income was higher than the Census average.

TABLE 3.1. COMPARISON OF SOCIO-DEMOGRAPHIC CHARACTERISTICS OF THE SAMPLE WITH CENSUS DATA

	Northern Virginia		**HamptonRoads/Tidewater**		**Richmond**	
Characteristic	**Survey**	**Census**	**Survey**	**Census**	**Survey**	**Census**
Male	55.7%	49.5%	51.2%	61.9%	54.6%	47.8%
Income (Mean)	$106,559.5	$113,578.7	$80,669.9	$71,486.7	$80,708.2	$73,211.7
White	64.2%	64.6%	63.2%	58.5%	69.0%	64.8%
African American	13.2%	11.8%	25.7%	32.0%	19.3%	26.1%
Asian	8.9%	14.3%	2.1%	3.9%	3.5%	4.6%
Other	10.5%	9.4%	9.1%	5.6%	6.2%	4.5%
Hispanics	8.7%	16.9%	6.8%	6.9%	3.5%	5.9%

Source: Census Data - (ACS 2011-15)

Overall, in the survey, 54% of the males responded to the survey. As shown in Figure 3.1. most of the male respondents were in the age group 50-54 compared to age group 55-59 for the females. The no of licensed drivers in both males and females' respondents were almost equal (95%). Amongst males it was seen that most of the licensed driver were in the age group 50-54 and amongst females in the age group 55-59 as shown in Figure 3.2.

In terms of travel choices, most of the respondents regularly used personal vehicles, with an average of 5.9 days per week, followed by walking/biking (1.66 days per week), carpool (.58 days per week), public transit (.28 days per week), TNCs (.22 days per week), and taxi (.09 days per week). Multiple types of transportation were used for a single trip by 8.2% of the respondents.

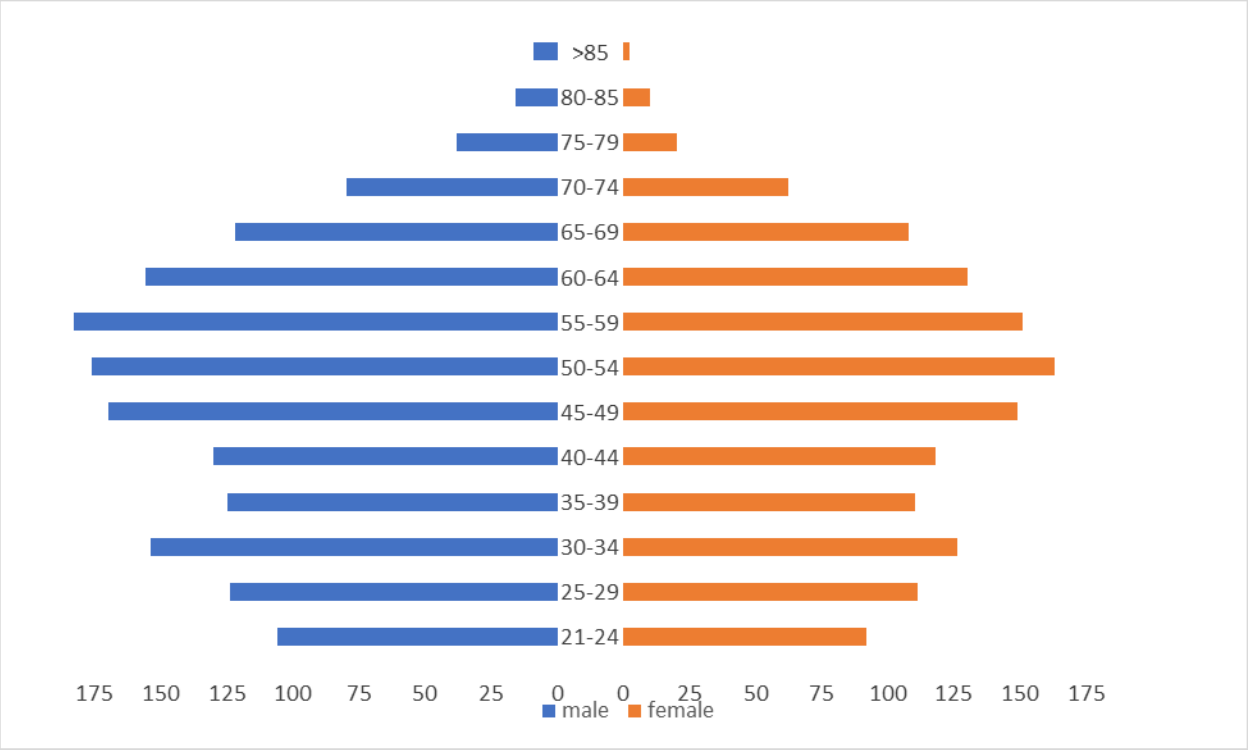

FIGURE 3.1: AGE-OVERALL

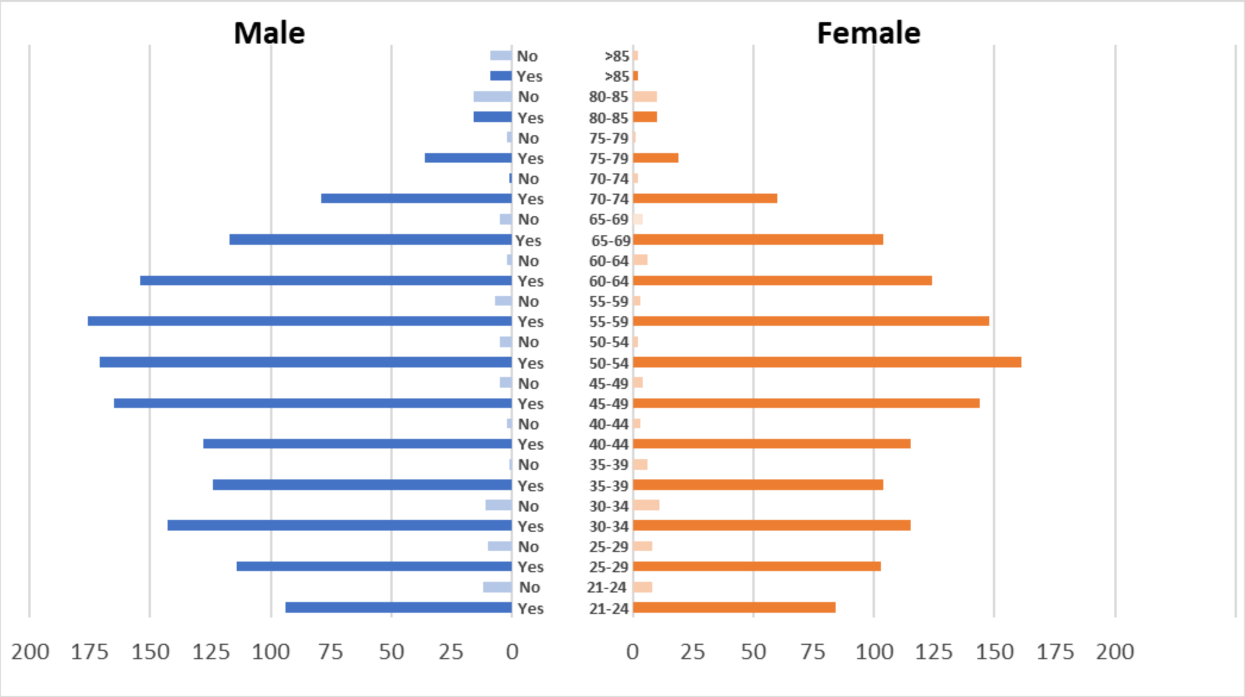

FIGURE 3.2: LICENSED DRIVER

Because Transportation Network Companies are relatively new both in concept and to Virginia, the survey asked respondents whether they were familiar with them. Among, the respondents that answered this question, approximately 71% were familiar with TNC as shown in figure 3.3. More than a quarter of those that answered were very familiar with TNCs. According to a previous study by the Pew Research Center (1) that looked at TNC users in America, half of all Americans (51%) are familiar with these services. It might be possible that in our study, we have a higher percentage of respondents familiar with TNCs because of the time gap between the two surveys. Similarly, as shown in figure 3.4. out of the respondents that answered questions about TNC use,66% have never used a TNC and only 18% of the respondents use them compared to a previous study that found that 15% of the respondents have used ride hailing service like Uber/Lyft.

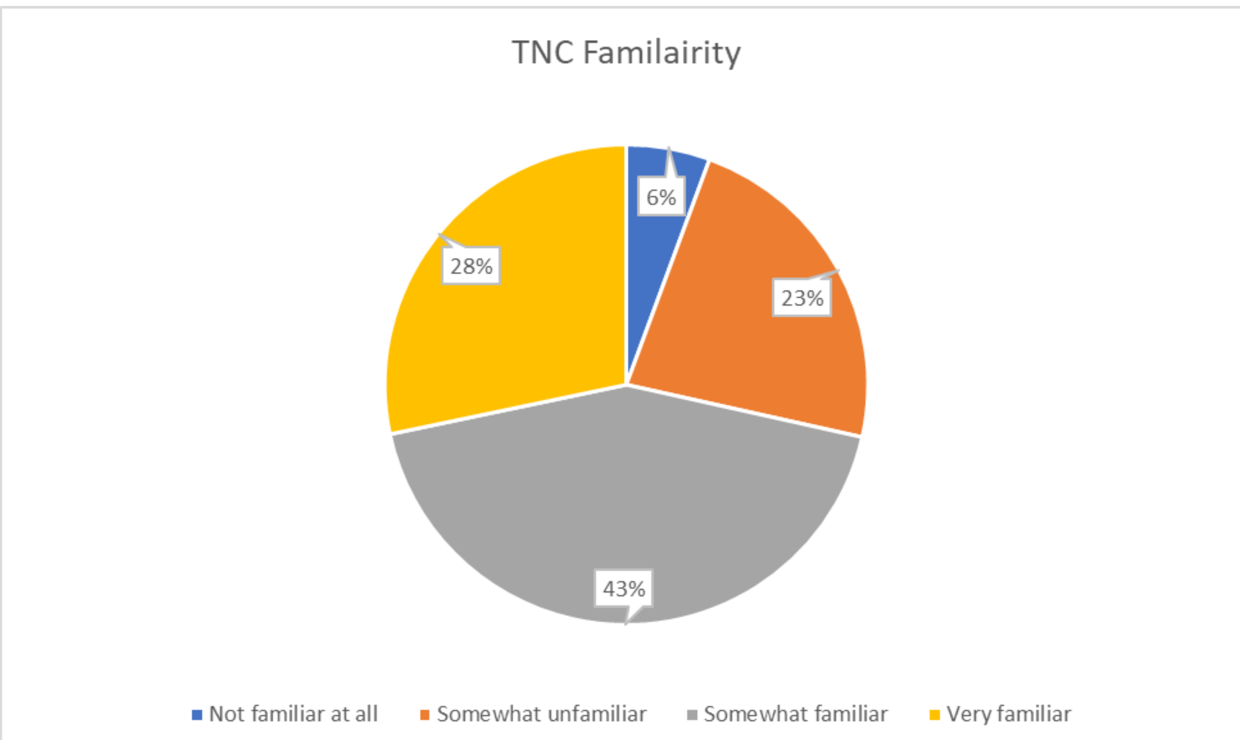

FIGURE 3.3: TNC FAMILIARITY

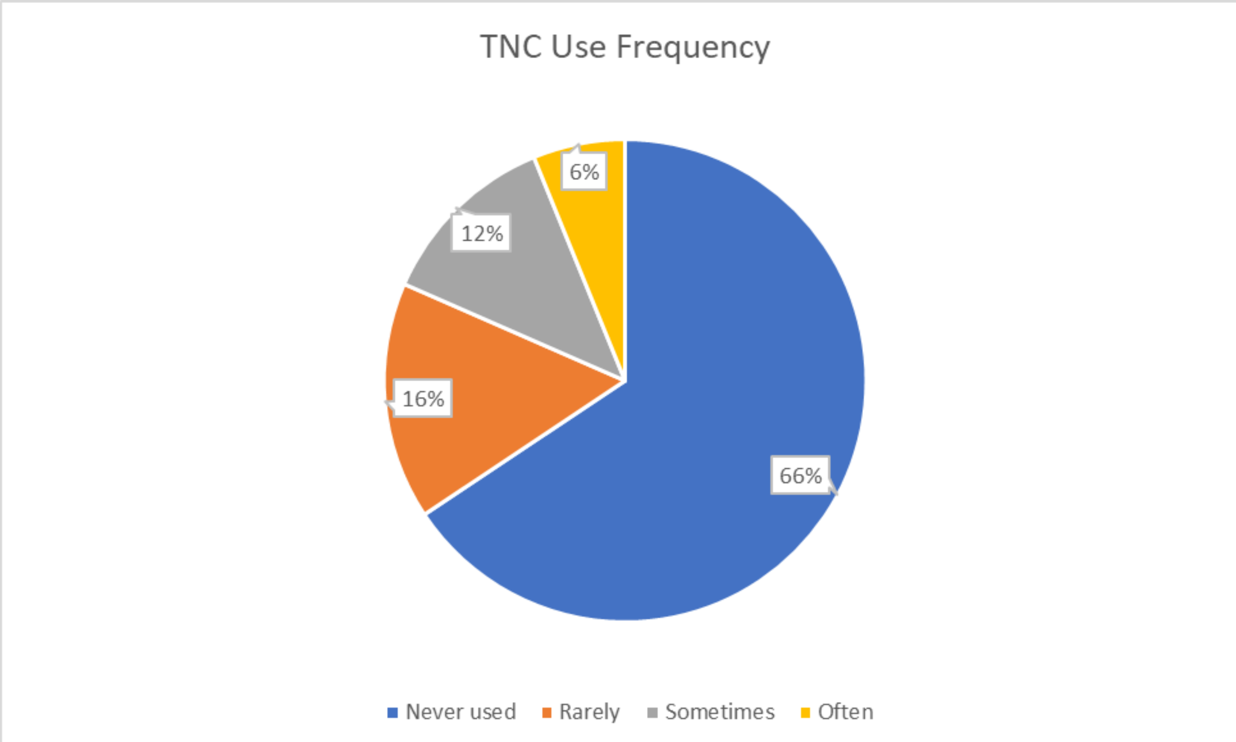

FIGURE 3.4: TNC USE FREQUENCY

While TNCs were infrequently used as a regular commute mode, the second most popular reason for using them was after consumption of alcohol (55.2%) as shown in figure 3.5. (The most popular reason was for out of town or airport travel – 69.8%).

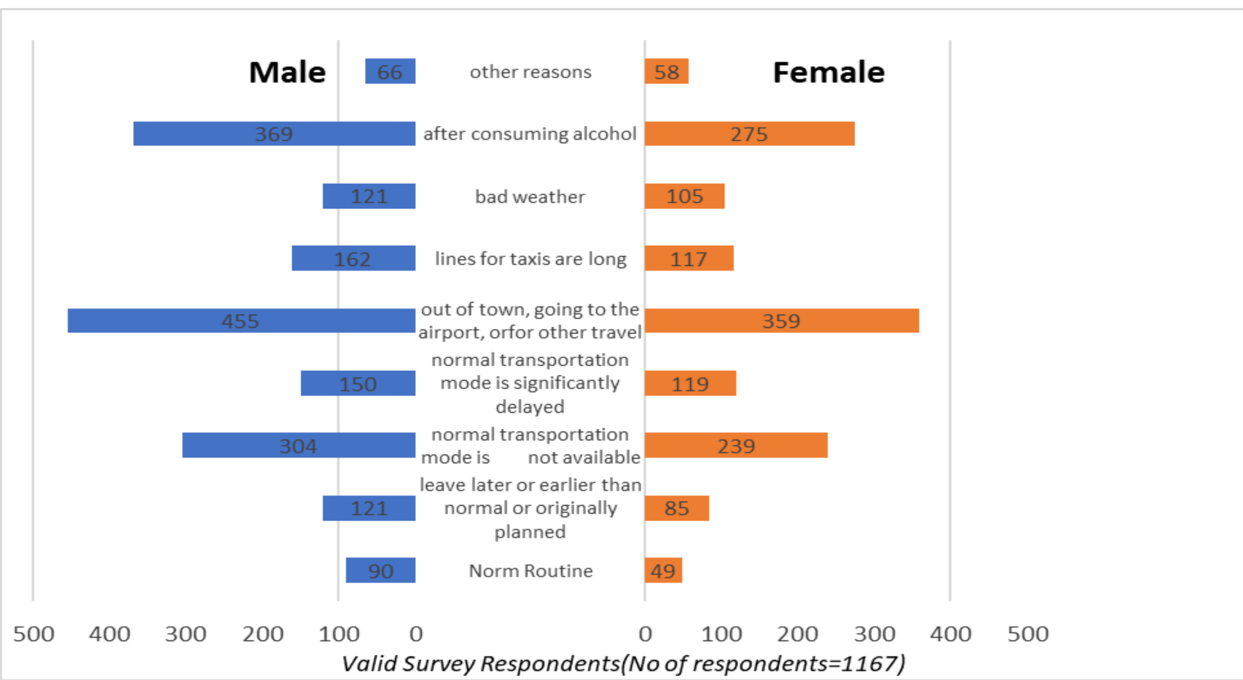

FIGURE 3.5: TNC USE REASON

3.2.1. ALCOHOL RELATED SITUATION

Most of the respondents (71.9%) had consumed alcohol in the past year. In response to questions about consumption of alcohol outside of home, 69% of the respondents stated that they consumed alcohol once or more in the 30 days before completing the survey. TNCs ranked higher than taxi and public transit in terms of preference (general) for alcohol situations, which can be seen from Table 3.2. Riding with a designated driver was the most likely choice in alcohol related situations for the respondents.

TABLE 3.2. STATED QUALITATIVE LIKELIHOOD OF MODE SELECTION AFTER ALCOHOL CONSUMPTION (IN %)

Mode	Very likely	Somewhat likely	Somewhat unlikely	Not at all likely
TNC (Uber/Lyft)	34.2	23.4	10.3	32.1
Designated driver	61.4	24.1	4.2	10.2
Friend/Family member	32.4	20.3	13.5	33.9
Taxi	12.5	22.1	12.8	52.6
Personal vehicle	29.9	17.6	13.3	39.2
Public transit	7.5	12.3	11.0	69.2
Walking	16.0	24.3	12.2	47.5
Biking	3.4	5.1	6.7	84.7

As seen from Figure 3.6, respondents were more likely to leave an alcohol-serving location by a TNC than they were to arrive with one. Most of the respondents indicated that they did not drive after consuming alcohol or ride with a driver who had consumed alcohol. Also, as seen in Figure 3.7., the second most likely preferred choice of Transportation if the respondent was drinking was TNCs with designated driver being the most preferred.

