University Transportation Research Center - Region 2

Final Report

Investigating Public Opinions towards Emerging Transportation Technologies and Service Forms

Performing Organization: Rensselaer Polytechnic Institute

August 2018

Sponsor:
University Transportation Research Center - Region 2

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The Region 2 University Transportation Research Center (UTRC) is one of ten original University Transportation Centers established in 1987 by the U.S. Congress. These Centers were established with the recognition that transportation plays a key role in the nation's economy and the quality of life of its citizens. University faculty members provide a critical link in resolving our national and regional transportation problems while training the professionals who address our transportation systems and their customers on a daily basis.

The UTRC was established in order to support research, education and the transfer of technology in the field of transportation. The theme of the Center is "Planning and Managing Regional Transportation Systems in a Changing World." Presently, under the direction of Dr. Camille Kamga, the UTRC represents USDOT Region II, including New York, New Jersey, Puerto Rico and the U.S. Virgin Islands. Functioning as a consortium of twelve major Universities throughout the region, UTRC is located at the CUNY Institute for Transportation Systems at The City College of New York, the lead institution of the consortium. The Center, through its consortium, an Agency-Industry Council and its Director and Staff, supports research, education, and technology transfer under its theme. UTRC's three main goals are:

Research

The research program objectives are (1) to develop a theme based transportation research program that is responsive to the needs of regional transportation organizations and stakeholders, and (2) to conduct that program in cooperation with the partners. The program includes both studies that are identified with research partners of projects targeted to the theme, and targeted, short-term projects. The program develops competitive proposals, which are evaluated to insure the mostresponsive UTRC team conducts the work. The research program is responsive to the UTRC theme: "Planning and Managing Regional Transportation Systems in a Changing World." The complex transportation system of transit and infrastructure, and the rapidly changing environment impacts the nation's largest city and metropolitan area. The New York/New Jersey Metropolitan has over 19 million people, 600,000 businesses and 9 million workers. The Region's intermodal and multimodal systems must serve all customers and stakeholders within the region and globally.Under the current grant, the new research projects and the ongoing research projects concentrate the program efforts on the categories of Transportation Systems Performance and Information Infrastructure to provide needed services to the New Jersey Department of Transportation, New York City Department of Transportation, New York Metropolitan Transportation Council , New York State Department of Transportation, and the New York State Energy and Research Development Authorityand others, all while enhancing the center's theme.

Education and Workforce Development

The modern professional must combine the technical skills of engineering and planning with knowledge of economics, environmental science, management, finance, and law as well as negotiation skills, psychology and sociology. And, she/he must be computer literate, wired to the web, and knowledgeable about advances in information technology. UTRC's education and training efforts provide a multidisciplinary program of course work and experiential learning to train students and provide advanced training or retraining of practitioners to plan and manage regional transportation systems. UTRC must meet the need to educate the undergraduate and graduate student with a foundation of transportation fundamentals that allows for solving complex problems in a world much more dynamic than even a decade ago. Simultaneously, the demand for continuing education is growing – either because of professional license requirements or because the workplace demands it – and provides the opportunity to combine State of Practice education with tailored ways of delivering content.

Technology Transfer

UTRC's Technology Transfer Program goes beyond what might be considered "traditional" technology transfer activities. Its main objectives are (1) to increase the awareness and level of information concerning transportation issues facing Region 2; (2) to improve the knowledge base and approach to problem solving of the region's transportation workforce, from those operating the systems to those at the most senior level of managing the system; and by doing so, to improve the overall professional capability of the transportation workforce; (3) to stimulate discussion and debate concerning the integration of new technologies into our culture, our work and our transportation systems; (4) to provide the more traditional but extremely important job of disseminating research and project reports, studies, analysis and use of tools to the education, research and practicing community both nationally and internationally; and (5) to provide unbiased information and testimony to decision-makers concerning regional transportation issues consistent with the UTRC theme.

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Abstract

Technology advancement is bringing many changes to the transportation system. Some well- known examples are connected and autonomous vehicles and on-demand mobility services (including the ride-hailing services such as Uber and on-demand home deliveries). In short term, these emerging technologies and services may enhance the efficiency of transportation system operation, improve traffic condition and residents' quality of life. In long term, they will change people's perception of travel time and traffic safety conditions, and reshape their behavior. It has already been shown that the on-demand deliveries increase freight trips without reducing personal shopping trips. Policy makers are concerned that these new technologies and service forms may further reduce people's perceived travel costs, inducing more travel activities and longer commuting distances, adding to the current congestion and urban sprawl conditions, and resulting in increased externalities. Some innovative demand management initiatives are thus being investigated, including new pricing schemes, new ride matching algorithms, and new facility planning and operation strategies. This research project conducted survey to acquire reliable public opinion information in a cost effective way. Based on an integrated dataset that contains comprehensive information about NYS residents' socioeconomic characteristics, built environment, and their attitudes, the paper then conducted descriptive and comparative data analysis that describes the characteristics of public opinions. A set of calibrated econometric models were developed to quantitatively explain the connections between residents' socioeconomic features and their attitudes towards technologies, service forms, their behavioral responses, and demand management initiatives.

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TABLE OF CONTENTS

1. INTRODUCTION

Throughout history, humans have been using technology to simplify a wide variety of processes. In recent years, there has been a significant shift in how people use the transportation system. This affects not only how individuals move around, but also how people obtain goods. At the same time, companies have been attempting to use new transportation technologies to both reduce costs and gain a larger market share, while local governments want to use new transportation technology to reduce congestion. Because of these new technologies, we are seeing new jobs and methods of obtaining goods appear, while traditional occupations and purchase methods go by the wayside. Autonomous vehicles are entering the initial stages of on-road testing and many new vehicles have begun to incorporate some autonomous technologies. There are increasing trends toward de-centralized methods of distributing goods and new technologies that could possibly make the transportation system more efficient.

With the rapid pace at which technology is evolving, it is necessary to continuously reassess public opinion regarding new trends in transportation. For this reason, a survey of New York residents was conducted in the spring of 2017. New York is a unique environment for emerging trends in transportation for several reasons. At the time of the survey, fully autonomous vehicles were not street-legal in the state, so most potential respondents had little to no in-person experience with this transportation trend. Certain other trends, such as delivery lockers, had been making inroads in the state, while crowd delivery programs had become widespread through GrubHub and related services, but still limited to urban and denser suburban areas.