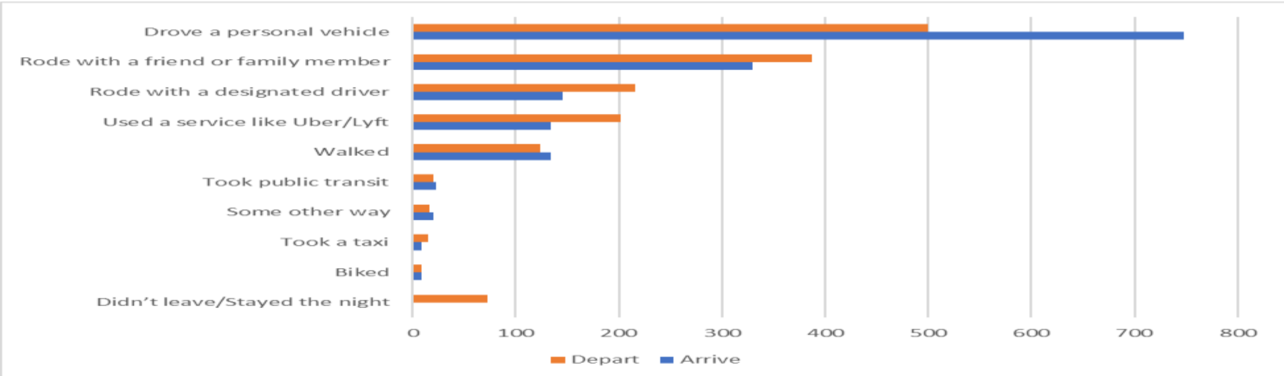

FIGURE 3.6: MODE USED TO ARRIVE VS DEPART FROM THE LOCATION WHERE THE RESPONDENT LAST CONSUMED ALCOHOL

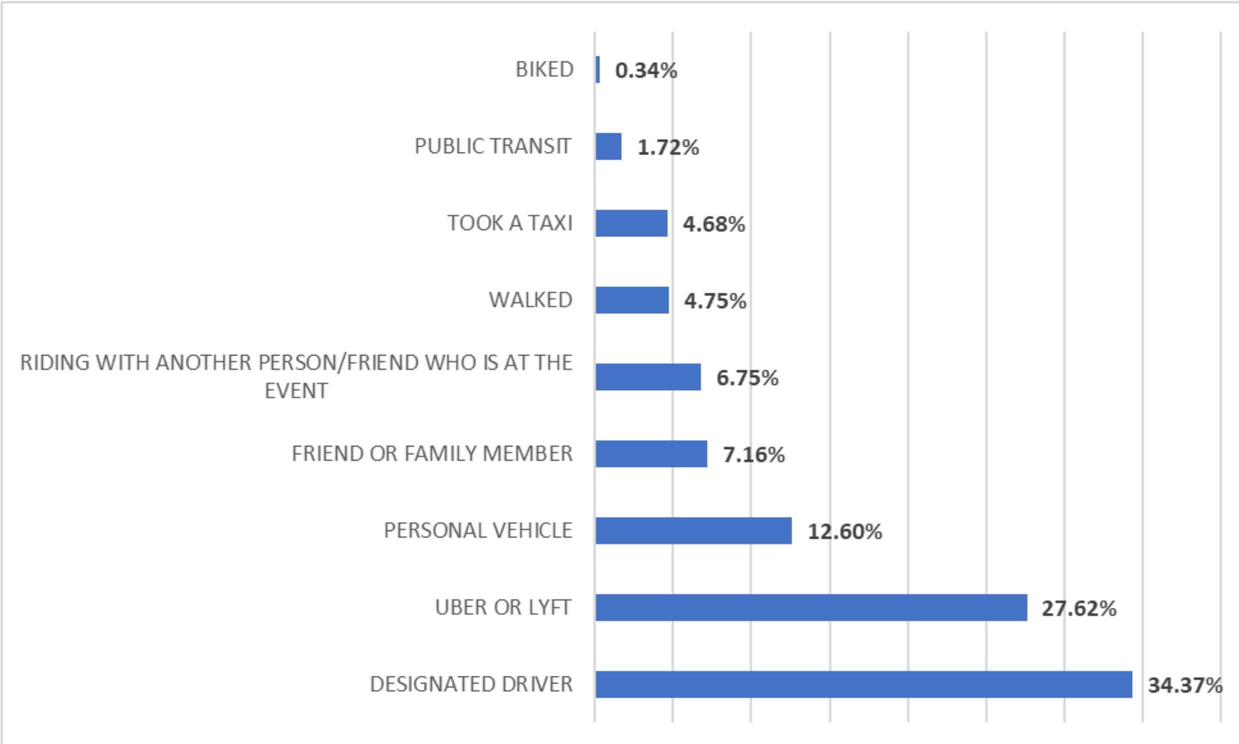

FIGURE 3.7: MOST LIKELY PREFERRED CHOICE OF TRANSPORTATION IF DRINKING

In response to a question that whether in the past year, the respondent has ridden in a motor vehicle with a driver who might have drunk too much to drive safely, 7.7% of the males and 6.8% of females responded that they had done so, as shown in Figure 3. 8.. However, as shown in Figure3.9., 17.4% of the males and 19.0% of females responded that they have deliberately avoided riding in a motor vehicle because they felt the driver might have drunk too much to drive safely. As shown in Figure 3.10., the respondents drove with Friends/family member (25.81%) followed closely by use of TNCs (24.47%) when respondents most recently deliberately avoided drunk driver. This shows the growing usage of TNCs as an alternative in alcohol related situations.

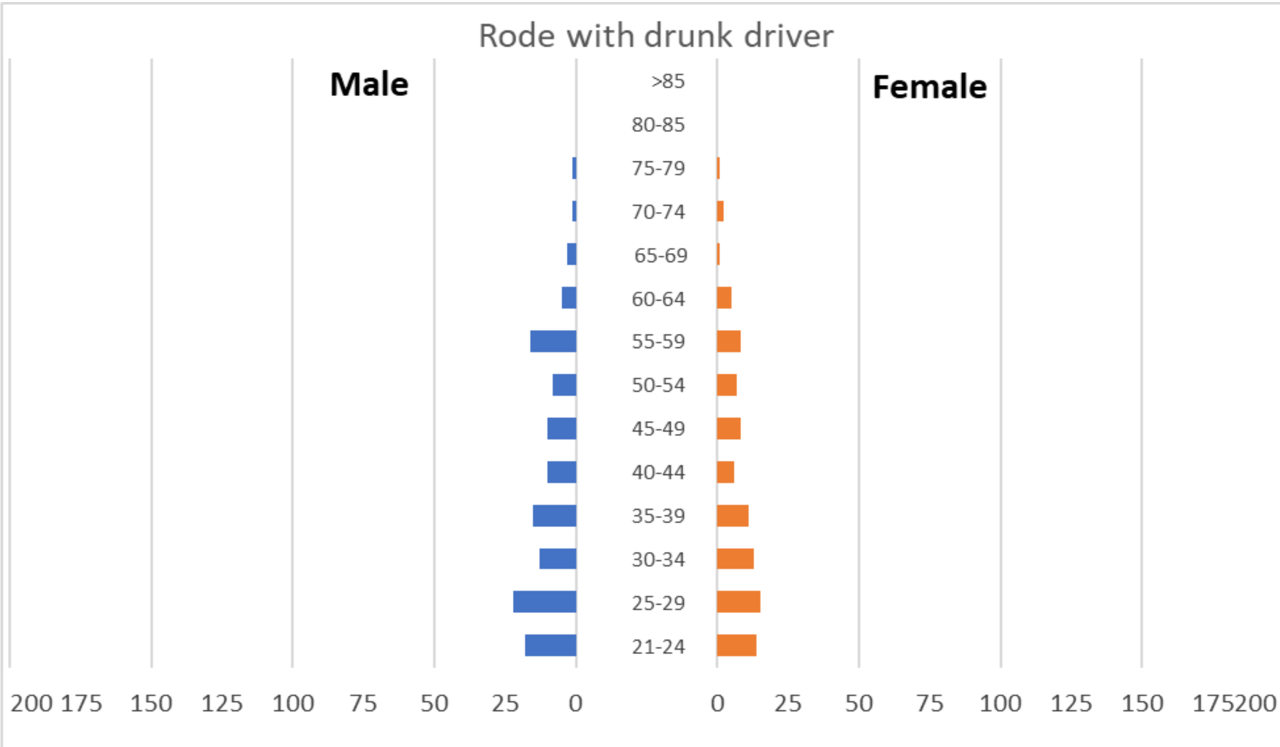

FIGURE 3.8: RODE WITH DRUNK DRIVER

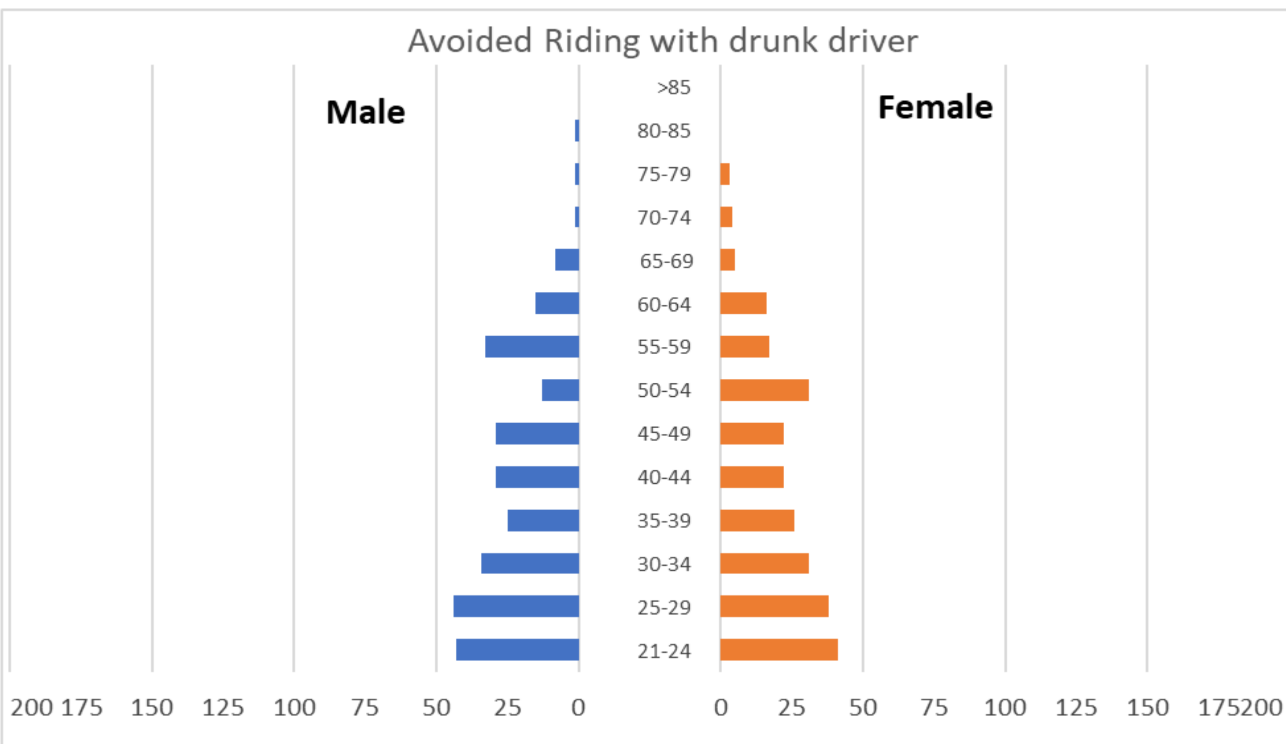

FIGURE 3. 9: AVOIDED RIDING WITH DRUNK DRIVER

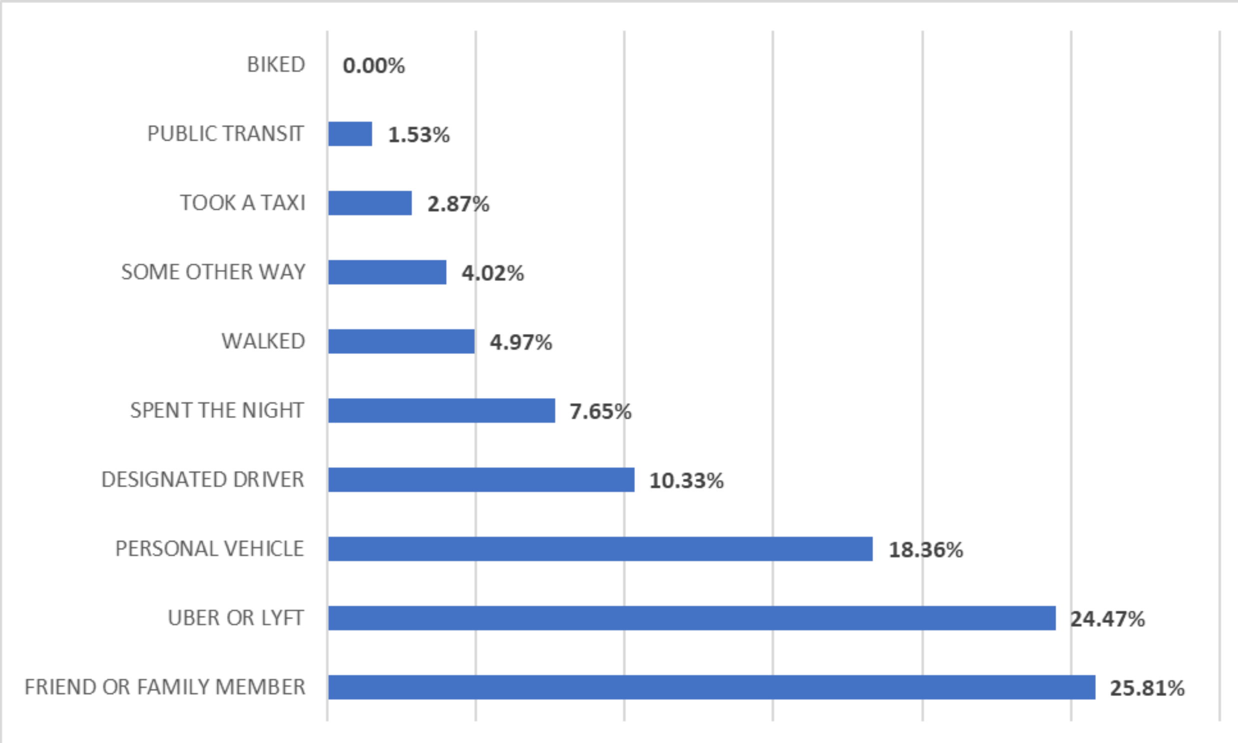

FIGURE 3.10: MODE OF TRANSPORTATION USED BY RESPONDENTS WHEN RESPONDENTS MOST RECENTLY DELIBERATELY AVOIDED DRUNK DRIVER

3.3. NEED FOR STATISTICAL MODELS

The graphs and discussions shown above represent exploratory representation of responses to individual questions. Questions, and therefore the graphs, have different numbers of responses depending on answers to earlier questions. For example, if a respondent responded that they do not drink alcohol, they were not asked any questions about driving or use of alternate modes of transportation after consuming alcohol. Respondents also had the option to refuse to answer any questions at any time during the survey. As a result, all graphs and the corresponding discussions present information as a percentage of the number responses to that question. To better understand the effect of various variables on TNC user's familiarity and use frequency and their use in alcohol related situations it is important to develop statistical models. Statistical models are required to ensure that data are interpreted correctly and that apparent relationships are significant and not simply chance occurrences.

It is important to develop predictive models of TNC familiarity and TNC use to identify the factors associated with the level of TNC familiarity and qualitative use frequency. Ordinal logistic regression models were used. The statistical model (Chapter 4) identified numerous factors that are associated with early TNC adopters such as younger people who are comfortable with (and users of) technology being more familiar with and more frequent users of TNC services. Similarly, it is important to identify factors associated with respondents' travel choices in different alcohol-related situations: (1) the last time the respondent consumed alcohol, (2) when avoiding driving after drinking, and (3) when avoiding riding with a driver who had been drinking. Multinomial logistic regression models were developed to identify factors associated with each of the three alcohol-related cases. The statistical model (Chapter 6) helps to understand the influence of several factors towards travel choice made by individuals in alcohol-related situations.

3.4. REFERENCE

1. Smith, A. Shared, Collaborative and On Demand: The New Digital Economy.Washington, DC Pew Internet Am. Life Proj. Retrieved August, Vol. 21, 2016, pp. 2016

CHAPTER 4: FAMILIARITY AND USE OF TRANSPORTATION NETWORK COMPANY (TNC) SERVICES IN VIRGINIA

(This chapter was presented in the form of a poster presentation at TRB 2018)

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ABSTRACT

Using survey data from 3004 respondents in Northern Virginia, Richmond, and the Hampton Roads/Tidewater area, this paper identifies factors associated with respondents' familiarity with transportation network companies (TNCs) and their use frequency. Ordinal logistic regression models were developed to understand the influence of variables related to technology use and comfort, normal travel choices, and socio-demographics and economics. Using a mobile wallet, a cell phone for entertainment, an app for taxi services, or an app for hotel booking/air transport arrangements, living in Northern Virginia, normally using multiple transportation modes for a single trip, higher education levels, and higher household income were associated with increased TNC familiarity and use frequency. Self-identifying as White/Caucasian was also associated with increased TNC use frequency. Increased age was associated with decreasing TNC familiarity and use frequency.

Keywords: transportation network companies; new transportation services

4.1. INTRODUCTION

Transportation network companies' (TNCs) growth has been rapid since 2011[1] in the US and globally, providing millions of rides per day around the world (*1*, *2*). By leveraging location-based technology and ride matching algorithms, TNCs provide real-time ridesharing to customers. Although ridesharing has been discussed as an alternative potentially reducing congestion and decreasing emissions and fuel dependency (*3*-*6*), the rapid growth has outpaced policies on transportation and elicited debates among policymakers and stakeholders. As a result, these services were restricted from operating in certain cities (*7*, *8*).

TNCs, such as Uber and Lyft, may reduce unmet demand for urban travel and help overcome employment barriers and achieve economic objectives among low-income workers as well as immigrants (*9*, *10*). Supporters of TNCs believe that they help reduce automobile use by providing the flexibility of an automobile to satisfy individual travel needs. Other potential benefits include reduced parking costs for both travelers and employers and improved worker productivity (*11*). However, TNC critics state that they flout regulations, endanger public safety and privacy, fail to comply with the American Disability Act, have inadequate labor standards, and discriminate against riders and passengers with African American-sounding names in the app platform (*12*, *13*).

While several studies investigated the impacts of TNC services (*14*–*16*), limited literature explored the individual familiarity and use frequency of such services. Smith (17) found that more than half of American adults have heard of ridesharing apps like Uber and Lyft, with 15% using the services. However, the degree of familiarity and use frequency was not discussed in detail. This study addresses this limitation using data from a cellular telephone survey of 3004 people in three different urban regions of Virginia: Northern Virginia, Richmond, and the Hampton Roads/Tidewater area. The objective of this paper is to identify the factors associated with the qualitative degree of familiarity with TNCs and their use frequency based on ordered logit models. This study considers factors associated with comfort with technology, general travel modes, and socio-demographics and economics.