This final report has five main focus areas. The first area, *Survey Description*, introduces the data collection process. The second area, *Data Description,* provides a general overview of the survey results. The third area, *Adoption of Delivery Lockers,* discusses respondents' familiarity with and opinions regarding delivery lockers. The fourth area, *Adoption of Crowd Deliveries,* discusses the familiarity of respondents with crowd deliveries. The fifth area, *Adoption of Autonomous Vehicles*, discusses opinions concerning autonomous vehicles.

2. Focus Area I: Survey Description

To adequately measure public opinion regarding an issue, the research population must be defined. In this project, we decided to survey residents of New York State using an online survey distributed via email. A list of approximately 62,000 randomly-selected email addresses belonging to New York residents was purchased from National Data Group. While not the preferred method of completing a survey, this is a fast method that, in theory, obtains a random sample of state residents.

The survey was designed to obtain as much information from the respondents as possible through relatively few questions. The first part of the survey collects demographic information from respondents, followed by information regarding shopping behavior. In the second part of the survey, respondents are asked about each of three emerging trends: delivery lockers, crowd delivery, and autonomous vehicles, specifically opinions regarding each of these trends and usage patterns. Based on answers to previous questions, respondents may have been asked follow-up questions.

Before full survey implementation, two rounds of pilot testing were conducted. Initially, the survey were given to friends and family members, evaluating the questions and assessing the time required to complete the survey. Once the survey was refined, a second round of pilot testing was conducted, using a randomly selected subset of the email list. 4,809 emails were sent using three different subject lines, of which 3,369 hit an inbox. The intent was to determine which subject line had the highest open rate in order to maximize the number of potential responses. The second round pilot test was sent at approximately 7:30 PM on Monday, April 10, 2017. The winning subject line was "NYS Research in Transportation: Inputs needed", with 11.63% of recipients opening the email.

Based on the pilot test results, the survey email was eventually sent to the remainder of the email list. The full solicitation email was sent at approximately 9:30 AM on Wednesday, April 12, 2017. 55.63% of the total sent hit an inbox. A reminder was sent at approximately 2:30 PM on Monday, April 17, 2017 to all individuals who had not opened the initial email. This reminder was modified to remove certain traits that may trigger spam filters, achieving a 73.49% hitting rate. The survey period concluded at 12:50 PM on Friday, April 21, 2017, at which point responses were downloaded.

In practice, using a purchased email list created many issues. As mentioned above, a large percentage of the sent survey emails did not reach an inbox for a variety of reasons. Most mass services do not allow the use of purchased lists, while many email providers block incoming emails from services that allow purchased lists. Of the emails that hit inboxes, the vast majority were not opened, while an even smaller amount produced responses. 59 responses were received, of which five were omitted for not providing a valid New York ZIP code.

The final questionnaire is provided in Appendix 1.

3. Focus Area II: Data Description

As mentioned in the previous section, 54 valid responses were obtained after invalid ZIP codes were removed. Of the 54 records providing complete information, 55.6% of the respondents were female, while 44.4% were male. Table 1, shown below, lists the age breakdown of respondents.

Table 1: Age Distribution

Age	26-34	35-44	45-54	55-64	65-74	75+
Percentage	5.6%	18.5%	27.8%	25.9%	16.7%	5.6%

The age distribution of the sample is heavily skewed toward the right, with respondents older than the general population on average. The median age of the distribution falls inside the 45-54 bracket, and there are no respondents under 26 years old.

Table 2 shows the income distribution of the sample. The income distribution is also highly skewed to the right, with the median lying inside the \$90,000 - \$109,000 bracket. A slight right skew is to be expected, as the lowest income levels are less likely to have internet access readily available. The highest percentage of incomes fall between \$30,000 and \$109,999, but there is no defined "peak", likely due to the small sample size.

Table 2: Income Distribution

Income	**Percentage**	**Income**	**Percentage**
Under $10,000	1.9%	$110,000 - $129,999	7.4%
$10,000 - $29,999	1.9%	$130,000 - $149,999	7.4%
$30,000 - $49,999	14.8%	$150,000 - $169,999	3.7%
$50,000 - $69,999	14.8%	$170,000 - $189,999	3.7%
$70,000 - $89,999	11.1%	$190,000 and above	11.1%
$90,000 - $109,999	13.0%	Prefer not to answer	9.3%

Table 3 summarizes the sample's education level distribution. 70.4% of the sample has a college degree of any level, with 59.3% having a bachelor's degree or higher and 42.6% having a graduate degree. This is a significant skew toward highly-educated individuals, as the proportion of population with a bachelor's or graduate degree is near ⅓ in the state.

Table 3: Education Levels

Education Level	Percentage	Education Level	Percentage
High School Graduate	3.7%	Associate's Degree	11.1%
Vocational Training	3.7%	Bachelor's Degree	16.7%
Some College	22.2%	Graduate Degree	42.6%

To gather information on location-based differences, the survey also asked respondents for the ZIP code they reside in. While this method could theoretically be used to estimate a likelihood for every community in the state, the small number of responses forced grouping respondents into four groups: New York City, Long Island, lower Hudson Valley and Upstate. New York City is defined as the five boroughs contained within the city limits, while Long Island is the entirety of Nassau and Suffolk Counties. For the lower Hudson Valley, the boundary between "Upstate" and "Downstate" is subject to much debate, so we roughly used areas that are serviced by commuter rail into New York City, as these areas are within New York City's sphere of influence more than places without frequent rail access. The "lower Hudson Valley" category included the entirety of Orange, Putnam, Rockland and Westchester counties, plus Dutchess County south of Poughkeepsie. 24.7% of the sample lives in New York City, 13.0% lives on Long Island and 16.7% lives in the lower Hudson Valley, with the remaining 46.3% living Upstate. Given that a simple random sample was used, the sample is slightly biased toward Upstate respondents.