The remainder of this paper is divided into six sections. The first section reviews the limited literature related to TNCs. The second presents a set of hypotheses on factors influencing respondents' familiarity with and use of TNCs. The third describes the data collection and

[1] Uber was created in 2009 but expansion began in 2011 and other TNCs (Lyft, Didi) started in 2012.

provides descriptive analyses of key variables. The fourth provides an overview of the statistical modeling approach used to develop the models on TNC familiarity and TNC use frequency presented in the fifth section. The concluding section summarizes the paper, provides conclusions in terms of hypothesis and suggests future directions.

4.2. BACKGROUND ON TNCS

TNCs represent new services that provide real time and demand responsive trips by utilizing advances in smart-phone-based technology. The potential benefits of technology in general and TNCs in particular are societal in nature; however, they rely on collective individual actions. In a study of app-based on-demand rideshare users in San Francisco, users revealed that in the absence of ridesharing they would have used taxi and their own personal vehicles, whereas 43% of users would likely use transit or active modes (*18*) so the societal benefits may be mixed.

With the relative newness of TNCs, few related studies are available; however, these services have some similarities with ridesharing, carpooling, and taxi services. The terminology can be a bit confusing. Rayle et al. (*18*) discussed how TNCs, or *ride-sourcing* services, have their roots in *ridesharing* and share traits with traditional taxis. They also mentioned that, compared to carpooling where individuals travel together towards the same destination to reduce congestion and save money, TNC drivers mostly use the platform to earn a profit. However, the current services provided by TNCs are a mix of traditional taxi services, carpooling (Uber Pool and Lyft Line), and ridesharing agreements (users can decide on a time to get picked up by a driver). Also, now that taxi services have started using apps, the difference between the services has further blurred. This study uses the term *transport network company (TNC)* which was defined by the California Public Utilities Commission (*19*) as a company that uses an online-enabled platform to connect passengers with drivers using their personal, non-commercial vehicles.

Travel time savings, cost savings, and travel flexibility are major motivators for carpooling (*20*). Traditional carpooling, or *ridesharing,* for commuting involves relatively inflexible, long-term arrangements with established schedules and driving responsibilities which can cause a power mismatch with the service provider dictating departure time (*11*). However, barriers to less traditional ridesharing which involves sharing rides with strangers include privacy issues and personal safety concerns. According to Census data, ridesharing modal share has increased in recent years after seeing a decline from 1970, despite the government promoting various ridesharing policies (*21*).

Taxis also fill a critical gap in transportation and have been regulated in. most large and medium sized cities since 1930 (*22*, *23*). Travelers lacking access to fare information in advance of the trip have difficulty comparing taxi price with the cost of other modes. By using technology, TNCs show fare rates and have implemented vetting policies. However, the regulatory framework under which TNCs operate is still under discussion. Among Americans who have heard of this issue, 42% feel that these services should *not* be required to follow the same rules and regulations as existing taxi companies when it comes to things like pricing, insurance, or disability access (*17*).

Users tend to view ridesharing/ ride-hailing apps as software platforms rather than transportation companies, and they view their drivers as independent contractors rather than employees. Some 58% of ride-hailing users view these apps as *software companies* that simply connect drivers with people who are looking for a ride, while 30% view them as *transportation companies* that have some measure of control over their drivers and the overall customer experience (*17*). Similarly, 66% of ride-hailing users think of the drivers who work for these services as *independent contractors*, while 23% view them as *employees* of the app or services (*17*). The rides obtained through ride-hailing apps are one example where a worker is hired through a digital marketplace to work on demand for a single task (*24*). Although some studies have begun to investigate TNC use, no researcher has mathematically modelled the degree of familiarity and use frequency of TNCs and identified the associated factors.

4.3. HYPOTHESES

The following hypotheses helped guide the selection of variables for the models of TNC familiarity and use frequency. The authors are unaware of previous studies on these exact issues and thus derived the hypotheses based on ridesharing, carpooling, and logic.

Hypothesis 1: Higher household incomes are associated with a) greater TNC familiarity and b) more frequent TNC use.

According to data obtained from the American Community Survey, as income rises, the percentage carpooling decreases (*25*). With rising disposable income, households tend to purchase more vehicles. Winn and Smith (*26*) found that Houston households with income between $25,000 and $35,000 were less likely to form casual carpools, which are impromptu carpools formed among strangers to meet occupancy requirement of HOV lanes, compared to income groups $50,000 to $75,000, $100,000 to $200,000, and $200,000 or more. Based on the casual carpool findings and since TNCs are fee-based service providers and not limited to HOV facilities, the researchers hypothesize that, with rising income, TNC use frequency and familiarity increase. Often associated with income, education may also be influential. Furthermore, individuals with higher levels of education may be more willing to use new technologies (*27*, *28*), suggesting that with increased educational attainment and income, TNC familiarity may increase.

Hypothesis 2: Increase in age is associated with a) lower TNC familiarity and b) less frequent TNC use.

Winn and Smith (*26*) found a higher percentage of Houston casual carpoolers were between ages 25 and 34 than above age 65. Ride-sourcing respondents were younger in an intercept survey in San Francisco (*18*). The authors anticipate that the findings of this current study will be consistent with the prior literature.

Hypothesis 3: An individual self-identifying as Asian has a) increased familiarity with TNCs and b) increased TNC use frequency.

In 2015, median hourly wages of Asians were higher than that of Caucasians/Whites, African Americans, and Hispanics. This may be attributed to education levels; a higher percentage of Asians had a bachelor's degree or more compared to Whites, African Americans, and Hispanics (*29*). Also, English speaking Asian Americans stand out for their use of technology - 95% use the internet and 91% own a smartphone (*30*). Thus, the authors hypothesize that self-identifying as Asian is associated with greater TNC familiarity and use.

Hypothesis 4: Using a cell phone app for taxis is associated with a) increased familiarity with TNCs and b) increased TNC use frequency.

Since the taxi and TNC services are somewhat similar, even though there are differences in pricing and regulations, logic suggests that travelers who use an app for taxis are also more likely to have greater familiarity with TNCs and to use them more frequently.

Hypothesis 5: Respondents who use mobile wallet are more likely to a) be more familiar with TNCs and b) use TNCs more frequently.

Since the payment for TNC services ordered using an app are mostly paid using mobile wallet (credit card tied to mobile wallet) or a credit card tied directly to the app, logic suggests that individuals who use mobile wallet are more likely to be familiar with TNC services and are more likely to use them. This payment also entails being comfortable with associating a credit card with an app.

Hypothesis 6: Compared to retirees, students are more likely to have a) increased familiarity with TNCs and b) increased TNC use frequency.

TNCs try to attract new customers by offering promotional offer for retirees (*31*) and students via Uber perks which would enable them to lower their transportation costs. However, with access to a large group of peers, students are more likely to be more open to money-saving opportunities and use of new apps. Retirees, on the other hand, may be less comfortable with technology and may be more set in their transportation habits.

4.4. DATA

To obtain information about individuals' familiarity with TNCs and use in three urban areas in Virginia, cellular telephone surveys were conducted in Northern Virginia, Hampton Roads, and Richmond. These three areas have the largest market penetration of TNCs in Virginia. TNCs were introduced in Northern Virginia in 2011 and in Richmond and Hampton Roads in 2014. The VT Center for Survey Research purchased 100,295 cell phone numbers from a vendor, of which 84,165 were eligible for the survey. The survey was conducted during the summer and fall of 2016 and generated 3,004 completions. Because the study included questions about alcohol consumption, the survey was restricted to the legal drinking age in Virginia (21 and above).

Survey questions pertained to TNC familiarity and qualitative use frequency in general situations; weekly travel frequency by different modes; whether multiple modes were used for a single trip; possession of a driver's license; access to a personal vehicle; technology ownership, use, and comfort;; and basic socio-demographic characteristics. Table 4.1 presents an overview of the independent and dependent variables considered for modeling. The categorical explanatory variables were coded as dummy variables and all the responses with "don't know" and "refused" were coded as missing values.

TABLE 4.1. OVERVIEW OF VARIABLES

Variable		Code	Number of observations	Min	Max	Mean	Standard deviation
Independent variables							
Location							
Location	Northern Virginia (yes=1, other=0)	IV2	3004	0	1	0.38	0.49
	Hampton Roads (yes=1, other =0)	IV3	3004	0	1	0.32	0.47
	Richmond (yes=1, other =0)	IV4	3004	0	1	0.30	0.46

Demographics								
Race/ethnicity	Male (yes=1, female=0)	IV1	3004	0	1	0.54	0.50
	White (yes=1, other =0)	IV5	2918	0	1	0.67	0.47
	African American (yes=1, other =0)	IV6	2918	0	1	0.19	0.39
	Asian (yes=1, other =0)	IV7	2918	0	1	0.05	0.22
	Another race (yes=1, other =0)	IV8	2918	0	1	0.09	0.29
	Hispanic or Latino (yes=1, no=0)	IV9	2935	0	1	0.07	0.25
Employment	Employed full time (yes=1, no=0)	IV13	2972	0	1	0.59	0.49
	Employed part time (yes=1, no=0)	IV14	2972	0	1	0.07	0.25
	Unemployed and looking for work (yes=1, no=0)	IV15	2972	0	1	0.03	0.17
	Retired (yes=1, no=0)	IV16	2972	0	1	0.16	0.36
	Going to school (yes=1, no=0)	IV17	2972	0	1	0.03	0.19
	Homemaker (yes=1, no=0)	IV18	2972	0	1	0.03	0.20
	Employment status: something else (yes=1, no=0)	IV19	2972	0	1	0.03	0.18
Occupation	Management and professional (yes=1, no=0)	IV20	2929	0	1	0.51	0.50
	Military (yes=1, no=0)	IV21	2929	0	1	0.05	0.21
	Service such as protective service, food service, or personal care (yes=1, no=0)	IV22	2929	0	1	0.07	0.25
	Sales or retail (yes=1, no=0)	IV23	2929	0	1	0.07	0.25
	Construction or trades (yes=1, no=0)	IV24	2929	0	1	0.06	0.24
	Student (yes=1, no=0)	IV25	2929	0	1	0.03	0.18
	Transport services (yes=1, no=0)	IV26	2929	0	1	0.03	0.16
	Some other occupation (yes=1, no=0)	IV27	2929	0	1	0.19	0.39
Education	Highest level of education: grade/elementary school (yes=1, no=0)	IV28	2968	0	1	0.00	0.05
	Some high school (yes=1, no=0)	IV29	2968	0	1	0.02	0.14
	High school graduate [or GED] (yes=1, no=0)	IV30	2968	0	1	0.14	0.35
	Trade/vocational school after high school (yes=1, no=0)	IV31	2968	0	1	0.02	0.14
	Some college	IV32	2968	0	1	0.15	0.36
	Completed community college/two-year degree (yes=1, no=0)	IV33	2968	0	1	0.09	0.29
	Four-year college/university graduate (yes=1, no=0)	IV34	2968	0	1	0.35	0.48
	Graduate/professional school (yes=1, no=0)	IV35	2968	0	1	0.23	0.42
Age	Age (continuous)	IV48	2941	21	92	47.95	15.38
House-hold	Income in thousands of dollars (continuous)	IV47	2520	7.5	150	90.27	44.79
	Household size (continuous)	IV49	2963	1	18	2.94	1.53
	Children in household (continuous)	IV50	2557	0	15	0.79	1.15
Smart Phone Use							
Phone Use	Communication such as talking, texting, or email (yes=1, no=0)	IV36	2600	0	1	1.00	0.06
	Social media (yes=1, no=0)	IV37	2600	0	1	0.72	0.45
	Entertainment (yes=1, no=0)	IV38	2600	0	1	0.68	0.47

	Searching the web (yes=1, no=0)	IV39	2600	0	1	0.89	0.31
	Shopping or ordering items (yes=1, no=0)	IV40	2600	0	1	0.58	0.49
	Navigation (yes=1, no=0)	IV41	2600	0	1	0.87	0.33
App Use	Restaurant reservations or food delivery (yes=1, no=0)	IV42	2600	0	1	0.23	0.42
	Hotel reservations and/or air transportation arrangements (yes=1, no=0)	IV43	2600	0	1	0.27	0.45
	Uber or Lyft rides or a similar service (yes=1, no=0)	IV44	2600	0	1	0.34	0.47
	Taxi (yes=1, no=0)	IV45	2600	0	1	0.04	0.21
	Don't use an app for any of these things (yes=1, no=0)	IV46	2600	0	1	0.48	0.50
Financial Use	Mobile wallet (yes=1, no=0)	IV10	2602	0	1	0.21	0.41
	Comfortable with tying a credit card to an app on a phone (yes=1, no=0)	IV11	2576	0	1	0.37	0.48
	Not comfortable with tying a credit card to an app on a phone (yes=1, no=0)	IV12	2576	0	1	0.63	0.48
Transportation Mode Use							
Transportation Mode Use	Personal vehicle weekly frequency (continuous)[a]	IV51	2868	0	6.5	5.91	1.39
	Taxi weekly frequency (continuous)	IV52	2997	0	6.5	0.10	0.48
	TNC weekly-frequency (continuous)	IV53	2998	0	6.5	0.22	0.70
	Carpool-weekly-frequency (continuous)	IV54	2995	0	6.5	0.59	1.39
	Public transit weekly frequency (continuous)	IV55	2996	0	6.5	0.29	1.05
	Walk or bike weekly frequency (continuous)	IV56	2993	0	6.5	1.66	2.34
	Own personal vehicle (yes=1, no=0)	IV57	2878	0	1	0.97	0.17
	Multi modal travel (yes=1, no=0)	IV58	2994	0	1	0.08	0.28
Dependent variables							
TNC familiarity	TNC familiarity	DV1	3000	1	4	2.94	0.86
	Not familiar at all		168				
	Somewhat unfamiliar		687				
	Somewhat familiar		1296				
	Very familiar		849				
TNC use	TNC use frequency	DV2	2527	1	4	1.59	0.92
	Never used		1659				
	Rarely		402				
	Sometimes		310				
	Often		156				

[a] The questions for these variables included a two day range for the alternatives. The coding for these variables were converted to a continuous approximation by using the midpoint for each range.

More of the respondents were from Northern Virginia followed by Hampton Roads. Most (87%) of the respondents owned a smartphone. Smartphones were used by most people for communications followed by social media, web search, entertainment and navigation. Questions regarding usage of a phone app for services elicited responses that they used apps for Uber/Lyft or similar services (29.2%), hotel reservations/air transportation arrangements (23.5%), restaurant reservation/food delivery (19.9%), and taxis (3.9%) while 48.4% did not use an app for any service. Only 21% of respondents answering the question used mobile wallets such as Google Wallet, Apple Pay, or similar apps. Similarly, the majority of the respondents (63%) were not comfortable with tying credit cards to mobile apps.

In terms of travel choices, most of the respondents regularly used personal vehicles, with an average of 5.9 days per week, followed by walking/biking (1.66 days per week), carpool (.58), public transit (.28), TNCs (.22), and taxi (.09). Multiple types of transportation were used for a single trip by 8.2% of the respondents.

The qualitative TNC familiarity measures consisted of four levels. Out of the 3000 complete responses, 5.6% of the respondents were not familiar at all with TNC services, 22.9% were somewhat unfamiliar with services, 43.2% were somewhat familiar with services and 28.3% were very familiar with the services.

Similarly, the qualitative TNC use frequency measures consisted of four levels. Out of the 2527 complete responses, 65.7% of the respondents had never used TNCs, 15.9% rarely used the services, 12.3% sometimes used the services, and 6.2% often used TNCs. Reasons for using TNCs included when out of town/going to airport/other travel (69.8%), after consumption of alcohol (55.2%), when their normal transportation mode is not available (46.5%), when lines for taxis are long (23.9%), when their normal transportation mode is significantly delayed (23.1%), in bad weather (19.4%), when the respondents have to leave later or earlier than normal or originally planned (17.7%), as part of the normal routine (11.9%), and for other reasons (10.6%).

To put the sample into context, Table 4.2 shows the comparison of the survey dataset with demographic information from the American Community Survey 2011-15. Males were slightly oversampled in the study survey in Northern Virginia and Richmond but under sampled in Hampton Roads. In Northern Virginia, race was well captured while the Hispanic ethnicity was under sampled. In Hampton Roads and Richmond, African Americans were under sampled and Whites were somewhat over sampled. The mean income of our Northern Virginia respondents was lower than the mean from the Census while for the other two regions, the mean income was higher than the Census average.

TABLE 4.2. COMPARISON OF SOCIO-DEMOGRAPHIC CHARACTERISTICS OF THE SAMPLE WITH CENSUS DATA

	Northern Virginia		Hampton Roads /Tidewater		Richmond	
Characteristic	**Survey**	**Census**	**Survey**	**Census**	**Survey**	**Census**
Male	55.7%	49.5%	51.2%	61.9%	54.6%	47.8%
Income (Mean)	$106,559.5	$113,578.7	$80,669.9	$71,486.7	$80,708.2	$73,211.7
White	64.2%	64.6%	63.2%	58.5%	69.0%	64.8%
African American	13.2%	11.8%	25.7%	32.0%	19.3%	26.1%
Asian	8.9%	14.3%	2.1%	3.9%	3.5%	4.6%
Other	10.5%	9.4%	9.1%	5.6%	6.2%	4.5%
Hispanics	8.7%	16.9%	6.8%	6.9%	3.5%	5.9%

Source: Census Data - (ACS 2011-15)(*32*)

4.5. STATISTICAL MODELING APPROACH

The researchers used ordered logit regression (OLR), also known as the proportional odds model (*33*) to model a) qualitative familiarity with TNCs and b) qualitative TNC use frequency. OLR was selected for several reasons. First, the ordinal logit model is designed for dependent variables that are defined on an ordinal scale (*33*). Since the TNC familiarity and TNC use were ordinal in nature, an ordinal model was appropriate. Second, logit and probit models provide comparable results (*34*) but OLR has the advantage that the coefficients can be interpreted in terms of odds ratios. Furthermore, OLR parameters are identified by maximum likelihood estimation (MLE), which does not require variables to be normally distributed.

We can formulate a random utility/ordered choice model for a variable Y as

$$U_i^* = \beta' x_i + \varepsilon$$

Equation (1) represents an ordered logit model in terms of probability (*35*) based on the variables included in the model (note there is also a random disturbance term ε).

$$\Pr(y_i > j \mid \boldsymbol{X}) = g(\boldsymbol{X}_i \boldsymbol{\beta}'_j) = \frac{\exp(\boldsymbol{X}_i \boldsymbol{\beta}'_j - \phi_j)}{1 + \exp(\boldsymbol{X}_i \boldsymbol{\beta}'_j - \phi_j)}, \; j = 1, \ldots, m-1 \qquad (1)$$

where

$\boldsymbol{X}_i$ is a vector of observed non-random explanatory variables;

$\boldsymbol{\beta}$ is a vector of unknown parameters to be estimated;

m is the number of categories of the ordinal dependent variable; and

ϕ represents the cutoff points.