All but one of the respondents (98.1%) have shopped online within the past 12 months. The remaining data in this paper only concerns individuals who have shopped online. Table 4 lists the online shopping frequency distribution for respondents who shopped online. The most common online shopping frequencies are once a month and three times a month, with these two containing almost half of our sample. Frequencies above once per week and the "other" frequency each had one respondent.

Table 4: Online Shopping Frequency

Frequency	Percentage	Frequency	Percentage
Every 3 months or less	11.3%	Once a week	5.7%
Every 2 months	18.9%	Twice a week	1.9%
Once a month	20.8%	Three times a week	1.9%
Twice a month	11.3%	Four or more times a week	1.9%
Three times a month	24.5%	Other	1.9%

Table 5 lists the percentage of respondents who purchase each category of good online. Note that respondents could select multiple categories. The items most commonly bought online by respondents are categorized as clothing, followed by books, household goods and electronics. Few respondents purchased an item that they did not put in one of these categories.

Table 5: Items Bought Online

Category	**Percentage**	**Category**	**Percentage**
Books	67.9%	Office Supplies	41.5%
Clothing	73.6%	Packaged Goods	15.1%
Electronics	52.8%	Pet Supplies	30.2%
Food	15.1%	Sporting Goods	32.1%
Household Goods	58.5%	Toys	18.9%
Home/Tools	41.5%	Other	3.8%
Luxury Goods	15.1%		

In addition, 50.9% of the respondents are members of Amazon Prime. This indicator could be potentially used as a proxy variable for willingness to shop online frequently. As Prime members have placed a financial investment and receive free expedited shipping, it is reasonable to believe that these individuals are, when pressed with a decision between shopping in stores or online, more likely to purchase online. 26.4% of respondents are members of an online subscription service.

4. Focus Area III: Adoption of Delivery Lockers

Each of the four topic areas had a dedicated subsection of the survey. These subsections contained questions specific to the area of interest. In the locker subsection, questions were asked regarding whether or not respondents had seen delivery lockers in the past, if they had used a delivery locker in the past, and conditions required for them to utilize a delivery locker in the future.

4.1 Data Description - Locker Survey

11.3% of respondents recall seeing a delivery locker, while 5.7% have actually used one in the past year. All users selected “unavailable for delivery at home” as one reason for using a locker. Table 6 shows the percentage of respondents selecting each likelihood value for using a delivery locker in the base case (no discount) and if a discount is provided. In the base case, the most common likelihood level is “likely”, followed by “unlikely”. “Extremely Unlikely” is the least common option. However, in the discount case, “unlikely” is the most common likelihood by far, with “extremely likely” and “likely” the two least common. When a discount was provided, 26.4% of respondents moved to a higher likelihood level, while 30.2% moved to a lower likelihood level. This is an unexpected result that may signal poor question wording or respondents not understanding the question as we intended it. For this reason, the likelihood of people to use a locker if provided with a discount was not modeled.

Table 6: Locker Usage Likelihood

Likelihood	Base (No Discount)	Discount
Extremely Likely	17.0%	15.1%
Likely	26.4%	15.1%
Neutral	18.9%	20.8%
Unlikely	24.5%	32.1%
Extremely Unlikely	13.2%	17.0%

Additionally, we asked about the longest distance one would travel to use a delivery locker. These distances were obtained in narrow categories, but these were combined in order to produce results that could be analyzed. Table 7 lists the distances obtained. The most common maximum distance was 5 miles, with 17% of total respondents, while 26.4% indicated they would not travel ANY distance to use a locker. Of the respondents who would travel to use a locker, the median maximum distance was 5 miles.

Table 7: Maximum Travel Distance

Maximum Distance	Percentage	Maximum Distance	Percentage
¼ mile or less	5.7%	5 miles	17.0%
½ mile	7.5%	10 miles	11.3%
1 mile	3.8%	20 miles	7.5%
2 miles	11.3%	Over 20 miles	1.9%
3 miles	7.5%	Would not use	26.4%

Figures 1a through 1i further shows the distributions of willingness level with respect to these key variables.