In this research, $g(\boldsymbol{X}_i \boldsymbol{\beta}'_j)$ represents the probability of the qualitative familiarity measure (use frequency) being a certain level (e.g., somewhat familiar). Because there is m ordered familiarity (use) measures, there are m−1 equations of the form given in equation (1) with each equation corresponding to one familiarity (use) level. Therefore, with four familiarity measures given as "not familiar at all", "somewhat unfamiliar", "somewhat familiar", and "very familiar", the OLR model for familiarity takes the forms shown in equations (2-4) and is constrained by (5). Similarly, the use frequencies can be modelled with the four use frequency measures given as "never," "rarely," "sometimes," and "often." The OLR model for use frequency relation also takes the forms shown in equations (3-5).

$$\text{Logit}(p_1) = log\,\frac{p1}{1-p1} = \alpha_1-\beta_1X_1-\beta_2X_2-\ldots-\beta_nX_n \tag{3}$$

$$\text{Logit}\,(p_1+p_2) = log\,\frac{p1+p2}{1-p1-p2} = \alpha_2-\beta_1X_1-\beta_2X_2-\ldots-\beta_nX_n \tag{4}$$

$$\text{Logit}\,(p_1+p_2+p_3) = log\,\frac{p1+p2+p3}{1-p1-p2-p3} = \alpha_3-\beta_1X_1-\beta_2X_2-\ldots-\beta_nX_n \tag{5}$$

$$p_1+p_2+p_3+p_4 = 1 \tag{6}$$

where

p_1 to p_4 are the probabilities of familiarities/use frequencies being perceived as measure 1 through measure 4,

x_1 to x_n are the context variables,

α_1 to α_3 are the three intercepts (however the intercepts or cut points are of little interest) (*36*), and

β_1 to β_n stand for the coefficients of the n explanatory variables.

The last category "very familiar" of the qualitative familiarity measure ("often" of the qualitative use frequency measure) does not have odds associated with it since the probability of scoring up to and including the last score is 1. The omitted level identifies the reference group. The model was applied simultaneously to the three-cumulative probabilities and it assumes identical effects of predictor variables on each of the cumulative probabilities.

4.6. RESULTS AND DISCUSSION

Prior to creating the OLR models, each variable in Table 4.1 was individually tested for association with the dependent variables. Table 4.3 presents the Chi-square analyses for the binary variables and single variable ordinal logistic regressions for continuous variables (p-values are given in parentheses). For purposeful selection of variables (*37*, *38*), independent variables meeting the 0.25 significance threshold for relationship with the dependent variables were considered. All variables that met the threshold levels (Table 3) were included in the preliminary models to examine the variables influence on TNC familiarity and TNC use. Insignificant variables were removed stepwise to arrive at a final model unless they were related to one of the hypotheses. The test of parallel lines or proportional odds indicated that the explanatory variables had identical effects on all thresholds/levels.

TABLE 4.3. INDIVIDUALLY POTENTIALLY SIGNIFICANT VARIABLES

Category	Variable	Identifier	TNC Familiarity	TNC Use Frequency
Category Variables[a]				
Location	Northern Virginia (Yes=1, No=0)	IV2	57.16 (.000)	91.94 (.000)
Race	White (Yes=1, No=0)	IV5	30.19 (.000)	5.19 (.159)
	Asian (Yes=1, No=0)	IV7	25.13 (.000)	31.91 (.000)
Financial app	Mobile wallet (Yes=1, No=0)	IV10	70.02 (.000)	121.09 (.000)
Employment	Retired (Yes=1, No=0)	IV16	120.92 (.000)	68.50 (.000)
	Going to school (Yes=1, No=0)	IV17	20.686 (.004)	18.93 (.001)
Education	High school graduate (Yes=1, No=0)	IV30	67.35 (.000)	27.04 (.000)
	Some college (Yes=1, No=0)	IV32	5.36 (.147)	6.58 (.087)
	Four-year college (Yes=1, No=0)	IV34	29.64 (.000)	8.29 (.040)
Smartphone Use	Entertainment (Yes=1, No=0)	IV38	89.57 (.000)	80.95 (.000)
App use	Hotel reservation/air transport arrangement (Yes=1, No=0)	IV43	111.79 (.000)	141.33 (.000)
	Taxi (Yes=1, No=0)	IV45	33.282(.000)	90.13 (.000)
Transportation Mode Use	Multi-modal travel (Yes=1, No=0)	IV58	39.98(.000)	108.11 (.000)
Continuous Variables[b]				
Income	Income (in thousand dollars)	IV47	106.68 (.000)	95.459 (.000)
Age	Age	IV48	275.558 (.000)	300.473 (.000)

[a] Chi square values are presented for category variables with p-values in parentheses.
[b] Chi square values are presented for continuous variables with p-values in parentheses.

Table 4.4 presents an inter-correlation matrix for the variables in Table 3 allowing the examination of relationships between variables and helping to understand possible confounding effects of correlated variables.

TABLE 4.4. CORRELATION MATRIX[A]

Variables	IV2	IV5	IV7	IV10	IV16	IV17	IV30	IV32	IV34	IV38	IV43	IV45	IV47	IV48	IV58
IV2	1	n.s.	**	n.s.	**	n.s.	**	**	**	n.s.	**	**	**	**	**
IV5	-0.004	1	**	**	**	**	**	**	**	**	n.s.	**	n.s.	**	**
IV7	0.137	-0.323	1	**	**	**	n.s.	*	n.s.	**	n.s.	**	n.s.	n.s.	**
IV10	0.031	-0.068	0.059	1	**	n.s.	n.s.	n.s.	*	**	**	**	**	**	**
IV16	-0.055	0.107	-0.077	-0.089	1	**	n.s.	n.s.	*	**	*	n.s.	**	**	**
IV17	-0.007	-0.082	0.092	0.022	-0.062	1	n.s.	*	n.s.	**	n.s.	n.s.	*	**	**
IV30	-0.094	-0.049	-0.024	-0.032	0.015	0.006	1	**	**	n.s.	**	n.s.	n.s.	**	*
IV32	-0.066	-0.057	-0.044	-0.008	-0.017	0.041	-0.17	1	**	*	*	n.s.	**	**	**
IV34	0.083	0.071	0.035	0.041	-0.047	0.007	-0.293	-0.31	1	n.s.	*	n.s.	n.s.	**	**
IV38	0.037	-0.097	0.061	0.176	-0.179	0.062	-0.002	0.05	0.018	1	**	**	n.s.	n.s.	**
IV43	0.055	-0.021	0.032	0.202	-0.042	-0.024	-0.079	-0.048	0.043	0.144	1	**	**	**	n.s.
IV45	0.062	-0.084	0.084	0.099	-0.010	0.021	0.005	-0.019	0.005	0.061	0.148	1	**	n.s.	*
IV47	.279	.224	.024	.073	-.095	-.054	-.217	-.142	.152	-.036	.152	.024	1	**	n.s.
IV48	-.055	.222	-.145	-.125	.549	-.188	-.037	-.059	-.051	-.400	.003	-.043	.127	1	**
IV58	.162	-.034	.017	.063	-.058	.037	-.033	-.068	.002	.013	.117	.062	.077	-.034	1

[a] See Tables 1 and 3 for variable descriptions.
** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).
n.s. Not significant

The final OLR models shown in Table 4.5 were highly significant compared to the intercept only models, as indicated by the Chi square statistics. The significance of each variable was indicated by Wald Chi square statistics. The goodness of fit measure (deviance) tested whether the observed data were consistent with the fitted model. Based on the Goodness of fit test, deviance Chi square analysis and significance of 1 (i.e p>.05), the data and the model predictions were similar, suggesting a good model. Also, the test of parallel lines which tests the assumption that regression coefficients have the same odds ratio for all the different thresholds, indicated that the assumption held (p>.05).

TABLE 4.5. FINAL OLR MODELS FOR TNC FAMILIARITY AND USE FREQUENCY

Variables		*TNC familiarity* Parameter estimates β	*TNC use frequency* Parameter estimates β
Smartphone use: entertainment		.353***	.283*
Employment: retired		-.241(n.s)	.211 (n.s)
Employment: Going to school		.662*	.580(n.s)
Location: Northern Virginia		.242**	.454***
Income (thousand)		.007***	.007***
Age		-.026***	-.050***
Mobile wallet		.373***	.704***
Multi modal travel		.409**	1.005***
App use: Taxi		.835***	1.059***
App use: Hotel/Air Transport reservation		.681***	.785***
Race: White		---------------------	.387**
Race: Asian		.318(n.s)	.372(n.s)
Education: high school graduate		-.457***	-.677***
Education: some college		---------------------	-.439**
Education: four year college		-.026***	-.284*
Threshold	Intercept=1	-3.536***	-.169*
	Intercept=2	-1.227***	.925**
	Intercept=3	.993**	2.336***
Model Fit			
Number of Observations		2156	1837
Pseudo R square			
Cox and Snell		.164	.245
Nagelkerke		.182	.278
McFadden		.077	.133
-2 Log Likelihood (intercept only)		4611.156	3809.698
-2 Log Likelihood (final)		4223.680	3293.468
Chi Square		387.476***	516.230***
Goodness of fit (deviance) Chi Square		3879.370[a]	3214.186[a]

*** Significant at the <0.001 level (2-tailed), ** Significant at the 0.01 level (2-tailed), * Significant at the 0.05 level (2-tailed), n.s. Non-significant

[a] Significance of 1.0 which indicates a good model fit.

As shown in Table 4.5, the final OLR models for TNC familiarity and use frequency had nine and twelve significant explanatory variables, respectively.

Tables 4.3 and 4.5 indicate that income was significantly associated with both familiarity and use frequency of TNCs. Supporting *hypothesis 1*, a $1000 increase in household income increases the odds of being more familiar with TNCs by .70% ({exp .007}-1=.0070) and increases the odds of use frequency by .70% ({exp .007}-1=.0070). Based on the survey data, most of the respondents who were very familiar with TNCs had household incomes over $150,000 and most of the respondents who were somewhat familiar with TNCs had household income between $101,000-150,000. In this study, familiarity with these services translated into increased use frequency. Among respondents who often used TNCs and sometimes used TNCs, most of the respondents had household income over $150,000. These results were fairly consistent with Smith's (*17*) study where only 14% of individuals having household income of $75,000 or more had never heard of these services, whereas, 49% of individuals with household income less than $30,000 were not at all familiar with these services. Households with an annual income of $75,000 or more were over 2.6 times more likely to use TNCs compared to households with an income below $30,000 (*17*). Households with higher income may be more likely to be able to pay for the service and the technology supporting the use of TNC services.

Somewhat related to income, educational attainment was also significant. An individual who had graduating from high school as their highest educational attainment had a 36.6% (exp(-.457)-1=-.3668) decrease in the odds of being *more familiar* with TNCs and a 49.18% (exp(-.677)-1=-.4918) decrease in the odds of more frequent TNC use. Similarly, an individual who has some college as their highest educational attainment, had a 35.53% (exp(-.439)-1=-.3553) decrease in the odds of TNC use. An individual whose highest educational attainment was graduating from a four year college/university had a 24.72% (exp(-.284)-1=-.2472) decrease in their odds of more frequent TNC use. Looking at the coefficients in Table 4.5 for the education variables and considering that completing graduate/professional school is one of the base education options, individuals with increasing education levels have higher odds of being familiar with and using these services. This is fairly consistent with Smith's (*17*) study, in which almost a third of the college graduates had used these services and only 13% were unfamiliar with these services. Compared to college graduates, individuals who had not attended college were less likely to be familiar with these services or to use them. This is also consistent previous research which indicated that young individuals with better education and income are more likely to be early adopters of modern technology (*39*, *40*).

As shown in Tables 4.3 and 4.5, age was significantly and negatively associated with TNC familiarity and use frequency, supporting *hypothesis 2*. A one unit increase in age decreased the odds of greater familiarity with TNCs by 2.6% ({exp -.026}-1=-.0256) and decreased the odds of use frequency by 4.87% (exp (-.050)-1=-.0487). This was consistent with previous research on Uber/Lyft users which found that more than 25% of individuals in the age group 18-29 years and 20% in the age group 30-49 years had used ride hailing compared to just 4% of Americans above the age of 65 (*17*). Individuals below the age of 29 used these services more frequently compared to individuals above the age of 30 (*17*). In this research, 39% of users who were very familiar and somewhat familiar with TNCs were below the age of 40. Similarly, 57.5% of the people who often or sometimes used TNCs were below the age of 40.

Although from Table 4.3, which reports individually significant variables, self-identifying race as Asian was significantly associated with both TNC familiarity and use frequency, the multi-variable models shown in Table 4.5 rejected *hypothesis 3*. However, individuals self-identifying as White/Caucasian were associated with a 47.25% (exp (.387) - 1 = 0.4725) increase in the odds of TNC use when compared to other races. Stark and Diakopoulos (*40*) suggested that TNCs like Uber offer better service (less wait time) in areas with a higher white population, which could lead to correspondingly greater familiarity with and use of these services. As shown in Table 2, Census data indicates a higher percentage of Caucasians in Northern Virginia when compared to Richmond and Hampton Roads.

TNCs have a greater market penetration in Northern Virginia than the other cities, which supports the 27.4% (exp(.242) – 1 = 0.2737) increase in the odds of respondents in Northern Virginia being more familiar with TNCs and the 57.45% (exp(.454) - 1 = 0.5745) increase in greater TNC use frequency.

While Northern Virginia has the most recognized public transportation of the three areas, each of the areas offers multiple modes of transportation. As shown in Table 4.4, the correlation between "Northern Virginia" and "multimodal travel" was relatively low. Individuals using multimodal travel had a 50.5% (exp (.409) - 1 = 0.5053) increase in the odds of being more familiar with TNCs and a 173.1% (exp (1.005) - 1 = 1.731) increase in the odds of greater TNC use frequency. This is reasonable since individuals using multimodal travel would be more likely to explore alternate options to meet their travel demand without being exclusively dependent on private vehicles. According to Murphy (*41*) individuals who used public transit and shared mobility services (TNCs) were making lifestyle changes that result in less driving. TNCs can act as a first and last mile connectivity options and complement public transit.

TNCs compete with taxis so it was not surprising that the use of a phone app for sourcing taxi rides was significantly and positively associated with both TNC familiarity and use frequency, supporting *hypothesis 4*. Individuals who used an app on their phone for sourcing a taxi ride had a 130% (exp(.835) – 1 = 1.30) increase in the odds of being more familiar with TNCs and a 188.3% (exp(1.059) – 1 = 1.883) increase in the odds of TNC use frequency.

Payment for TNCs typically involves connecting an app to a credit card, which has similarities with mobile wallets. Individuals using mobile wallets had a 45.2% (exp(.373) – 1 = 0.4520) increase in the odds of being more familiar with TNCs and a 102.1% (exp (.704) - 1 = 1.021) increase in the odds of greater TNC use frequency, supporting *hypothesis 5*. Based on the survey data, 83.7% of individuals who used a mobile wallet were very familiar or somewhat familiar with TNCs.

Two other technology related variables were significant in the models. Individuals who used their smartphones for entertainment had a 42.3% (exp(.353) – 1 = 0.4233) increase in the odds of being more familiar with TNCs and a 32.71% (exp(.283) – 1 = 0.3271) increase in the odds of greater TNC use frequency. Individuals who used an app on their phone for hotel reservations and air transport arrangements had a 97.6% (exp(.681) – 1 = 0.9758) increase in the odds of being more familiar with TNCs and a 119.2% (exp(.785) - 1 = 1.192) increase in the odds of greater TNC use frequency. Since these apps basically use the same concept of sourcing services from cellphones, it is reasonable that comfort with similar apps was associated with an increase in TNC familiarity and use.

Finally, despite the significance of the individual employment variable classified as “retired” or “student,” in the multi-variable models containing age, these employment classification “retired” was insignificant in both models but “student” was significant in the familiarity model. As a result, *hypothesis 6* was supported for familiarity, but rejected in the TNC use frequency model potentially due to the inclusion of the moderately (*42*) correlated age variable. The employment classification “student” was associated with 93.9% (exp(.662) – 1 = 0.9386) increase in the odds of being more familiar with TNCs.

4.6. CONCLUSIONS

This research is among the first to present predictive models of TNC familiarity and TNC use. Based on a survey of 3004 respondents 21 years and older from three different urban regions of Virginia, ordinal logistic regression models were developed to identify the factors associated with the level of TNC familiarity and qualitative use frequency. The key findings of this study included:

- Individuals located in Northern Virginia (compared to Richmond and Hampton Roads) were associated with increased TNC familiarity and use frequency.
- Greater household income was associated with increased TNC familiarity and use frequency, supporting *hypothesis 1*.
- With better education, individuals had a higher propensity of using TNCs.
- An increase in age was associated with decreased TNC familiarity and use frequency, supporting *hypothesis 2*.
- Self-identifying race as Asian did not have an influence on TNC familiarity and use frequency in the multi-variable context, rejecting *hypothesis 3*. However, individuals self-identifying their race as Whites had a higher probability of using TNCs.
- Use of an app for sourcing taxi services was associated with increased TNC familiarity and use frequency, supporting *hypothesis 4*. Similarly, using an app for hotel reservations and/or air transportation arrangements was associated with increased TNC use frequency. In addition, individuals using their phone for entertainment were more likely to be familiar with and use TNCs.
- Use of mobile wallet was associated with increased TNC familiarity and use frequency, supporting *hypothesis 5*.
- Individuals who used multi-modal transport had a higher likelihood of being familiar with and using TNCs more frequently.
- Employment status “student” was significantly associated with TNC familiarity. *Hypothesis 6* was supported in the multi-variable context for familiarity but not for use frequency. As individual variables, both employment classification “student” and “retired” were significant.

These findings revealed information about relatively early adopters of TNC services. The results were generally expected from previous studies (*43*) with people who were younger and comfortable with (and users of) technology being more familiar with and more frequent users of TNC services. However, the study's findings also suggested that duration in the market was an important consideration.

Income was associated with TNC use, with higher incomes associated with greater TNC familiarity and use. Thus, the ability of TNCs to serve the needs of lower income household may be debatable. On one hand, for some households, TNC use may be more efficient than owning a personal vehicle or using a taxi. However, TNCs still operate on a fee basis, which may limit the usability of such services for lower income households. A future cost analysis for public transportation, TNCs, taxis, and per trip personal vehicle costs may reveal more information on the cost efficiency of the different modes for different income categories and locations.

Individuals normally using multiple transportation modes for a single trip were more likely to use TNCs, which supports the consideration that they contribute to options for the last mile issue associated with public transportation. While contributing to the option set, TNCs may also create competition with other modes, which has regulatory implications (e.g., in the case of competing with taxis). There may also be some reduction in active transport and transit, as suggested by previous literature (*18*). This issue could be further investigated in future studies.

Additional future research could explore younger age groups, participants in this study were at least 21 years old, group travel, and other locations in the US and around the world. Such data could provide greater insight into individual TNC familiarity and use and the impact it has on changes in mobility behavior. This study's results can be used by regional planning authorities to understand who might use TNCs in their region, which could affect predictions of mode choice and vehicle miles traveled. TNC's which is effectively promoted as a means of reducing VMT's, might end up failing to achieve this objective due to their convenience and relatively low cost. It would merely shift the responsibility of increased miles to a fewer drivers. VMT increase would ultimately end up having a negative impact on cities as it would lead to constraint in road space and may shift trips away from low-impact transit, bicycling or walking modes, and future research needs to consider this aspect.

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CHAPTER 5: LIMITATIONS OF CHAPTER 6 AND BENEFITS OF MIXED MULTINOMIAL LOGISTIC REGRESSION

The paper “Factors influencing choice of travel mode in Alcohol related situations in Virginia” as presented in Chapter 6 was submitted to the Transportation Journal on October 4, 2017 for publication and reviewer’s comments were received on April 27, 2017 which suggested the authors to use Mixed multinomial logistic regression to account for the possibility of unobserved heterogeneity, which will help to improve the quality and focus of the manuscript. This chapter describes the benefits of mixed multinomial logistic regression model over general multinomial logistic regression which was used for modeling choice of travel mode as presented in chapter 6.

5.1. BENEFITS

Mixed logit model and Multinomial logit model are types of discrete choice models based on random utility choice theory. Individuals look to choose an option which would maximize their total utility (1). For example, when applied to destination choice or mode choice, this typically means that an individual would choose a location or mode which gives them a higher utility. Mathematically, if the utility of individual i choosing location/mode j is represented as U_{ij}, then location/mode j will be chosen if and only if $U_{ij} > U_{ik}$ for $j \neq k$, i.e., the utility that individual i derives from choosing alternative j exceeds the utility derived from choosing alternative k (2).

Let the utility equation be

$$U_{ij} = X_i\beta_j + \varepsilon_{ij}, \text{ for all } j;\ i = 1,2,...,N \quad (1)$$

Where X_i is a vector of observable explanatory variables specific to the i^{th} individual, ε_{ij} is unobservable random disturbance term and β_j is a vector of unknown parameters to be estimated (12). Here, $X_i\beta_j$ is the deterministic component of utility from choice j while ε_{ij} is the random component of the utility (12). The choice of an alternative is modelled in terms of probability as seen in equation 2(3,4)

$$P_{ij}=P\ ((\varepsilon_{ij}-\varepsilon_{ik}) <(X_i\beta_k - X_i\beta_j) \qquad (2)$$

In order to solve equation 2, it requires imposing a probability density function on ε_{ij}..Also, the above equation 2 shows that probability of a choice depends on the error term difference. MNL restricts all ε_{ij} to be independent and identically distributed (4). This is one of first assumptions of MNL model which basically states, “that the random components of the utilities of the different alternatives are independent and identically distributed (IID) with a Type I extreme-value (or Gumbel) distribution.” (5) Also, the other two assumptions of an MNL model, i.e response homogeneity and error variance homogeneity allow it to form a simple mathematical structure as shown in equation 3(4,5)

$$P_{ij}=\frac{\exp(Xi\beta j)}{\sum_j \exp(Xi\beta j)} \qquad (3)$$

However, there are issues that arise due to the 3 assumptions of the MNL model and they are as follows:

a) The assumption of identically distributed random utility terms across alternatives indicates that the variation would be same across all the modes, however, there is no theoretical consideration for it (5). For example, if value on comfort is an unobservable component and the values on the degree of comfort on different modes (TNC and Public transit) is different, it would lead to different variances which would affect the competitive structure

b) The assumption of response homogeneity due to which sensitivity variation to an attribute due to unobserved individual characteristic is not allowed in the model is a significant drawback (5). For example, an adult with preference for using designated drivers is an unknown heterogeneity, they will have a different preference order than others

c) The assumption of error variance-covariance homogeneity due to which identical variance is considered might also fail (5). For example, this assumption implies that a particular mode (public transit) offers the same level of service throughout the day, however, it might have different levels of service across different times of day which would affect its comfort level, and its error variance would be different.

As discussed by some studies, the inability of MNL model to account for heterogeneity can result in inferior model specification, spurious test results and invalid conclusions (6,7), and to overcome this, Mixed Multinomial logit models are formulated since they accommodate heterogeneity (8). They allow parameters associated with each variable to vary randomly across individuals and across alternatives to capture heterogeneity (9). As shown by utility equation 4, in a Mixed Multinomial logit model, the error terms are treated similarly like MNL model (i.e. random components are independent and identically distributed), however there is a relaxation in the model that restricts parameter estimates to be identical for all the alternatives to which they apply in general MNL models and in Mixed MNL models it can vary (4,5,12). This allows to thus incorporate heterogeneity by relaxing the independence of alternatives property (4).

$$U_{ij} = X_i\beta_j + \varepsilon_{ij}, \quad (4)$$

The possible limitations that the Mixed Multinomial Logit model can address over Multinomial logit model would be:

a) The empirical results might reveal the need to capture unobserved attributes for the different travel mode along with other measures, both for improved data fit as well as for more realistic policy evaluations of transportation control measures (4).
b) The Mixed Multinomial Logit model would provide more accurate parameter estimates than the Multinomial logit model where, due to the possibility of unobserved heterogeneity, biased estimations may occur which is not accounted for (4).

Also, it is to be noted that in a multinomial logistic regression models, all the alternatives should be considered simultaneously and decomposing it into a series of binary logistic regressions is not suggested because then each analysis would be based on a different sample. Since, in the MNL model, it is assumed that the response categories are mutually exclusive and exhaustive hence the probability should add up to 1, however, the probabilities of choosing all the outcomes would possibly be greater than 1 if we do not constrain the logistic models (10,11). Hence, care should be taken while modelling polytomous variable. For our study we developed general multinomial models for the 3 different alcohol-related situations where all the alternatives were considered simultaneously with the reference category being the use of TNC's; however, since each alternative was compared only against the reference category, it formed a set of binary logit models.

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CHAPTER 6 FACTORS INFLUENCING CHOICE OF TRAVEL MODE IN ALCOHOL RELATED SITUATIONS IN VIRGINIA

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Abstract

Using survey data from 3004 respondents aged 21 and older in Northern Virginia, Richmond, and the Tidewater area, this paper identifies factors associated with respondents' travel choices in alcohol-related situations: (1) the last time the respondent consumed alcohol, (2) when avoiding driving after drinking, and (3) when avoiding riding with a driver who had been drinking. Travel options included using various transportation modes and no travel (spending the night). Multinomial logistic regression models were developed to identify factors associated with each of the three alcohol-related cases. For (1), significant factors included use of a personal vehicle to arrive at the location where last consuming alcohol, being comfortable with having a credit card tied to a cell phone app, age, income, travelling alone when leaving the location where last consuming alcohol, having the highest educational attainment of high school graduate (GED), consumption of alcohol at bar/tavern/club, consumption of alcohol at home of friends/acquaintance place, and transportation network company (TNC – e.g., Uber, Lyft) weekly use frequency. For (2), use of a personal vehicle to arrive at the location where last consuming alcohol, consumption of alcohol at a bar/tavern/club, consumption of alcohol at the home of friends/acquaintance place, comfort with tying of credit card to apps, age, gender, income, multi-modal travel for a regular trip, TNC weekly use frequency, and use of an app for hotel reservations and/or air transportation arrangements are significant factors. For (3), use of a personal vehicle to arrive at the location where last consuming alcohol, walking to the location where last consuming alcohol, consumption of alcohol at a bar/tavern/club, comfort with tying a credit card to apps, age, income, TNC weekly use frequency, previously riding in a car with a driver who may have drunk too much to drive safely, and being employed full time are the significant factors. Based on the data (rather than a model), for the subset of those last consuming alcohol in a bar, more people reported using TNCs than driving. It is possible that TNCs are drawing from other sober driver alternatives.

Highlights

- This paper identifies factors associated with respondents' travel choices in alcohol-related situations.
- TNCs were more likely to be used by younger people.
- Familiarity with, and regular use of TNCs increased the likelihood of using TNCs

Keywords: Transportation Network Companies; new transportation services

6.1. INTRODUCTION

Despite decades of awareness, alcohol related traffic fatalities remain a concern. Data from the National Highway Traffic Safety Administration (NHTSA) revealed that nearly 10,000 people in the United States died in 2014 in crashes involving an alcohol-impaired driver, accounting for nearly one-third of all traffic fatalities (National Center for Statistics and Analysis, 2015). Although strategies for reducing driving under the influence (DUI) of alcohol involve added cost and penalty measures, arrests were made in only about 1% of the roughly 121 million incidents of drunk driving in 2014 (Brazil & Kirk, 2016; Jewett, Shults, Banerjee, & Bergen, 2015). This suggests that deterrence through cost and penalties has not effectively eliminated driving while intoxicated, indicating that other approaches are needed.

Access to convenient, on-demand transportation (by a sober driver) may help reduce DUI incidents. Transportation network companies (TNCs), defined as companies that use an online-enabled platform to connect passengers with drivers using their personal vehicles (California Public Utilities Commission, 2013), offer this type a service. In the past half-decade, discussions have surrounded the potential societal benefits of TNCs for reducing DUI incidents. Reports by TNCs like Uber and others have suggested decreased DUI arrests and drunk driving deaths due to the introduction of ride sharing services (Dills and Mulholland, 2016; Greenwood and Wattal, 2015; Peck, 2017; Uber and Mothers Against Drunk Driving, 2015). However, Brazil and Kirk (2016) analyzed drunk driving statistics in the 100 most populated metropolitan areas in the United States for 2009 through 2014 and found that the rise of Uber did not correspond to any decrease in fatalities, overall or during peak drinking times like weekend nights.

Studies that investigate travel and mode choices in alcohol-related situations can help identify the role TNCs play in these situations and whether they have an impact on DUIs. The objective of this paper is to identify the factors associated with travel choice, including the use of TNCs, in three alcohol related situations: (1) the last time the respondent consumed alcohol, (2) when avoiding driving after drinking, and (3) when avoiding riding with a driver who had been drinking. Similar to other travel choice studies(Lave and Train, 1979; Manski and Sherman, 1980) the authors adopted the multi-nomial logit model for use with data obtained from a cellular telephone survey of 3004 residents in three Virginia metropolitan areas: Northern Virginia, Richmond, and Hampton Roads/Tidewater area.

The remainder of this paper consists of five sections. The next section provides an overview of previous research examining mode choice under alcohol related situations and discusses the study's hypotheses. The subsequent section introduces the data used for empirical analysis. Then the modeling approach is discussed, followed by a discussion of the results. Finally, conclusions and future directions are presented.

6.2. LITERATURE REVIEW

Previous studies have examined relationships between alcohol consumption and transportation. Smith and Geller's (2014) study of college students' mode choice after consumption of alcohol revealed that the majority planned on walking home while another quarter planned on travelling with designated drivers. MacLeod et al. (2015) examined whether residential accessibility and perceived risk impacted travel choice and transportation attitudes in the context of drinking alcohol outside one's home and found that higher accessibility was associated with decreased utility for driving, and binge drinking was associated with greater utility for taxis. Jackson and Owens (2011) found that availability of late-night public transportation likely increased alcohol consumption, leading to more arrests for minor crimes near bars but fewer DUI arrests in those areas. Although literature related to mode choice after consumption of alcohol exists, travel (mode) choice models after the introduction of TNCs are limited.

Potential societal benefits of TNCs, particularly in reducing DUIs, have been considered in several studies (Brazil and Kirk, 2016; Greenwood and Wattal, 2015; Peck, 2017; Uber and Mothers Against Drunk Driving, 2015). Grove (2013) suggested that the regulatory system of limiting taxis on roads to increase demand leads to individuals using their private vehicles after consuming alcohol. Private vehicles might be selected to save money and reduce the inconvenience of returning to retrieve their personal vehicles if they had departed by an alternative mode. Without similar regulations, TNCs could partially fill the shortage of rides. Uber and Mothers Against Drunk Driving (2015) argued that the rapid rise of TNCs in the past half-decade could potentially curtail the volume of drunk driving that occurs in the United States. Dill and Mulholland (2016) found a 6% decline in general and an 18% decline in night time fatal crashes after the introduction of TNC services in their study of 2010-2013 panel data from NHTSA's Fatality Analysis Reporting System and the FBI's Uniform Crime Reports Statistics from over 150 cities and counties. They also found a robust decline in DUI arrest rates. Similarly, based on a California Highway Patrol (CHP) safety and crash dataset, Greenwood and Wattal (2015) found that low cost Uber X services were associated with a significant reduction in traffic fatalities. A study by Uber and Mothers Against Drunk Driving (2015) found that DUI arrests and accidents were reduced significantly in areas where ride-sharing was available. In Miami, this study found that the Uber ridership peaked at the same time as historical drunk driving crashes (midnight), while in Pittsburgh, an unusual peak in Uber requests around bar closing time was identified. In a more recent study, Peck (2017), using a difference-in-difference estimation based on alcohol-related collision data maintained by the New York State Department of Motor Vehicles, found a 25 to 35% decrease in alcohol related collision rates after the introduction of Uber in four boroughs of New York City, excluding Staten Island. Although a few studies (Dills and Mulholland, 2016; Greenwood and Wattal, 2015; Peck, 2017) found a reduction in DUI arrests and fatal crashes after the introduction of Uber and other TNCs, there is limited understanding on the mechanism of reduction in DUIs. It might be due to the availability of vehicles for hire or it might be related to education programs, technology, or other factors. Contrary to the previously mentioned studies, Brazil and Kirk (2016) found that deployment of Uber services in a given metropolitan county had no association with the number of subsequent traffic fatalities. Their study examined the relationship between traffic fatalities and Uber entry using negative binomial regression models in the 100 most populated metropolitan areas in the United States between 2005 and 2014.

Studies examining the influence of TNCs on alcohol related situations have been limited and most of them have focused on the overall change in DUI related incidents using crash or police conviction records. To the best of the authors' knowledge, no studies have examined the influence of specific factors on TNC use in alcohol-related situations, which is examined in the present paper. This manuscript also considers the possibility of spending the night, which has rarely been considered an option in the extant literature.

6.3. HYPOTHESES

This study extends the discussion of TNC use in alcohol-related scenarios and identifies factors associated with TNCs and other travel choices. Seven hypotheses, largely grounded in the literature, helped guide the selection of potential explanatory variables.

Hypothesis 1: Males are more likely to drive personal vehicles in relevant alcohol-related situations.

Previous studies have established a relationship between gender and drinking. Approximately 58% of adult men reported drinking alcohol in the last 30 days (CDC, 2016a, 2016b) and men were four times as likely as women to drink and drive (CDC, 2010). Potential reasons for this difference might be that men drive more than women and men are more likely to make risky decisions. This behavior results in men consistently having higher rates of alcohol-related deaths and hospitalizations than women. Among drivers in fatal motor-vehicle traffic crashes, men are almost twice as likely as women to have been intoxicated (CDC, 2016a). Thus, the authors hypothesize that males are more likely to have driven personal vehicles in alcohol-related situations (1 and 3) examined in this study.

Hypothesis 2: Consumption of alcohol at a bar is positively associated with the use of personal vehicles in the relevant alcohol-related situations examined in this study.

Morrison et al. (2002) found that compared with sober driver incidents, DUI incidents were more likely to have been associated with drinking at a bar. This leads the authors to hypothesize that the location of alcohol consumption influences mode choice decisions and specifically that consumption of alcohol at a bar is positively associated with the use of personal vehicles.

Hypothesis 3: Younger people are more likely to use TNCs in all three alcohol-related situations.

Compared with 2002, 38% fewer young adults of legal drinking age were driving under the influence of alcohol in 2014 (Azofeifa et al., 2015). This might be due to stricter enforcement and education campaigns. Approximately 7% of people between the ages of 16 and 20 in 2014 said they drank and drove, compared with 16% in 2002. However, children and teens who become involved with alcohol at an early age are 7 times more likely to be involved in an alcohol-related crash in their lives (Alcohol Alert, 2006). Hadland et al. (2017) examined the relationship between state alcohol policies and motor vehicle crashes for people under the age of 21 and found that states with stronger alcohol policies are associated with reduced alcohol-related motor vehicle crash deaths. Smith (2016) found that TNC apps were used mostly by young people, which suggested that young people would be more likely to use these apps in alcohol related situations. Thus, the authors hypothesized that younger people are more likely to use TNCs in alcohol-related situations, as well as for general transportation needs.

Hypothesis 4: People who regularly use TNCs more frequently are more likely to use them in alcohol-related situations.

Previous research from wayfinding reported that people familiar with a surrounding environment were more accurate in wayfinding than those who reported being less familiar (Prestopnik and Roskos–Ewoldsen, 2000). Familiarity also helps negate effects of complex environments on wayfinding abilities (O'Neill, 1992). Extending these findings to mode choice behavior, the research team expected familiarity with a mode to influence an individual's mode selection in alcohol-related situations. Thus, travelers who regularly used TNCs more frequently were also expected to be more likely to use them in alcohol related situations.

Hypothesis 5: Those who use cell phone apps for ordering taxis are also likely to use TNCs in alcohol-related situations.

This hypothesis relates to familiarity with technology for transportation services. Based on the same premise of familiarity with transport mode, individuals using apps to order taxis are expected to be more likely to use their phone to order TNC services under general and alcohol-related situations. Since taxi and TNC services have similarities even though differences in pricing and regulations exist, travelers who use an app for taxis are probably more likely to have greater familiarity with TNCs services and to be comfortable using them in alcohol-related situations.

Hypothesis 6: Those who are comfortable with a credit card being tied to apps are more likely to use TNCs in alcohol-related situations.

Since most TNCs' apps require a credit card to pay for services, individuals who are comfortable with a credit card being tied to apps in general are expected to be more familiar with TNC services and more likely to use them in alcohol-related situations.

Hypothesis 7: Individuals with higher household income are more likely to use TNCs in alcohol-related situations.

TNC rides require payment, thus the authors hypothesize that those with more income are more likely to use TNCs in any situation, and specifically in alcohol-related situations.

6.4. DATA DESCRIPTION

To obtain information about individuals' travel choices in alcohol-related situations after the introduction of TNCs in Virginia, cellular telephone surveys were conducted in the Northern Virginia, Hampton Roads (Tidewater), and Richmond areas. These three areas have the largest market penetration of TNCs in Virginia. Of the 84,165 purchased numbers eligible for the survey, 3,004 completions were obtained during the summer and fall of 2016. Since there were questions about alcohol consumption, the survey was restricted to individuals of legal drinking age in Virginia (21 and above). Survey questions pertained to TNC familiarity and qualitative use frequency in general situations; weekly travel frequency by different modes; whether multiple modes were used for a single trip; possession of a driver's license; access to a personal vehicle; technology ownership, use, and comfort; consumption of alcohol in the past year; being a designated driver in the last 30 days; type of establishment where an individual consumed alcohol; qualitative preference of mode in alcohol-related situations; the modes used in the most recent situation to leave the location where an individual last consumed alcohol, when an individual avoided driving after consuming alcohol, and when an individual avoided driving with a driver who consumed alcohol; and basic socio-demographic characteristics. Table 6.1 summarizes the independent and dependent variables used in this study. The categorical explanatory variables were coded as dummy variables and all responses with "don't know" were coded as missing values.