Figure 1a: Male vs Female

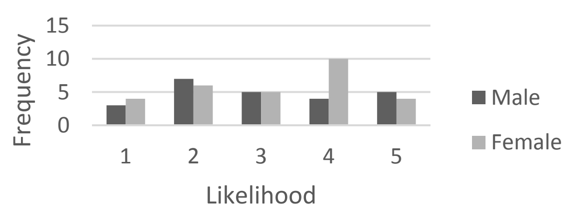


Figure 1b: Age Differences

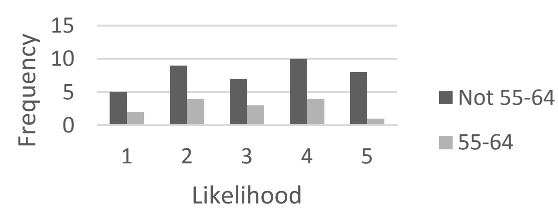


Figure 1c: Frequencies

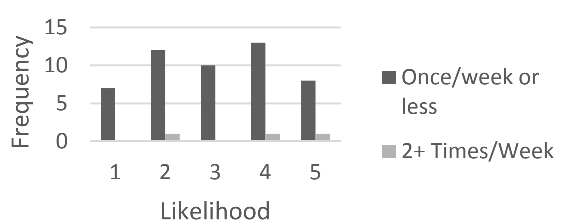


Figure 1d: Clothing

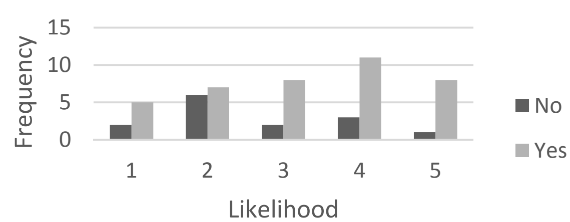


Figure 1e: Electronics

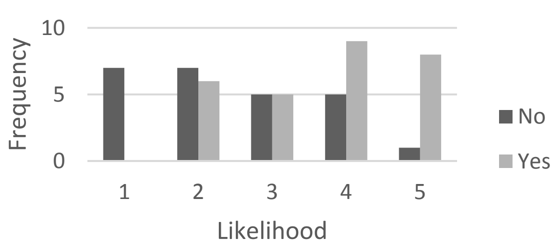
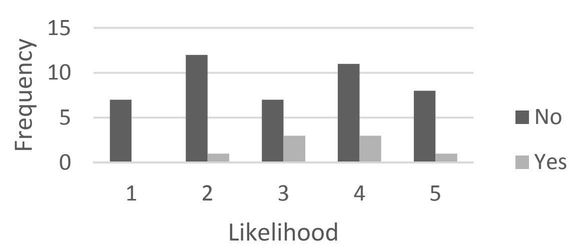
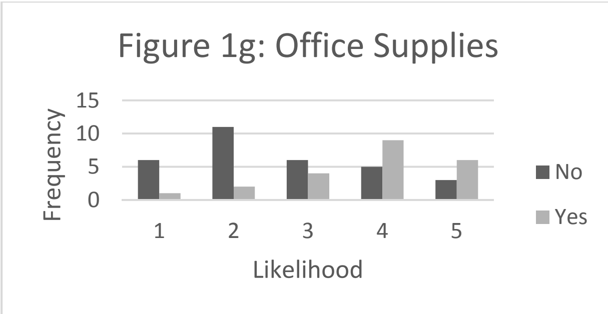
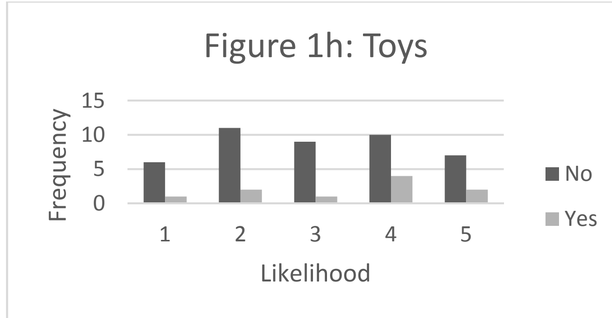


Figure 1f: Luxury Goods







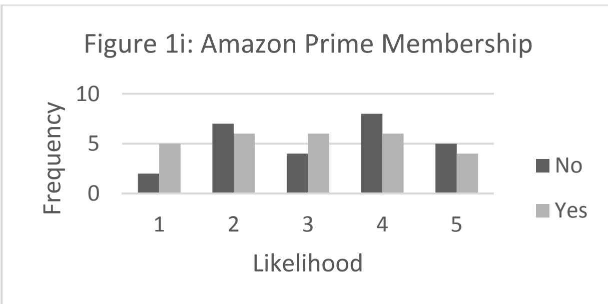


Figure 1a indicates that the most common response for women was "likely", compared to "not likely" for men. Figure 1b, exhibiting the differences between the two age groups, has similarly-shaped distributions for both age groups. The 55-64 group has "extremely likely" as the least common response, while the "other" group has "extremely unlikely" as the least common response. While Figure 1c does not provide much insight regarding high-volume users, it does indicate that the "unlikely" and "likely" responses are more common than the other three, showing that most people have some opinion regarding the use of delivery lockers. The likelihood of people who purchase clothing to use a locker has a noticeable peak at "likely" per Figure 1d, with those who do not having a peak at "not likely". No respondents who purchase electronics online are "extremely unlikely" to use a locker, with Figure 1e showing the frequency increasing with an increase in likelihood. Conversely, Figure 1e shows that individuals who do not purchase electronics are bunched at the "unlikely" end of the likelihood spectrum. Figure 1f shows that people that purchase luxury goods have a much flatter distribution with respect to likelihood of using a delivery locker than purchasers of any other category. Figure 1g has significant bunching at the "likely" end for people who purchase office supplies online, with significant bunching at the "unlikely" end for people who do not purchase office supplies online. Per Figure 1h, many people who purchase toys are on the "likely" end of the spectrum. Figure 1i indicates that Amazon Prime users plateaued in the middle three likelihood values, while other respondents had dual peaks at "likely" and "unlikely".

4.2 Willingness Analysis

The survey's main intent was to determine how likely a person is to use a delivery locker based on various factors. It was determined that the most logical type of model to use an ordered probit model. As the "extremely unlikely, unlikely, neutral, likely, extremely likely" ranking system we used is ordinal, the ordered probit model can be used, with 1 representing "extremely unlikely" and 5 representing "extremely likely".

Several ordered probit models were developed and compared in Stata 14.2. Due to the relatively-small dataset size, few variables were significant in the final models and only limited analysis could be completed. For these models, location and income were shown to be insignificant, as was any purchasing frequency of less than twice per week. Excluding the 55 to 64 age group, age was not a significant determinant of likelihood to use a delivery locker. Five of the nine significant independent variables are indicators categories of products purchased by respondents and a sixth is an indicator for Amazon Prime membership. Table 8 lists all variables used in the final model, while model results are contained in Table 9.

Table 8: Variable Definitions

Variable Name	Definition
LikelihoodLocker	Ordinal likelihood variable for a respondent's likelihood of using a delivery locker
Female	Indicator for a female respondent
Bt55to64	Respondent is between the ages of 55 and 64
x234Wk	Respondent shops online two or more times per week
Cloth	Buys clothes online
Elect	Buys electronics online
LuxGd	Buys luxury goods online
OffSup	Buys office supplies online
Toys	Buys toys online
Prime	Respondent is a member of Amazon Prime

Generally, the results of this model show that women are less likely to use a delivery locker than men. The 55 to 64 age group, the core of the "baby boomer" generation, is more likely to use lockers than other age groups. Extremely-frequent online shoppers that make an internet purchase at least twice per week are more likely to use lockers than those who purchase less frequently, generally increasing the predicted likelihood by approximately one level. Individuals who purchase electronics, clothing and office supplies, in order of decreasing effect on likelihood, have an increased likelihood to use delivery lockers, while those purchasing luxury goods and toys, in order of decreasing effect on likelihood, have a decreased likelihood to use delivery lockers. Amazon Prime members are less likely to use lockers than the general population. Due to the relatively small number of observations, it is not possible to obtain anything other than general trends from this model. Yet, it is evident that benefits would come from encouraging placement of lockers.