TABLE 6. 1. OVERVIEW OF VARIABLES

Variable		Code	Number of observations	Min	Max	Mean	Standard deviation
Independent variables							
Location							
Location	Northern Virginia (yes=1, other=0)	IV2	3004	0	1	0.38	0.49
	Hampton Roads (yes=1, other =0)	IV3	3004	0	1	0.32	0.47
	Richmond (yes=1, other =0)	IV4	3004	0	1	0.30	0.46
Demographics							
Race/ethnicity	Male (yes=1, female=0)	IV1	3004	0	1	0.54	0.50
	White (yes=1, other =0)	IV5	2918	0	1	0.67	0.47
	African American (yes=1, other =0)	IV6	2918	0	1	0.19	0.39
	Asian (yes=1, other =0)	IV7	2918	0	1	0.05	0.22

	Another race (yes=1, other =0)	IV8	2918	0	1	0.09	0.29
	Hispanic or Latino (yes=1, no=0)	IV9	2935	0	1	0.07	0.25
Employment	Employed full time (yes=1, no=0)	IV13	2972	0	1	0.59	0.49
	Employed part time (yes=1, no=0)	IV14	2972	0	1	0.07	0.25
	Unemployed and looking for work (yes=1, no=0)	IV15	2972	0	1	0.03	0.17
	Retired (yes=1, no=0)	IV16	2972	0	1	0.16	0.36
	Going to school (yes=1, no=0)	IV17	2972	0	1	0.03	0.19
	Homemaker (yes=1, no=0)	IV18	2972	0	1	0.03	0.20
	Employment status: something else (yes=1, no=0)	IV19	2972	0	1	0.03	0.18
Occupation	Management and professional (yes=1, no=0)	IV20	2929	0	1	0.51	0.50
	Military (yes=1, no=0)	IV21	2929	0	1	0.05	0.21
	Service such as protective service, food service, or personal care (yes=1, no=0)	IV22	2929	0	1	0.07	0.25
	Sales or retail (yes=1, no=0)	IV23	2929	0	1	0.07	0.25
	Construction or trades (yes=1, no=0)	IV24	2929	0	1	0.06	0.24
	Student (yes=1, no=0)	IV25	2929	0	1	0.03	0.18
	Transport services (yes=1, no=0)	IV26	2929	0	1	0.03	0.16
	Some other occupation (yes=1, no=0)	IV27	2929	0	1	0.19	0.39
Education	Highest level of education: grade/elementary school (yes=1, no=0)	IV28	2968	0	1	0.00	0.05
	Some high school (yes=1, no=0)	IV29	2968	0	1	0.02	0.14
	High school graduate [or GED] (yes=1, no=0)	IV30	2968	0	1	0.14	0.35
	Trade/vocational school after high school (yes=1, no=0)	IV31	2968	0	1	0.02	0.14
	Some college(yes=1, no=0)	IV32	2968	0	1	0.15	0.36
	Completed community college/two-year degree (yes=1, no=0)	IV33	2968	0	1	0.09	0.29
	Four-year college/university graduate (yes=1, no=0)	IV34	2968	0	1	0.35	0.48
	Graduate/professional school (yes=1, no=0)	IV35	2968	0	1	0.23	0.42
Age	Age (continuous)	IV48	2941	21	92	47.95	15.38
House-hold	Income in thousands of dollars (continuous)	IV47	2520	7.5	150	90.27	44.79
	Household size (continuous)	IV49	2963	1	18	2.94	1.53
	Children in household (continuous)	IV50	2557	0	15	0.79	1.15

Smart Phone Use							
Phone Use	Communication such as talking, texting, or email (yes=1, no=0)	IV36	2600	0	1	1.00	0.06
	Social media (yes=1, no=0)	IV37	2600	0	1	0.72	0.45
	Entertainment (yes=1, no=0)	IV38	2600	0	1	0.68	0.47
	Searching the web (yes=1, no=0)	IV39	2600	0	1	0.89	0.31
	Shopping or ordering items (yes=1, no=0)	IV40	2600	0	1	0.58	0.49
	Navigation (yes=1, no=0)	IV41	2600	0	1	0.87	0.33
App Use	Restaurant reservations or food delivery (yes=1, no=0)	IV42	2600	0	1	0.23	0.42
	Hotel reservations and/or air transportation arrangements (yes=1, no=0)	IV43	2600	0	1	0.27	0.45
	Uber or Lyft rides or a similar service (yes=1, no=0)	IV44	2600	0	1	0.34	0.47
	Taxi (yes=1, no=0)	IV45	2600	0	1	0.04	0.21
	Don't use an app for any of these things (yes=1, no=0)	IV46	2600	0	1	0.48	0.50
Financial Use	Mobile wallet (yes=1, no=0)	IV10	2602	0	1	0.21	0.41
	Comfortable with tying a credit card to an app on a phone (yes=1, no=0)	IV11	2576	0	1	0.37	0.48
	Not comfortable with tying a credit card to an app on a phone (yes=1, no=0)	IV12	2576	0	1	0.63	0.48
Transportation Mode Use							
Transportation Mode Use	Personal vehicle weekly frequency (continuous)	IV51	2868	0	6.5	5.91	1.39
	Taxi weekly frequency (continuous)	IV52	2997	0	6.5	0.10	0.48
	TNC weekly-frequency (continuous)	IV53	2998	0	6.5	0.22	0.70
	Carpool-weekly-frequency (continuous)	IV54	2995	0	6.5	0.59	1.39
	Public transit weekly frequency (continuous)	IV55	2996	0	6.5	0.29	1.05
	Walk or bike weekly frequency (continuous)	IV56	2993	0	6.5	1.66	2.34
	Own personal vehicle (yes=1, no=0)	IV57	2878	0	1	0.97	0.17
	Multi modal travel (yes=1, no=0)	IV58	2994	0	1	0.08	0.28
	Mode used to arrive at location where last consumed alcohol: Personal Vehicle(yes=1, no=0)	IV59	1486	0	1	0.50	0.50
	Mode used to arrive at location where last consumed alcohol: Walk(yes=1, no=0)	IV60	1486	0	1	0.09	0.29
	On the last occasion on which you consumed alcohol outside of	IV61	1482	0	1	0.17	0.37

	your home, where did you drink: Home of an Acquaintance or Friend(yes=1, no=0)						
	On the last occasion on which you consumed alcohol outside of your home, where did you drink: Bar/Tavern/Club (yes=1, no=0)	IV62	1482	0	1	0.24	0.43
	Were you a designated driver during the last 30 days? (yes=1, no=0)	IV63	2998	0	1	0.27	0.45
	In the past year, have you ever ridden in a motor vehicle with a driver you felt might have drunk too much to drive safely? (yes=1, no=0)	IV64	2991	0	1	0.07	0.26
	Did you travel alone when you left the location where you last consumed alcohol? (yes=1, no=0)	IV65	1484	0	1	0.24	0.43
Dependent variables							
Situation 1: Leave location where last consumed alcohol	Used a Service like Uber or Lyft		187				
	Personal Vehicle		478				
	Didn’t leave/Stayed the Night		61				
	Walk		114				
	Rode with Friends/Family Member		350				
	Rode with Designated Driver		179				
	Other Modes		43				
Situation 2: Avoided driving after consumption of alcohol	Used a Service like Uber or Lyft		201				
	Didn’t leave/Stayed the Night		70				
	Walk		24				
	Picked Up by Friends and Family		92				
	Ride with Designated Driver		260				
	Other Modes		25				
Situation 3: Avoided riding with drunk driver	Used a Service like Uber or Lyft		129				
	Didn’t leave/Stayed the Night		40				
	Drove Personal Vehicle		96				
	Walk		26				
	Was Picked up by a Friend or Family Member		135				
	Rode with a Designated Driver		55				
	Other Modes		45				

More of the respondents were from Northern Virginia (38.2%) followed by Hampton Roads/Tidewater (31.7%) and Richmond (30.01%). In terms of travel choices, most of the respondents regularly used personal vehicles, followed by walking/biking, carpool, public transit, TNCs, and taxi. Multiple types of transportation were used by 8.2% of the respondents for a single trip. While TNCs were infrequently used as a regular commute mode, the second most popular reason for using them was after consumption of alcohol (55.2%). (The most popular reason was for out of town or airport travel – 69.8%).

Most of the respondents (71.9%) had consumed alcohol in the past year. In response to questions about consumption of alcohol outside of home, 69% of the respondents stated that they consumed alcohol once or more in the 30 days before completing the survey. TNCs ranked higher than taxi and public transit in terms of preference (general) for alcohol situations, which can be seen from Table 6.2. Riding with a designated driver was the most likely choice in alcohol related situations for the respondents.

TABLE 6.2. STATED QUALITATIVE LIKELIHOOD OF MODE SELECTION AFTER ALCOHOL CONSUMPTION(IN %)

Mode	Very likely	Somewhat likely	Somewhat unlikely	Not at all likely
TNC (Uber/Lyft)	34.2	23.4	10.3	32.1
Designated driver	61.4	24.1	4.2	10.2
Friend/Family member	32.4	20.3	13.5	33.9
Taxi	12.5	22.1	12.8	52.6
Personal vehicle	29.9	17.6	13.3	39.2
Public transit	7.5	12.3	11.0	69.2
Walking	16.0	24.3	12.2	47.5
Biking	3.4	5.1	6.7	84.7

As seen from Figure 6.1, respondents were more likely to leave an alcohol-serving location by a TNC than they were to arrive with one. Most of the respondents indicated that they did not drive after consuming alcohol or ride with a driver who had consumed alcohol.

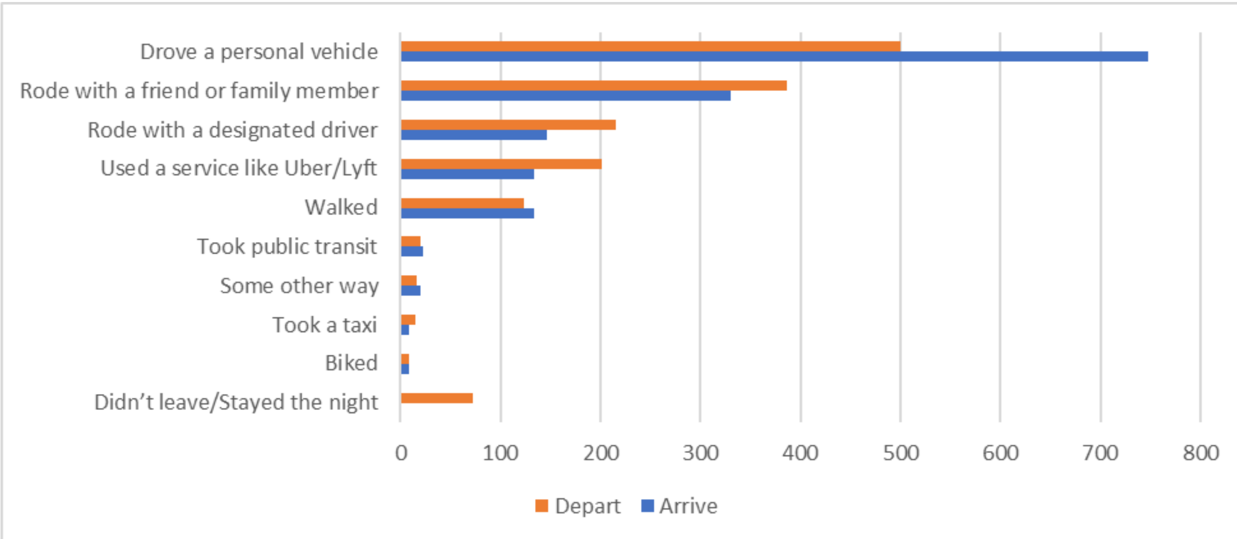

FIGURE 6.1. MODE USED TO ARRIVE VS DEPART FROM THE LOCATION WHERE THE RESPONDENT LAST CONSUMED ALCOHOL

Table 6.3 shows the comparison of the survey dataset with the data extracted from American Community Survey data 2010-15. Males were slightly oversampled in our survey. In the Northern Virginia part of the sample, race was well captured while the Hispanic ethnicity was under sampled. In Hampton Roads and Richmond, African Americans were under sampled and Whites were somewhat over sampled. In Hampton Roads and Richmond, the survey respondents had higher mean income compared to the Census data whereas in the Northern Virginia part of the survey, the respondents had lower mean income.

TABLE 6.3. COMPARISON OF SOCIO-DEMOGRAPHIC CHARACTERISTICS OF THE SAMPLE WITH CENSUS DATA

	Northern Virginia		Hampton Roads /Tidewater		Richmond	
Characteristic	**Survey**	**Census**	**Survey**	**Census**	**Survey**	**Census**
Male (%)	55.7%	49.5%	51.2%	61.9%	54.6%	47.8%
Mean income ($)	$106,556	$113,579	$80,670	$71,487	$80,708	$73,212
White (%)	64.2%	64.6%	63.2%	58.5%	69.0%	64.8%
African American (%)	13.2%	11.8%	25.7%	32.0%	19.3%	26.1%
Asian (%)	8.9%	14.3%	2.1%	3.9%	3.5%	4.6%
Other (%)	10.5%	9.4%	9.1%	5.6%	6.2%	4.5%
Hispanic (%)	8.7%	16.9%	6.8%	6.9%	3.5%	5.9%

Census Data Source: American Community Survey 2010-15 (United States Census Bureau, 2016)

6.5. STATISTICAL MODELING APPROACH

The researchers used multinomial logistic (MNL) regression to model the travel choices when a) leaving the location where the individual last consumed alcohol, b) last avoiding driving under the influence of alcohol, and c) last avoiding riding with a driver who had been drinking.

The MNL model is a popular discrete choice model and is used to represent the unordered response mechanism assuming that a random utility is associated with each option. These utilities include a systematic component that is a function of distinctive characteristics. Each individual is assumed to select the alternative with the highest utility. The MNL model was developed by McFadden (1973) by assuming that the disturbance ε_{nj} is independent and identically distributed and follows a Gumbel (type I extreme value) distribution. The probability $P_n(j)$ that individual *n* selects alternative *j* can be expressed as in equation (1).

$$P_n(j)=\frac{\exp(V_{nj})}{\sum_{k\in B}\exp(V_{nk})} \qquad (1)$$

Where V_{nj} is often assumed to be a linear function of attributes of alternative *j* (Wichmann et al., 2016) and individual *n* and is considered the utility of alternative *j*.

In MNL regression, using the software SPSS, the categories of the response measures are analyzed simultaneously in response to the base category. It produces separate log odds for each set of relationships analyzed. If the dependent variable contains J categories, the MNL model produces J-1 logits yielding distinct parameter estimates and intercept values (Rodríguez, 2017). A MNL regression is modelled as shown in equation 2 (Rodríguez, 2007).

$$log\frac{P(category\, i)}{P(category\, J)} = \beta_{i0}+\beta_{i1}X_1+\beta_{i2}X_2+\ldots+\beta_{in}X_n \qquad (2)$$

Where the Jth category serves as the base category for i^{th} response option. The β represents the regression coefficients and the X represents the individual variables in the multivariate MNL model. The MNL regression uses maximum likelihood estimation to evaluate the probability of categorical membership and a generalized logit serves as the link function. The MNL model assumes that response categories are mutually exclusive and exhaustive, with every observation assigned to only one category of the dependent variable (Golder, 2007).

6.6. RESULTS AND DISCUSSION

The inter-correlation matrix shown in Table 6.4 allowed the examination of relationships among the independent variables, which helped identify correlated variables. Highly and significantly correlated variables should not be included in the same model. As shown in Table 6.4, the greatest (in terms of absolute value) correlation was -0.32 (between age and last consuming alcohol at a bar), on a scale of -1.0 (perfect negative correlation) to 1.0 (perfect positive correlation).

Selection of initial variables was also guided by the proposed hypotheses and the purposeful selection technique (Hosmer and Lemeshow, 2000). The purposeful selection technique involved examining the individual effects of variables on travel choice in the three alcohol-related situations. Chi square analyses were conducted for the binary variables in Table 6.1. All of the variables which had p-values less than 0.25 (Hosmer and Lemeshow, 2000) were considered for inclusion in the MNL models. Similarly, MNL models were created for continuous variables.

The results of the individual variable analyses are shown in Table 6.5 for variables meeting the significance threshold in at least one of the alcohol-related situations. As shown in Table 6.5, variables related to the seven hypotheses, i.e., gender, alcohol consumption location, age, TNC use frequency for general travel, using an app for taxis, comfort with a credit card being tied to an app, and income, met the significance threshold for inclusion in the multi-variable models.

The initial multi-variable MNL models included the variables from Table 6.5. The insignificant variables that were not related to hypotheses were removed in a stepwise manner. The preferred models are provided in Tables 6.6 through 6.8.

All three models passed the Chi Square test of significance, indicating that the models were preferred to an intercept only model. Also, since the models were based on differences in utility and because the variables were not alternative-specific, a base case was selected that had the default utility of zero. The other utilities were interpreted as relative to the base case, which for this case was TNCs.