Table 9: Model Results

Variable	Coefficient	Standard Error	95% Confidence Interval	
Female	-0.6043†	0.3532	-1.2966	0.0881
Bt55to64	0.5686	0.4093	-0.2336	1.3707
x234Wk	1.4134†	0.7377	-0.0325	2.8593
Cloth	1.3847**	0.4422	0.5180	2.2513
Elect	1.7764***	0.4122	0.9685	2.5843
LuxGd	-1.0250*	0.4977	-2.0004	-0.0496
OffSup	1.2532**	0.3687	0.5306	1.9759
Toys	-0.8879*	0.4488	-1.7676	-0.0082
Prime	-0.8344*	0.3323	-1.4857	-0.1830
1-2 Boundary	-0.0415	0.4787	-0.9797	0.8966
2-3 Boundary	1.1660	0.4940	0.1978	2.1341
3-4 Boundary	1.8614	0.5212	0.8399	2.8828
4-5 Boundary	3.0317	0.5826	1.8898	4.1736
χ^2 Coefficient	35.52			
Probability > χ^2	0.0000			
Pseudo R^2	0.2241			
Log Likelihood	-64.9531			

NOTE: † = significant at 10% level, * = significant at 5% level, ** = significant at 1% level, *** = significant at 0.1% level

Listed in Table 10 are marginal effects generated from the estimated model. A positive marginal effect indicates that a likelihood level is more likely if the binary variable in question equals one, while a negative marginal effect indicates it is less likely if the variable in question equals one. The signs of marginal effects for a given variable can be inferred from the variable's model coefficient: variables with negative coefficients have positive effects for levels 1, 2 and 3 and negative effects for levels 4 and 5; this is reversed for variables with positive coefficients. No marginal effects are statistically significant for either gender or age, nor are they significant for likelihood level 3 (corresponding to a "neutral" response) for any variable. In all cases, magnitudes of effects had a minimum at level 3, increasing toward both extreme values (1 and 5). Effects for high-frequency online shoppers were marginally significant at levels 1, 2 and 4. For all five good types and Amazon Prime membership, all likelihood values other than 3 were significant at 10% or better. Electronics and luxury goods both had significance levels that were 1% or better, while clothing and Prime membership had all significance levels at 5% or better.

Table 10: Marginal Effects

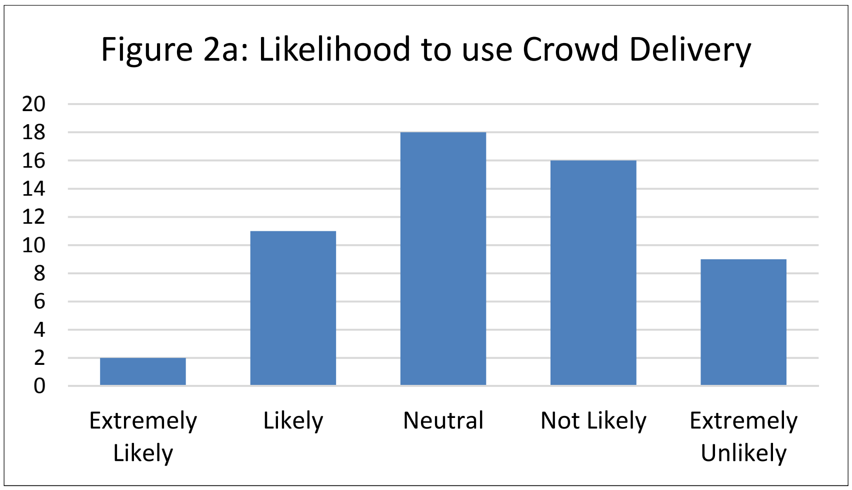
Variable	Likelihood Level	Marginal Effect	Standard Error	95% Confidence Interval	
Female	1	0.0887	0.0546	-0.0184	0.1958
	2	0.0645	0.0393	-0.0126	0.1416
	3	0.0038	0.0092	-0.0142	0.0218
	4	-0.0543	0.0346	-0.1221	0.0135
	5	-0.1027	0.0597	-0.2198	0.0143
Bt55to64	1	-0.0835	0.0613	-0.2036	0.0367
	2	-0.0607	0.0438	-0.1465	0.0251
	3	-0.0036	0.0093	-0.0218	0.0147
	4	0.0511	0.0362	-0.0199	0.1221
	5	0.0967	0.0718	-0.0440	0.2374
x234Wk	1	-0.2075†	0.1138	-0.4306	0.0156
	2	-0.1509†	0.0834	-0.3144	0.0125
	3	-0.0086	0.0220	-0.0520	0.0342
	4	0.1270	0.0733	-0.0166	0.2706
	5	0.2403†	0.1263	-0.0073	0.4879
Cloth	1	-0.2033**	0.0686	-0.3377	-0.0689
	2	-0.1479*	0.0599	-0.2653	-0.0304
	3	-0.0087	0.0215	-0.0509	0.0335
	4	0.1244*	0.0542	0.0182	0.2306
	5	0.2354**	0.0750	0.0884	0.3824
Elect	1	-0.2608***	0.0731	-0.4041	-0.1174
	2	-0.1897**	0.0569	-0.3012	-0.0782
	3	-0.0112	0.0272	-0.0645	0.0422
	4	0.1596**	0.0526	0.0565	0.2627
	5	0.3020***	0.0744	0.1561	0.4479
LuxGd	1	0.1505†	0.0788	-0.0039	0.3049
	2	0.1095†	0.0593	-0.0067	0.2256
	3	0.0064	0.0152	-0.0233	0.0362
	4	-0.0921†	0.0557	-0.2012	0.0170
	5	-0.1743*	0.0793	-0.3297	-0.0188
OffSup	1	-0.1840**	0.0615	-0.3046	-0.0634
	2	-0.1338**	0.0477	-0.2272	-0.0404
	3	-0.0079	0.0190	-0.0450	0.0293
	4	0.1126**	0.0433	0.0278	0.1974
	5	0.2131**	0.0627	0.0902	0.3359
Toys	1	0.1304†	0.0670	-0.0011	0.2618
	2	0.0948†	0.0545	-0.0120	0.2016
	3	0.0056	0.0141	-0.0220	0.0331
	4	-0.0798†	0.0476	-0.1732	0.0136
	5	-0.1510*	0.0764	-0.3006	-0.0013
Prime	1	0.1225*	0.0497	0.0251	0.2199
	2	0.0891*	0.0418	0.0073	0.1709
	3	0.0052	0.0134	-0.0210	0.0315
	4	-0.0750*	0.0367	-0.1470	-0.0030
	5	-0.1419*	0.0582	-0.2559	-0.0278