	IV1	IV11	IV13	IV30	IV38	IV43	IV45	IV47	IV48	IV53	IV58	IV59	IV60	IV61	IV62	IV63	IV64	IV65
IV1	1	**	**	**	n.s	*	n.s	**	n.s	**	*	**	n.s	n.s	**	**	n.s	**
IV11	0.11	1	**	**	**	**	**	**	**	**	**	n.s	n.s	n.s	*	n.s	**	n.s
IV13	0.20	0.12	1	**	**	**	n.s	**	**	**	*	n.s	n.s	**	*	**	**	n.s
IV30	0.05	-0.05	-0.05	1	n.s.	**	n.s	**	*	*	n.s	n.s	n.s	**	n.s	**	n.s	n.s
IV38	-0.02	0.21	0.06	-0.002	1	**	**	n.s	**	**	n.s	n.s	n.s	n.s	**	**	**	n.s
IV43	0.05	0.22	0.09	-0.08	0.14	1	**	**	n.s	**	**	n.s	n.s	n.s	n.s	**	n.s	n.s
IV45	0.04	0.06	0.01	0.01	0.06	0.15	1	n.s	*	**	**	n.s	n.s	n.s	n.s	n.s	**	*
IV47	0.11	0.15	0.21	-0.22	-0.04	0.15	0.02	1	**	**	**	n.s	n.s	**	**	**	**	*
IV48	0.02	-0.19	-0.25	-0.04	-0.40	.003	-0.04	0.13	1	**	n.s	**	**	*	**	**	**	n.s
IV53	0.05	0.16	0.09	-0.04	0.12	0.14	0.12	0.06	-0.19	1	**	**	n.s	n.s	**	**	**	n.s
IV58	0.04	0.08	0.04	-0.03	0.01	-0.12	0.06	0.08	-0.03	0.15	1	**	**	n.s	n.s	n.s	n.s	*
IV59	0.18	-0.04	0.04	0.02	-0.05	-0.01	-0.03	0.01	0.16	-0.15	-0.07	1	**	**	**	n.s	n.s	**
IV60	0.01	0.004	0.02	0.01	-0.02	-0.01	0.01	0.02	-0.08	0.02	0.10	-0.30	1	n.s.	**	n.s	n.s	*
IV61	-0.03	0.004	-0.07	0.10	0.03	-0.01	-0.02	-0.10	-0.06	-.02	0.01	0.13	-0.01	1	**	n.s	n.s	**
IV62	0.09	0.06	0.07	0.02	0.16	0.01	0.03	-0.13	-0.32	0.12	0.03	-0.13	0.09	-0.25	1	**	**	**
IV63	-0.05	0.02	0.08	-0.08	0.10	0.08	0.01	0.09	-0.18	0.09	0.02	-0.03	-0.02	0.01	0.08	1	**	**
IV64	0.02	0.07	0.06	0.02	0.11	0.02	0.05	-0.08	-0.16	0.12	0.002	-0.03	0.03	0.03	0.20	0.10	1	*
IV65	0.09	0.01	0.02	0.02	-0.01	-0.03	-0.06	-0.07	0.02	0.02	0.06*	0.20	0.06	0.12	0.08	-0.14	0.05	1

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).
n.s Not-significant

TABLE 6.4. CORRELATION MATRIX

Variable	Leaving the Location Where an Individual Last Consumed Alcohol	Avoiding Driving After Drinking	Avoiding Riding with a Driver Who Had Been Drinking
	Chi square value[a] or parameter estimate[b] (p-value)		
Mode used to arrive at location where last consumed alcohol: Personal Vehicle (yes=1, no=0)	765.04 (< .01)	49.04 (< .01)	30.88 (< .01)
Mode used to arrive at location where last consumed alcohol: Walk (yes=1, no=0)	954.50 (< .01)	95.76 (< .01)	41.40 (< .01)
On the last occasion on which you consumed alcohol outside of your home, where did you drink: Bar/Tavern/Club (yes=1, no=0)	123.97 (< .01)	48.42 (< .01)	22.99 (< .01)
On the last occasion on which you consumed alcohol outside of your home, where did you drink: Home of an Acquaintance or Friend (yes=1, no=0)	75.70 (< .01)	58.95 (< .01)	10.85 (.09)
Did you travel alone when you left the location where you last consumed alcohol? (yes=1, no=0)	193.04 (< .01)	52.86 (< .01)	4.24 (.644)
Age (continuous)	141.09 (< .01)	52.80 (< .01)	38.19 (< .01)
Income in thousands of dollars (continuous)	24.68 (< .01)	12.05 (< .01)	22.23 (< .01)
High school grad [or GED] (yes=1, no=0)	19.57 (< .01)	11.28 (.05)	14.04 (.03)
Male (yes=1, female=0)	48.88 (< .01)	3.17 (.67)	8.16 (.23)
Employed full time (yes=1, no=0)	19.69 (< .01)	11.56 (.04)	9.45 (.15)
TNC_weekly_frequency (continuous)	140.40 (< .01)	99.76 (< .01)	62.15 (< .01)
Multi_modal_travel (yes=1, no=0)	32.78 (< .01)	8.57 (.13)	7.89 (.25)
Use a phone app to get a taxi (yes=1, no=0)	7.08 (.31)	3.31 (.65)	9.53 (.15)
Use a phone app for hotel reservations and/or air transportation arrangements (yes=1, no=0)	17.15 (< .01)	26.70 (< .01)	16.98 (< .01)
Use your smart phone for: entertainment(yes=1, no=0)	24.98 (< .01)	13.43 (.02)	11.76 (.07)
Comfortable with tying a credit card to an app on a phone (yes=1, no=0)	40.12 (< .01)	28.33 (< .01)	20.39 (< .01)
Were you a designated driver during the last 30 days? (yes=1, no=0)	49.30 (< .01)	5.18 (.40)	25.68 (< .01)
In the past year, have you ever ridden in a motor vehicle with a driver you felt might have drunk too much to drive safely? (yes=1, no=0)	22.52 (< .01)	12.13 (.03)	11.74 (.07)

[a] Chi square values are presented for category variables

[b] Parameter estimates are presented for continuous variables.

TABLE 6.5. INDIVIDUALLY POTENTIALLY SIGNIFICANT VARIABLE

Variable	Didn't leave/ stayed the night	Walked	Rode with friends/ family members	Rode with designated driver	Drove a personal vehicle	Others
Intercept	-2.370**	-0.582 n.s	1.434**	0.298 n.s	-4.595***	-2.257*
Mode used to arrive at location where last consumed alcohol: Personal Vehicle	2.297***	-1.309**	0.202 n.s	0.916**	5.648***	-0.916 n.s
Comfortable with tying a credit card to an app on a phone	-0.629 n.s	-0.284 n.s	-0.676**	-0.289 n.s	-0.343 n.s	0.014 n.s
Age	0.037*	0.019 n.s	0.034***	0.025*	0.055***	0.026 n.s
Income in thousands of dollars	-0.015**	-0.003 n.s	-0.010***	-0.007*	-0.003 n.s	-0.007 n.s
Male	0.001 n.s	0.528 n.s	-0.316 n.s	-0.149 n.s	-0.165 n.s	0.663 n.s
TNC_weekly_frequency	-0.862 n.s	-0.609***	-0.573***	-0.530***	-0.575 n.s	-0.139 n.s
Did you travel alone when you left the location where you last consumed alcohol	0.663 n.s	0.455 n.s	-1.833***	-1.529***	0.632 *	0.682 n.s
High school grad [or GED]	1.498**	0.399 n.s	0.452 n.s	0.012 n.s	0.800 n.s	-19.816 [a]
On the last occasion on which you consumed alcohol outside of your home, where did you drink: Bar/Tavern/Club	-1.756*	-0.847*	-1.153***	-0.731*	-1.128 ***	-0.476 n.s
On the last occasion on which you consumed alcohol outside of your home, where did you drink: Home of an Acquaintance or Friend	1.441**	0.576 n.s	-0.007 n.s	0.561 n.s	-0.405 n.s	-0.141 n.s
Use a phone app to get a taxi	-18.998 [a]	-0.105 n.s	0.098 n.s	-0.648 n.s	-0.782 n.s	0.696 n.s
Number of Observations	1125					
Pseudo R square						
Cox and Snell	0.637					
Nagelkerke	0.660					
McFadden	0.303					
-2 Log Likelihood (intercept only)	3736.524					
-2 Log Likelihood (final)	2596.579					
Chi Square	1139.945***					

*** Significant at the <0.001 level (2-tailed), ** Significant at the 0.01 level (2-tailed), * Significant at the 0.05 level (2-tailed), n.s. Non-significant

Base Category: Used a TNC service like Uber/Lyft

[a] Little (1 positive response) to no variation for this variable for this alternative.

TABLE 6.6. FINAL MNL MODEL FOR LEAVING THE LOCATION WHERE AN INDIVIDUAL LAST CONSUMED ALCOHOL

Variable	Didn't leave/ stayed the night	Walked	Rode with friends/ family members	Rode with designated driver	Others
Intercept	-1.380 n.s	-2.014 n.s	0.003 n.s	0.143 n.s	-2.539*
Mode used to arrive at location where last consumed alcohol: Personal Vehicle	1.285**	-0.536 n.s	0.831**	0.615*	1.618**
On the last occasion on which you consumed alcohol outside of your home, where did you drink: Bar/Tavern/Club	-0.992*	0.001 n.s	-0.825*	-0.998***	-1.087 n.s
On the last occasion on which you consumed alcohol outside of your home, where did you drink: Home of an Acquaintance or Friend	1.570***	-0.570 n.s	-0.188 n.s	0.071 n.s	-0.585 n.s
Comfortable with tying a credit card to an app on a phone	-1.079**	0.107 n.s	-1.178***	-0.474 n.s	-0.918 n.s
Male	0.427 n.s	2.044**	0.422 n.s	-0.043 n.s	0.156 n.s
TNC_weekly_frequency	-0.431 n.s	-1.783*	-0.875***	-0.813***	-2.146 n.s
Use a phone app for hotel reservations and/or air transportation arrangements	-0.852*	-2.249**	-0.384 n.s	-0.827***	-0.508 n.s
Age	0.037*	-0.021 n.s	0.019 n.s	0.045***	0.062**
Use a phone app to get a taxi	0.142 n.s	1.255 n.s	-0.077 n.s	0.170 n.s	0.983 n.s
Income in thousands of dollars	-0.011*	0.003 n.s	-0.007 n.s	-0.007*	-0.018**
Multi_modal_travel	-0.601 n.s	-0.218 n.s	0.635 n.s	0.569 n.s	2.149**
Number of Observations	569				
Pseudo R square					
Cox and Snell	0.381				
Nagelkerke	0.402				
McFadden	0.163				
-2 Log Likelihood (intercept only)	1661.470				
-2 Log Likelihood (final)	1388.946				
Chi Square	272.524***				

*** Significant at the <0.001 level (2-tailed), ** Significant at the 0.01 level (2-tailed), * Significant at the 0.05 level (2-tailed), n.s. Not-significant
Base Category: Used a service like Uber/Lyft

TABLE 6.7. FINAL MNL MODEL FOR AVOIDING DRIVING AFTER DRINKING

Variable	Didn’t leave/ stayed the night	Walked	Rode with friends/ family members	Rode with designated driver	Drove a personal vehicle	Others
Intercept	0.470 n.s	-1.044 n.s	0.478 n.s	-0.337 n.s	-0.392 n.s	-2.462 n.s
Mode used to arrive at location where last consumed alcohol: Personal Vehicle	1.800***	1.457 n.s	1.316***	1.261**	2.107***	1.213*
Mode used to arrive at location where last consumed alcohol: Walk	-0.283 n.s	2.562**	-0.461 n.s	-1.545 n.s	1.151 n.s	1.201 n.s
In the past year, have you ever ridden in a motor vehicle with a driver you felt might have drunk too much to drive safely?	1.248*	1.428 n.s	0.413 n.s	0.525 n.s	1.101 n.s	-0.960 n.s
On the last occasion on which you consumed alcohol outside of your home, where did you drink: Bar/Tavern/Club	-1.238*	-0.236 n.s	-1.354***	-0.848 n.s	-0.387 n.s	-0.500 n.s
Use your smart phone for: entertainment	0.009 n.s	-1.784 n.s	0.016 n.s	-0.367 n.s	-1.332*	0.489 n.s
Comfortable with tying a credit card to an app on a phone	-1.308*	-0.129 n.s	-1.126**	-1.157*	-0.847 n.s	-0.183 n.s
Age	-0.018 n.s	-0.016 n.s	0.022 n.s	0.020 n.s	0.059**	0.036 n.s
Income in thousands of dollars	-0.003 n.s	-0.008 n.s	-0.007 n.s	0.001 n.s	-0.005 n.s	-0.012 n.s
Use a phone app to get a taxi	0.336 n.s	-17.973 [a]	-0.615 n.s	0.893 n.s	-1.700 n.s	-0.340 n.s
Male	-0.216 n.s	1.415 n.s	0.097 n.s	-0.500 n.s	-0.076 n.s	0.374 n.s
TNC_weekly_frequency	-0.504 n.s	-2.654 n.s	-0.856***	-0.736**	-5.444***	-0.548 n.s
Employed full time	-0.451 n.s	0.179 n.s	0.193 n.s	-0.009 n.s	-1.867**	0.562 n.s
Number of Observations	297					
Pseudo R square						
Cox and Snell	0.507					
Nagelkerke	0.523					
McFadden	0.203					
-2 Log Likelihood (intercept only)	1031.772					
-2 Log Likelihood (final)	821.996					
Chi Square	209.777***					

*** Significant at the <0.001 level (2-tailed), ** Significant at the 0.01 level (2-tailed), * Significant at the 0.05 level (2-tailed), n.s. Not significant

Base Category: Used a service like Uber/Lyft

TABLE 6.8. FINAL MNL MODEL FOR AVOIDING RIDING WITH A DRIVER WHO HAD BEEN DRINKING

Hypothesis 1: Males are more likely to drive personal vehicles in relevant alcohol-related situations.

As shown in Tables 6.6 and 6.8, gender was insignificant in the two models where driving was an option, thus hypothesis 1 was rejected in the multi-variable context for these alcohol-related situations. However, as shown in Table 6.7, when a male avoided driving after consuming alcohol, he was more likely to walk home rather than use TNC services (7.7 times more likely).

Hypothesis 2: Consumption of alcohol at a bar is positively associated with the use of personal vehicles in the relevant alcohol-related situations examined in this study.

As shown in Table 6.6, consumption of alcohol at a bar/tavern/club was significant in the model for the last time the respondent consumed alcohol in the options walking, staying the night, riding with friends/family, riding with a designated driver, and driving a personal vehicle. The likelihood of using a TNC increased compared to these alternatives. A model (not shown here) was also developed with personal vehicle as the base case so that the alternatives could be directly compared to driving personal vehicles. In this (unshown) model, the only alternative for which consuming alcohol at a bar was significant was using TNCs. Since consuming alcohol at a bar was insignificant for all of these alternatives compared to using personal vehicles and consuming alcohol at a bar increased the likelihood of using TNCs compared to using personal vehicles (both in the model not shown and in the model shown in Table 6.6), hypothesis 2 was rejected for alcohol situation (1). This was somewhat unexpected since previous studies (Chang et al., 1996; Harrison, 1998; Lapham et al., 1998; Morrison et al., 2002) reported that if drinking events took place in a bar, it was more common that it would result in a DUI incident. However, these studies were before the increase in TNCs. Now, it appears that consuming alcohol in a bar is associated with a greater likelihood of using TNCs compared to driving personal vehicles (3 times more likely to use TNCs), although there is the possibility that respondents felt socially pressured to not indicate driving after drinking.

In this first alcohol-related situation, consuming alcohol at a friend's/acquaintance's place was associated with a higher propensity to spend the night (4.22 times more likely compared to using TNCs). A friend's home logically provided a comfortable and reasonable place to spend the night rather than travel after consuming alcohol. (For the unshown model with driving a personal vehicle as the base, respondents who last consumed alcohol at a friend's/acquaintance's place were 6.33 times as likely to spend the night as they were to drive home.)

Although driving a personal vehicle was not an option in the second context, Table 6.7 shows that when avoiding driving after drinking, respondents were more likely to use TNC services compared to other travel options. Respondents who had last consumed alcohol in a bar were 0.37, 0.44, and 0.37 times as likely to spend the night, be picked up by friends/family, or ride with a designated driver, respectively, compared to using TNC services. (The variable was insignificant for the other alternatives). The direction of effects made sense. TNCs may have been viewed as more convenient than calling friends or family members. Designated drivers may not have been available or not viewed as necessary with the availability of TNC drivers. In terms of spending the night, using TNC services is a more feasible option than spending the night in a bar. On the other hand, consuming alcohol at a friend's/acquaintance's place was associated with a higher propensity towards spending the night (4.8 times more likely compared to using TNC services).

Similarly, as shown in Table 6.8, if an individual avoided riding with a driver who had been drinking, having the last time he/she consumed alcohol be in a bar was associated with a lower propensity for spending the night and getting picked up by friends/family, compared to using TNC services. The variable was insignificant in the alternative driving a personal vehicle. A separate model (not shown here) was developed with personal vehicle as the base. In this model, consuming alcohol at a bar was insignificant to all of the alternatives, rejecting hypothesis 2 in this context. With TNCs as the base, TNCs might have been considered a convenient option compared to being picked up by friends/family members or TNCs might have targeted individuals drinking at bars as their potential patrons. When considering the driving option, the respondent may also have been drinking and not elected to drive another person's vehicle.

Hypothesis 3: Younger people are more likely to use TNC in all three alcohol-related situations.

As shown in Table 6.6, for the last time the respondent consumed alcohol, with increasing age, individuals were more likely to use personal vehicles, stay the night, ride with friends/family members, and ride with designated drivers compared to using TNCs. Thus, hypothesis 3 was supported in the multi-variable context for this situation.

For the second situation (avoiding driving after consuming alcohol), Table 6.7 indicated that an increase in age was associated with an increase in the likelihood of spending the night, riding with a designated driver, and “other” compared to using TNC services, supporting hypothesis 3 in this context.

As shown in Table 6.8, if an individual avoided riding with a driver who had been drinking, they had a higher propensity of driving a personal vehicle as age increased compared to using TNC services. This supported hypothesis 3 in the multi-variable context for this alcohol-related situation.

Hypothesis 4: People who regularly use TNCs more frequently are more likely to use them in alcohol-related situations.

As shown in Tables 6.6-6.8, frequency of TNC use was significant in all three alcohol-related situations, supporting hypothesis 4 in the multi-variable context. As shown in Tables 6.6 and 6.7, the last time the respondent consumed alcohol and avoided driving after consumption of alcohol, increased general TNC use frequency was associated with lower propensity towards walking, riding with friends/family members, and riding with a designated driver compared to using TNC services. Similarly as shown in Table 6.8, when avoiding riding with a driver who had been drinking, the individual had a lower likelihood of using a personal vehicle, riding with a designated driver and getting picked up by friends/family members compared to using TNC services.

Hypothesis 5: Those who use cell phone apps for ordering taxis are also likely to use TNCs in alcohol-related situations.

As shown in Tables 6.6-6.8, use of cell phone apps for ordering taxis was insignificant in all three models, thus hypothesis 5 was rejected in the multi-variable context for these alcohol-related situations.

Using another type of app – for hotel reservations or air transportation arrangements – was significant in the second alcohol-related situation, as shown in Table 6.7. Use of these apps was associated with a lower propensity to walk, spend the night, and ride with a designated driver when avoiding driving after consuming alcohol, compared to using TNCs services. The variable was insignificant for the other alternatives.

As shown in Table 6.8, the use of a smartphone for entertainment was associated with a decreased propensity towards driving personal vehicles when the individual avoided riding with a driver who had been drinking. When considered in the relative sense, this also meant an increase in the propensity for using TNCs. While not specific to an app, this variable suggested that comfort with technology influenced mode selection.

While the type of app varied by the alcohol-related situation, the latter two models suggested that familiarity with cell phone technology encouraged TNC use at least relative to one of the other options.

Hypothesis 6: Those who are comfortable with a credit card being tied to apps are more likely to use TNCs in alcohol-related situations.