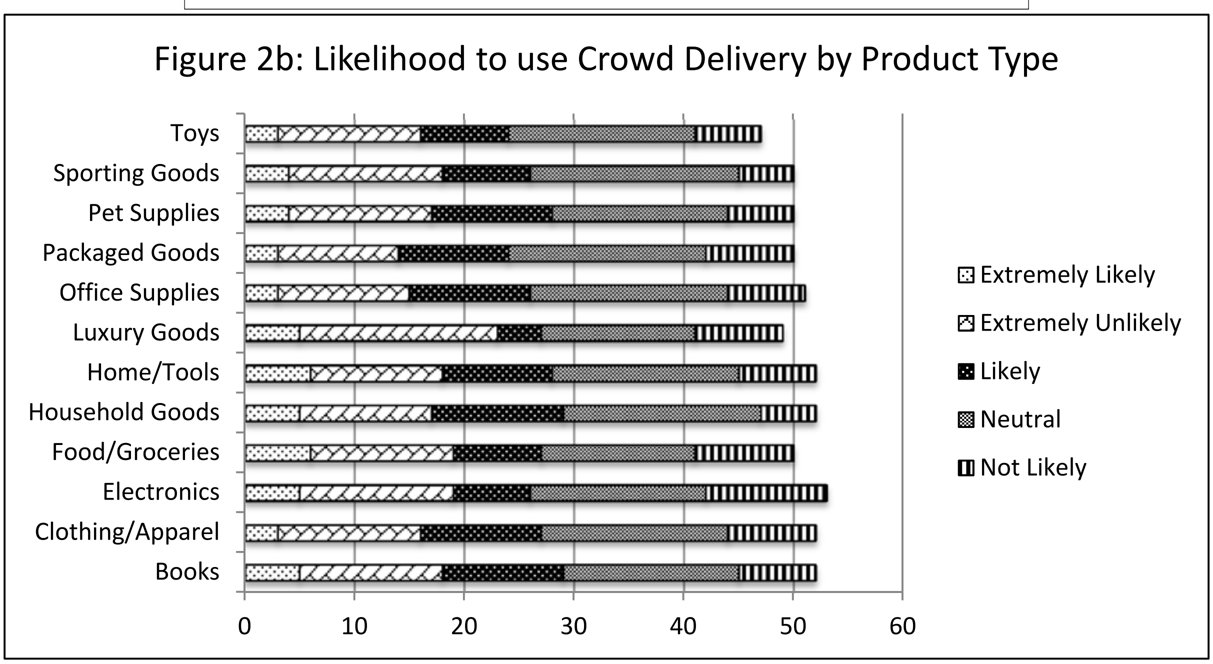
NOTE: † = significant at 10% level, * = significant at 5% level, ** = significant at 1% level, *** = significant at 0.1% level

5. Focus Area IV: Adoption of Crowd Deliveries

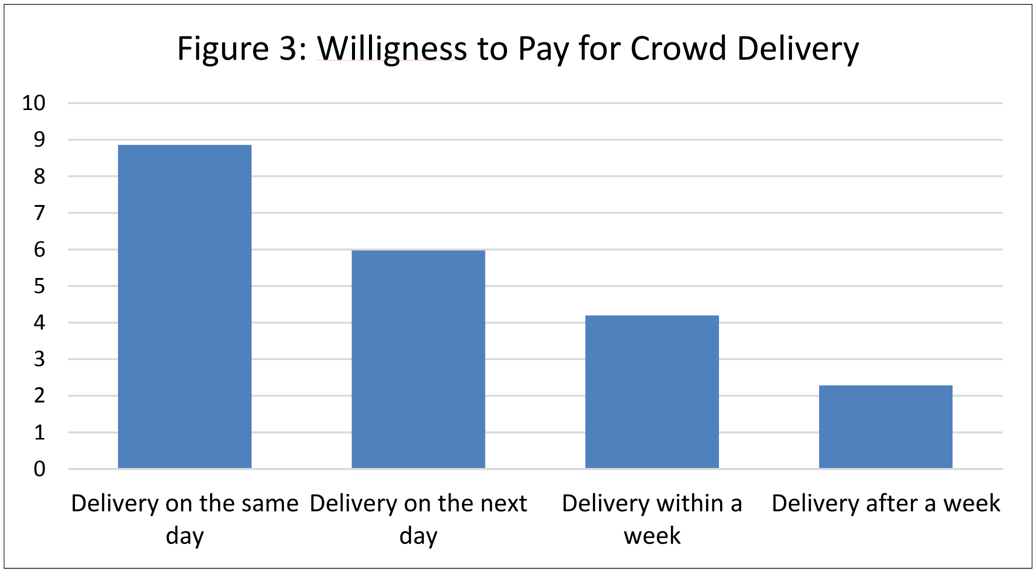
5.1 Data Description: Crowd Deliveries Survey

In the crowd deliveries section of the survey, respondents were asked if they were familiar with the concept of crowd deliveries, their likelihood to utilize crowd delivery services both in general and for specific product types, and whether or not they would act as a driver for a crowd delivery service. 90% of respondents understood the general concept of "crowd delivery", which can be defined as using a pool of independent individuals to make deliveries instead of a courier service. Figure 2a shows the overall likelihood of respondents to utilize a crowd delivery service, while Figure 2b shows the likelihood for various product types.





The most common response is “neutral”, but “not likely” and “extremely unlikely” are far more common than “likely” and “extremely likely”. This may be related to the high median age of survey respondents. Respondents are far less likely to use crowd delivery services for expensive goods than less expensive goods. Figure 3 shows the amount respondents were willing to pay for crowd delivery.



Unsurprisingly, respondents were willing to pay more for crowd delivery services with a short delivery time. 16% of the sample was interested in becoming a crowd delivery driver. Table 11 lists possible reasons given by respondents for not using crowd delivery.

Table 11: Reasons for Not Using Crowd Delivery

Reason	Frequency
I do not trust other people handling my goods	25
I prefer a courier service because it is more reliable	22
I can't think of a reason for not using crowd deliveries	11
Concern about security/damage	7
I do not like trying new things	1
I am not sure I understand it	1
Need to know more	1
Depends on the cost	1
Most likely not available near me	1
Other reasons	4

Slightly under half of respondents indicated that they do not trust other people handling their goods, with a similar amount indicating they prefer a courier service.

5.2 Methodology

Given the ordinal format of the likelihood variable, an ordered logit model was determined to be the best fit. In an ordered logit model, similar to the ordered probit model, responses are on an ordinal scale. With the case of crowd delivery, responses were on a scale of 1 to 5. 1 indicated "extremely likely", 3 indicated "neutral", and 5 indicated "extremely unlikely". Due to the lack of responses, all "extremely likely" and "likely" responses were combined and labeled "1", neutral responses were labeled "2", and "not likely' and "extremely unlikely" responses were combined and labeled "3". The observed ratings could eventually determine the odds or probability by the following equations:

$$\theta_1 = \frac{prob(rating = 1,2)}{prob(rating > 2)}$$

$$\theta_2 = \frac{prob(rating = 1,2,3)}{prob(rating > 3)}$$

$$\theta_3 = \frac{prob(rating = 1,2,3,4,5)}{prob(rating > 5)}$$

Which can be generalized as:

$$\theta_j = \frac{prob(rating \leq j)}{1 - prob(rating \leq j)}$$

From this, the ordered logit model is defined as follows:

$$\ln(\theta_j) = \alpha_j - \sum \beta_i X_{ij}$$

Where α_j is the threshold value for each likelihood level and β_i are coefficients.

5.3 Results Analysis

Ordered logit models to predict the likelihood of respondents to utilize crowd delivery services were developed for both the general case and each individual product type. The ordered model included geographic, socioeconomic and demographic variables, as well as e-commerce related variables. Resulting models show only statistically significant variables at an 80% confidence level. Table 12 lists variables used in these models.

Table 12: Variables for Crowd Delivery Models

Variables	Description
cdlevels	Level of likelihood of Crowd deliveries (more likely=1, neutral=2, more unlikely=3)
pop	Population per zip code
hunits	Housing units per zip code
landsqmi	Land area in square miles per Zip Code
female	1 if female, 0 if male
age	Age of respondent
inc_low	Low Income: Annual Income less than USD$50,000
inc_med	Medium Income: Annual Income between USD $50,000 and USD $109,999
ugrad	Undergraduate level of education (Associate or Bachelor's degree)
grad	Graduate level of education
week	Frequency for buying online is once or multiple times in one week
month	frequency for buying online is once or multiple times in one month
empl	1 if currently employed, 0 otherwise

5.3.1 General Model

Table 13 lists results for the general model.

Table 13: General Model Results

Levels:	More Likely = 1, Neutral = 2, Less Likely=3					
Variables	**Parameter**	**St.Error**	**t-stat**	**P-Value**	**95% Confidence Interval**	
landsqmi	0.019	0.014	1.37	0.169	-0.008	0.046
age	0.03	0.02	1.49	0.136	-0.009	0.069
inc_low	-2.046	0.812	-2.52	0.012	-3.637	-0.454
inc_med	-2.186	0.736	-2.97	0.003	-3.629	-0.743
/cut1	-0.794	1.236			-3.218	1.629
/cut2	0.751	1.251			-1.701	3.203
Model Statistics						
Number of Observations		50		Prob > c		0.005
LR Chi2		14.86		Pseudo R		0.1396

The positive coefficient for land area indicates that respondents in larger ZIP codes are less likely to use crowd delivery, as were older respondents. This is not surprising, as rural and older individuals are generally slower to adopt new trends. Households with an annual income under $110,000 are more likely to utilize crowd delivery than wealthier households.

5.3.2 Books

The remainder of the models in this section consider only one commodity. Table 14 lists results for the model considering only books.

Table 14: Model Results, Books

Levels:	More Likely = 1, Neutral = 2, Less Likely=3					
Variables	**Parameter**	**St.Error**	**t-stat**	**P-Value**	**95% Confidence Interval**	
age	0.049	0.021	2.36	0.018	0.008	0.089
inc_low	-1.077	0.781	-1.38	0.168	-2.607	0.453
inc_med	-1.251	0.642	-1.95	0.051	-2.509	0.006
/cut2	0.903	1.137			-1.325	3.131
/cut2	2.172	1.173			-0.127	4.471
Model Statistics						
Number of Observations		50		Prob > c		0.0217
LR Chi2		9.66		Pseudo R		0.0895

In the case of books, the model is not particularly conclusive, only explaining 9% of the variability of the data. This could be due to the level of randomness in responses for this category. The key variables present in the general model, age and income, were present here with similar trends.

5.3.3 Clothing/Apparel

Table 15 lists results for the model considering only clothing and apparel.

Table 15: Model Results, Clothing/Apparel

Levels:	More Likely = 1, Neutral = 2, Less Likely=3					
Variables	**Parameter**	**St.Error**	**t-stat**	**P-Value**	**95% Confidence Interval**	
landsqmi	0.017	0.014	1.26	0.209	-0.01	0.044
age	0.051	0.025	2.04	0.041	0.002	0.1
inc_med	-1.196	0.596	-2.01	0.045	-2.364	-0.029
ugrad	1.27	0.873	1.45	0.146	-0.442	2.982
grad	1.166	0.861	1.35	0.176	-0.521	2.853
empl	-1.473	1.107	-1.33	0.183	-3.642	0.697
/cut2	0.965	1.793			-2.549	4.478
/cut2	2.504	1.832			-1.086	6.095
Model Statistics						
Number of Observations		50		Prob > c		0.0132
LR Chi2		16.1		Pseudo R		0.1499

While many factors were similar to the general model, new variables are present in the model for clothing. Increasing education level results in a lower likelihood of using crowd deliveries for clothing, while currently employed respondents were more likely to use crowd deliveries.

5.3.4 Electronics

Table 16 lists results for the model considering only electronics.