This hypothesis was supported, as shown in Tables 6.6-6.8. For the last time that the respondent consumed alcohol, Table 6.6 indicates that being comfortable with tying a credit card to an app was associated with lower propensity to be picked up by friends/family members, which means higher propensity to use TNC services. For the other two situations - avoiding driving after drinking and avoiding riding with a driver who had been drinking, Tables 6.7 and 6.8 indicated that individuals who are comfortable with a credit card being tied to apps are more likely to use TNCs compared to spending the night and riding with friends/family members. In the latter situation, TNCs were also more likely to be used than riding with a designated driver.

Hypothesis 7: Individuals with higher household income are more likely to use TNCs in alcohol-related situations.

This hypothesis was supported in the first two alcohol-related situations but rejected in the multi-variable context for the third – when avoiding riding with a driver who had been drinking, for which the variable was insignificant. As shown in Table 6.6, for the last time the respondent consumed alcohol, an increase in household income was associated with lower propensity to spend the night, ride with friends/family and ride with a designated driver, compared to using TNC services. Similarly, as shown in Table 6.7, when the individual avoided driving after consuming alcohol, an increase in household income was associated with lower propensity to spend the night, ride with a designated driver, and use “other” which indicates a higher propensity to use TNC services.

As shown in Tables 6.6, 6.7, and 6.8, each model contained variables in addition to those specifically mentioned in the hypotheses. These tables indicated that arriving by personal vehicle at the location where the individual last consumed alcohol was significant to each model. Table 6.6 indicated in the situation when they last consumed alcohol, those who arrived by driving were significantly more likely to use a personal vehicle to leave, spend the night, and ride with designated drivers compared to using TNC services. This could reflect a reluctance to leave a vehicle overnight and/or either low volume drinking or driving while intoxicated. In the second situation, use of a personal vehicle when avoiding driving after drinking was not an option. As shown in Table 6.7, arriving by personal vehicle was associated with a higher propensity to use "other" modes, ride with a designated driver, spend the night, and be picked up by friends/family members, compared to using TNC services. Table 6.8 indicated that, in the third situation, arriving by personal vehicle at the location where the respondent last consumed alcohol (not necessarily the same situation as when they avoided riding with a driver who had been drinking) decreased the likelihood of using TNCs relative to all other options except for walking.

Other variables in the models differed across the three alcohol-related situations. For the last time the respondent consumed alcohol, Table 6.6 indicated that having high school graduation as the highest educational attainment was associated with a lower propensity to use TNCs compared to spending the night. Also, having a companion when leaving the location where last consuming alcohol was associated with lower likelihood of riding with friends/family or designated drivers compared to using TNCs and a higher likelihood of driving a personal vehicle compared to using TNCs. Table 6.7 indicated that for the situation when avoiding driving after drinking, normally using multiple transportation modes increased the likelihood of selecting the "other" option. Table 6.8 indicated that for the situation when avoiding riding with a driver who had been drinking, walking to the location where alcohol was last consumed was associated with an increased likelihood of walking upon departure in this context, compared to using TNCs. Individuals who were employed full time were less likely to drive home, compared to using TNCs. Finally, individuals who had previously ridden in a motor vehicle with a driver who the respondent thought had drunk too much to drive safely were more likely to spend the night compared to using TNCs services.

The overall prediction success of each of the models varied by alternative, as shown in Tables 6.9 through 6.11. Table 6.9 shows that the first MNL model well predicted driving personal vehicles and performed reasonably well in predicting riding with friends or family members. The model was unsuccessful in predicting "others," spending the night, and riding with a designated driver. Most of the errors for the designated driver category were in predicting riding with friends/family members instead, which still involved not driving after drinking. In contrast, Table 6.10 shows that the second MNL model well predicted riding with a designated driver but largely misclassified riding with fiends/family members as either riding with a designated driver or using TNCs. With many fewer observations, the third model was less accurate overall. Table 6.11 shows that the model well predicted the use of TNCs. Walking and “others” were not well predicted.

Observed	Predicted							
	Didn't leave/ stayed the night	Walked	Used TNCs	Rode with friends/ family members	Rode with designated driver	Drove a personal vehicle	Others	Percent Correct
Didn't leave/ stayed the night	4	0	1	7	1	28	0	9.8%
Walked	0	18	20	47	0	8	0	19.4%
Used TNCs	0	8	74	55	1	28	0	44.6%
Rode with friends/ family members	2	8	24	180	2	57	0	65.9%
Rode with designated driver	0	4	17	67	1	55	0	0.7%
Drove a personal vehicle	3	1	4	4	5	363	0	95.5%
Others	0	4	12	9	0	3	0	0.0%
Overall Percentage	0.8%	3.8%	13.5%	32.8%	0.9%	48.2%	0.0%	56.9%

TABLE 6.9. CLASSIFICATION SUCCESS RATES FOR LEAVING THE LOCATION WHERE AN INDIVIDUAL LAST CONSUMED ALCOHOL

Observed	Predicted						
	Didn't leave/ stayed the night	Walked	Used TNCs	Rode with friends/ family members	Rode with designated driver	Others	Percent Correct
Didn't leave/ stayed the night	17	0	11	2	29	0	28.8%
Walked	0	1	10	0	7	0	5.6%
Used TNCs	3	0	120	1	54	0	67.4%
Rode with friends/ family members	6	0	21	0	49	0	0.0%
Rode with designated driver	8	0	44	2	163	0	75.1%
Others	0	0	0	0	21	0	0.0%
Overall Percentage	6.0%	0.2%	36.2%	0.9%	56.8%	0.0%	52.9%

TABLE 6.10. CLASSIFICATION SUCCESS RATES FOR AVOIDING DRIVING AFTER DRINKING

Observed	Predicted							
	Didn't leave/ stayed the night	**Walked**	**Used TNCs**	**Rode with friends/ family members**	**Rode with designated driver**	**Drove a personal vehicle**	**Others**	**Percent Correct**
Didn't leave/ stayed the night	1	0	10	11	1	3	0	3.8%
Walked	0	3	4	3	0	2	0	25.0%
Used TNCs	0	1	75	17	1	1	0	78.9%
Rode with friends/ family members	0	1	19	42	2	9	0	57.5%
Rode with designated driver	0	0	11	14	7	5	0	18.9%
Drove a personal vehicle	0	0	4	13	0	17	0	50.0%
Others	0	2	10	6	0	0	2	10.0%
Overall Percentage	0.3%	2.4%	44.8%	35.7%	3.7%	12.5%	0.7%	49.5%

TABLE 6.11. CLASSIFICATION SUCCESS RATES FOR AVOIDING RIDING WITH A DRIVER WHO HAD BEEN DRINKING

6.7. CONCLUSIONS

This paper investigated the location of last alcohol consumption and the characteristics of individuals associated with travel decisions (transportation mode selection or spend the night) in three alcohol-related situations (1) the last time the respondent consumed alcohol, (2) when avoiding driving after drinking, and (3) when avoiding riding with a driver who had been drinking. This study is among the few to consider the relatively new option of using TNCs and of spending the night. Multinomial logistic regression models were developed for the three alcohol-related situations based on a survey of 3004 respondents 21 years and older from three different urban regions of Virginia. All three models had Chi Square statistics that indicated superiority to intercept only models.

Consumption of alcohol at a bar was statistically associated with use of TNC services in all three alcohol-related situations. For situation (1), consuming alcohol at a bar was associated with a reduction in the likelihood of driving a personal vehicle compared to using TNCs. The number of people driving the last time they consumed alcohol (anywhere) was still the largest of any of the options. When only considering those who last drank at a bar, slightly more people used a TNC (96) than drove a personal vehicle (82). However, this does not mean that those driving were under the influence; quantity of alcohol was not considered and is a recommended area of future research. In situation (2), personal vehicles were not an option. Riding with designated drivers was the most popular choice (39%) but TNC use was close behind (30%) and more common than calling a friend or family member for a ride. In situation (3), consumption of alcohol at a bar was not associated with driving a personal vehicle, but it did encourage TNC use compared to calling a friend or family member. These two alternatives, together, comprised the vast majority of the selections for this alcohol scenario. Targeted advertising of TNCs in bars and other alcohol serving establishments may further encourage use of TNCs.

TNCs were more likely to be used by younger people in all three alcohol-related situations examined in this study. Older people were more likely to ride with designated drivers than to use TNCs when avoiding driving after drinking and the last instance of consuming alcohol. Older respondents may have been educated on the importance of designated drivers while younger respondents may see TNCs as an alternative to the traditional designated driver.

Familiarity with, and regular use of TNCs increased the likelihood of using TNCs in all three alcohol-related situations in this study. As knowledge of and experience with the option in general increase and TNCs increase market penetration in a given area as well as in new areas, it is likely that the use of these services in alcohol-related situations will grow.

TNC services are often arranged with cell phone technology. It was not surprising that variables reflecting comfort with and use of this technology were associated with the selection of TNCs in alcohol-related situations. The particular variable – using an app for hotel reservations or air transportation, using a smartphone for entertainment, and comfort with a credit card tied to an app – varied by alcohol-related scenario but all increased the likelihood of using TNCs compared to at least one alternative. As smartphones and their use grow as well as TNC services, TNC use could be expected to increase as well. However, some travelers may exchange TNC services for other options with a sober driver. Continued education on the perils of drinking and driving and the penalties of being caught driving under the influence may be needed to shift modes away from driving personal vehicles.

TNC services require payment, thus it was not surprising that households with higher incomes were more likely to use TNCs in the first two situations. In the first situation, the alternative of driving a personal vehicle did not have income as a significant variable, suggesting that income did not influence the decision between TNCs and driving. Rather, greater income may have encouraged TNC use, making post-alcohol travel more convenient for other drivers, such as family/friends or designated drivers.

Although, TNCs contribute to the option set for travel choice after consumption of alcohol, they may also create competition with other modes (e.g., with taxis or designated drivers). This issue could be investigated in future studies. Additional future research could explore younger age groups (participants in this study were at least 21 years old), group travel, and other locations in the US and around the world. Also, with the high penetration of social networks it might be useful to see how targeted ads can reduce risk behavior among individuals and influence their mode choice. These future studies could help determine mode shifts outside of the survey respondents in this study but should be considered in the context of regional development and changes in TNC services.

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CHAPTER 7: CONCLUSIONS AND RECOMMENDATIONS

7.1. SUMMARY AND SIGNIFICANT CONCLUSIONS

This thesis work is one of the first to expand our understanding of the characteristics of early adopters of TNCs and individual travel choice behavior in alcohol-related situations. The study is based on a telephone survey of over 3000 respondents conducted in three metropolitan areas of Virginia; Northern Virginia, Hampton Roads/Tidewater, and the Richmond urban area. The participants were asked questions on demography, technology familiarity and use, and normal and alcohol-related situational travel likelihood and use. The reported responses were statistically analyzed and used to develop models to represent the familiarity and use frequency of TNCs and travel behavior choices in alcohol-related situations. This thesis presents the resulting ordinal logit models of the familiarity and use frequency of TNCs and the multinomial logistic regression models to determine travel behavior of individuals in alcohol-related situations.

Based on the surveys, ordinal logit models were developed to predict the degree of familiarity and use frequency of TNCs. The dependent variable *familiarity with TNC* consisted of four levels: not familiar at all, somewhat unfamiliar, somewhat familiar, very familiar; and similarly use frequency was measured on a four-factor scale: never used, rarely, sometimes, often The results showed that income was significantly associated with both increased familiarity and increased use frequency of TNCs. Households with higher income are more likely to be able to pay for the service and the technology supporting the use of TNC services. The ability of TNCs to serve the needs of lower income households is an area for further research. Somewhat related to income, educational attainment was also significant and positively associated with familiarity and use frequency, i.e. with better education, individuals had a higher propensity of being familiar with and using TNCs. Age was significantly and negatively associated with TNC familiarity and use frequency which suggests that older adults(age>60) are less likely to be familiar with and use TNCs. This may be important in understanding TNC use in locations with older populations. Individuals located in Northern Virginia (where it started its operation in 2011 compared to the Richmond urban area and Hampton Roads where it started its operation in 2014) were associated with increased TNC familiarity and use frequency. This suggests that duration of such services in the market might be a crucial factor. Individuals who used multiple modes to commute had a higher likelihood of being familiar with and using TNCs more frequently, which is reasonable since individuals using multimodal travel would be more likely to explore alternate options to meet their travel demand. This may also secondarily support the consideration that TNCs contribute to travel options for the last mile connectivity issue associated with public transportation. Use of an app for sourcing taxi services was associated with increased TNC familiarity and use frequency. Similarly, using an app for hotel reservations and/or air transportation arrangements was associated with increased TNC use frequency. In addition, individuals using their phone for entertainment were more likely to be familiar with and use TNCs. Since these apps basically use the same concept of sourcing services from cellphones, it is reasonable that comfort with similar apps was associated with an increase in TNC familiarity and use. Use of mobile wallet was associated with increased TNC familiarity and use frequency, probably because these services involve payment for their services through such wallets and credit cards. Employment status “student” was significantly associated with TNC familiarity which suggests that information is easily accessible for this group of people. Also, individuals self-identifying their race as white had a higher probability of using TNCs which might be because Uber offers better service (less wait time) in areas with a higher white population, which could lead to correspondingly greater familiarity with and use of these services (1).

The second part of the research analysis included multinomial logistic regression models which identified factors associated with respondents’ travel choices in alcohol-related situations: (1) the last time the respondent consumed alcohol, (2) when avoiding driving after drinking, and (3) when avoiding riding with a driver who had been drinking. From the model results, it was found that consumption of alcohol at a bar was statistically associated with use of TNC services in all three alcohol-related situations. For situation (1), consuming alcohol at a bar was associated with a reduction in the likelihood of driving a personal vehicle compared to using TNCs. The number of people driving the last time they consumed alcohol (anywhere) was still the largest of any of the options. When only considering those who last drank at a bar, slightly more people used a TNC than drove a personal vehicle. In situation (2), personal vehicles were not an option. Riding with designated drivers was the most popular choice but TNC use was close behind and more common than calling a friend or family member for a ride. In situation (3), consumption of alcohol at a bar was not associated with driving a personal vehicle, but it did encourage TNC use compared to calling a friend or family member. These two alternatives, together, comprised most of the selections for this alcohol scenario. Targeted advertising of TNCs in bars and other alcohol serving establishments may further encourage use of TNCs.

TNCs were more likely to be used by younger people in all three alcohol-related situations examined in this study. Older people were more likely to ride with designated drivers than to use TNCs when avoiding driving after drinking and the last instance of consuming alcohol. Older respondents may have been educated on the importance of designated drivers while younger respondents may see TNCs as an alternative to the traditional designated driver.

Familiarity with, and regular use of TNCs increased the likelihood of using TNCs in all three alcohol-related situations in this study. As knowledge of and experience with the option in general increase and TNCs increase market penetration in a given area as well as in new areas, it is likely that the use of these services in alcohol-related situations will grow.

TNC services are often arranged with cell phone technology. It was not surprising that variables reflecting comfort with and use of this technology were associated with the selection of TNCs in alcohol-related situations. The significant variables-using an app for hotel reservations or air transportation, using a smartphone for entertainment, and comfort with a credit card tied to an app – varied by alcohol-related scenario but all increased the likelihood of using TNCs compared to at least one alternative. As smartphones and their use increase and as TNC availability increases, TNC use could be expected to increase as well. However, some travelers may exchange TNC services for other options with a sober driver. Continued education on the perils of drinking and driving and the penalties of being caught driving under the influence should remain part of any initiative to shift individuals who consume alcohol away from driving personal vehicles.

TNC services require payment, thus it was not surprising that households with higher incomes were more likely to use TNCs in the first two situations. In the first situation, the alternative of driving a personal vehicle did not have income as a significant variable, suggesting that income did not influence the decision between TNCs and driving. Although, TNCs contribute to the option set for travel choice after consumption of alcohol, they may also create competition with other modes (e.g., with taxis or designated drivers). This issue could be investigated in future studies.

7.2. CONTRIBUTIONS OF THIS STUDY

This thesis contributes to the field of mode choice, and travel behavior, in general. The first part of the study improves understanding of the characteristics of early adopters of TNC services, while the second part of the study contributes towards understanding travel choices made by individuals in alcohol-related situations. This study incorporates the increasing variety of alternate transportation modes, which includes services like TNCs, and models the degree of familiarity and use frequency of these in general situations and travel choice behaviors in alcohol-related situations, considering a wide variety of options including the option of staying over at the place of alcohol consumption.

The study helps to bridge the gap in the travel behavior literature, regarding early adopters and the travel behavior in alcohol-related situations with the advent of TNCs. The thesis identified numerous factors that are associated with early TNC adopters such as younger people who are comfortable with (and users of) technology being more familiar with and more frequent users of TNC services. The significant factors, which were associated with the travel choice in alcohol-related situations, revealed that TNCs were more likely to be used by younger people and familiarity with, and regular use of TNCs increased the likelihood of using TNCs in such situations. These results confirmed common sense expectations.

These results can be considered by agencies to expand and better target programs for reducing DUIs by taking into consideration alternate modes and directing countermeasures for deterring alcohol-impaired driving to specific populations. The points identified during this research can provide a better understanding of the factors that play a role in decision making for individuals in such situations. Also, this study's results can be used by regional planning authorities to understand who might use TNCs in their region, which could affect predictions of mode choice and vehicle miles traveled in their respective regions.

7.3. FUTURE RESEARCH DIRECTIONS AND RECOMMENDATIONS

Considering that this decade has seen the exponential growth of TNCs (2,3), studies designed to understand the early adopter of these new mode choices and the travel choice adaptation behavior in alcohol-related situations are important. Future related research should consider larger, more diverse samples across different regions of United States. More complex models such as joint models of familiarity and use frequency should be explored.

Possible research areas could also include a) cost analysis of public transportation, TNCs, taxis, and per trip personal vehicle costs which may reveal information on the cost efficiency of different modes for different individuals in different income brackets and locations and b) analysis of the effect of targeted ads in social networks on the influence of mode choice and reducing risk behavior among individuals. These would provide additional insight into factors that have an impact on user behavior on travel choice in alcohol-related situations. The results of this study show that travel choice is affected by characteristics such as use of a personal vehicle to arrive at the location where consuming alcohol, being comfortable with having a credit card tied to a cell phone app, age, income which can be leveraged for designing strategies to prevent DUIs.

By acquiring sufficient knowledge on the travel choice behaviors and identifying strategies to reduce impaired driving, agencies like Virginia DMV have more complete information to target education and enforcement campaigns to better address DUIs. Examples of such strategies include advertising the availability and importance of using TNCs in bars and other establishments that serve alcohol(since consuming alcohol at a bar increased the likelihood of using TNCs compared to using personal vehicles) and educating adults about the use and benefits of TNCs as an alternative travel mode in alcohol-related situations(since with increasing age, individuals were more likely to use modes other than TNCs, as they might have been educated on the benefits of using modes like using designated driver in such situation).

7.4. REFERENCES

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