Table 16: Model Results, Electronics

Levels:	More Likely = 1, Neutral = 2, Less Likely=3					
Variables	**Parameter**	**St.Error**	**t-stat**	**P-Value**	**95% Confidence Interval**	
age	0.035	0.021	1.7	0.089	-0.005	0.075
inc_low	-1.369	0.806	-1.7	0.089	-2.949	0.211
inc_med	-1.784	0.706	-2.53	0.012	-3.169	-0.400
month	-0.842	0.586	-1.44	0.151	-1.991	0.307
/cut2	-1.063	1.254			-3.520	1.394
/cut2	0.333	1.244			-2.106	2.771
Model Statistics						
Number of Observations		50		Prob > c		0.0192
LR Chi2		11.76		Pseudo R		0.1132

Trends for electronics generally reflected those in the general model. The *month* variable, not present in the general model, indicates that respondents who shop online 1 to 3 times per month were more likely to accept crowd deliveries.

5.3.5 Food/Groceries

Table 17 lists results for the model considering only food and groceries.

Table 17: Model Results, Food/Groceries

Levels:	More Likely = 1, Neutral = 2, Less Likely=3					
Variables	**Parameter**	**St.Error**	**t-stat**	**P-Value**	**95% Confidence Interval**	
age	0.053	0.022	2.45	0.014	0.011	0.095
grad	0.790	0.546	1.45	0.148	-0.281	1.860
month	-0.699	0.541	-1.29	0.196	-1.759	0.361
/cut2	1.493	1.160			0.781	3.767
/cut2	2.754	1.201			0.400	5.108
Model Statistics						
Number of Observations		56		Prob > c		0.0189
LR Chi2		9.96		Pseudo R		0.0855

This model combines several trends from the general model and other commodity models. Older and more-educated individuals are less likely to accept crowd deliveries for food, but frequent online shoppers are more likely to accept crowd deliveries.

5.3.6 Household Goods

Table 18 shows results for the model considering only household goods.

Table 18: Model Results, Household Goods

Levels:	More Likely = 1, Neutral = 2, Less Likely=3					
Variables	**Parameter**	**St.Error**	**t-stat**	**P-Value**	**95% Confidence Interval**	
landsqmi	0.017	0.012	1.34	0.181	-0.008	0.041
age	0.057	0.022	2.56	0.011	0.013	0.101
inc_low	-1.077	0.749	-1.44	0.15	-2.544	0.391
inc_med	-1.285	0.655	-1.96	0.05	-2.568	-0.002
/cut2	1.771	1.330			-0.837	4.379
/cut2	3.297	1.392			0.570	6.024
Model Statistics						
Number of Observations		50		Prob > c		0.0152
LR Chi2		12.31		Pseudo R		0.1123

Trends here are nearly identical to the general case, with an identical set of included variables. This may be due to the more generalized nature of this commodity type.

5.3.7 Home/Tools

Table 19 shows results for the model considering home and tool items.

Table 19: Model Results, Home/Tools

Levels:	More Likely = 1, Neutral = 2, Less Likely=3					
Variables	**Parameter**	**St.Error**	**t-stat**	**P-Value**	**95% Confidence Interval**	
landsqmi	0.018	0.013	1.38	0.168	-0.007	0.043
age	0.061	0.023	2.68	0.007	0.016	0.105
inc_low	-1.448	0.767	-1.89	0.059	-2.952	0.056
inc_med	-1.509	0.672	-2.24	0.025	-2.826	-0.191
/cut2	1.634	1.315			-0.943	43.212
/cut2	3.124	1.372		0.435	5.814	6.024
Model Statistics						
Number of Observations		50		Prob > c		0.0057
LR Chi2		14.55		Pseudo R		0.1338

As with household goods, this model is very similar to the general model, possibly due to the wide variety of items in the category.

5.3.8 Luxury Goods

Table 20 shows results for the model considering only luxury goods.

Table 20: Model Results, Luxury Goods

Levels:	More Likely = 1, Neutral = 2, Less Likely=3					
Variables	**Parameter**	**St.Error**	**t-stat**	**P-Value**	**95% Confidence Interval**	
age	0.035	0.023	1.53	0.127	-0.010	0.079
inc_low	-0.957	0.881	-1.09	0.277	-2.684	0.769
inc_med	-1.153	0.685	-1.68	0.093	-2.496	0.190
empl	-1.573	1.201	-1.31	0.19	-3.928	0.781
/cut2	-1.998	1.885			-5.693	1.696
/cut2	-0.619	1.878			-4.300	3.061
Model Statistics						
Number of Observations		50		Prob > c		0.0402
LR Chi2		10.01		Pseudo R		0.1035

The model for luxury goods is reminiscent of the model for electronics. As with the model for clothing, employed individuals are more likely to use crowd deliveries.

5.3.9 Office Supplies

Table 21 lists results for the model considering only office supplies. This model does not have a good fit, but it is included for completion.

Table 21: Model Results, Office Supplies

Levels:	More Likely = 1, Neutral = 2, Less Likely=3					
Variables	**Parameter**	**St.Error**	**t-stat**	**P-Value**	**95% Confidence Interval**	
age	0.043	0.020	2.16	0.031	0.004	0.082
inc_low	-1.374	0.774	-1.78	0.076	-2.891	0.142
inc_med	-0.934	0.634	-1.47	0.141	-2.175	0.308
/cut2	0.485	1.117			-1.705	2.675
/cut2	1.936	1.152			-0.322	4.195
Model Statistics						
Number of Observations		50		Prob > c		0.0432
LR Chi2		8.14		Pseudo R		0.0752

5.3.10 Packaged Goods

Table 22 lists results for the model considering only packaged goods. This model does not have a good fit, but it is included for completion.

Table 22: Model Results, Packaged Goods

Levels:	More Likely = 1, Neutral = 2, Less Likely=3					
Variables	**Parameter**	**St.Error**	**t-stat**	**P-Value**	**95% Confidence Interval**	
age	0.045	0.020	2.20	0.028	0.005	0.084
inc_low	-0.906	0.741	-1.22	0.222	-2.359	0.547
inc_med	-0.915	0.642	-1.42	0.154	-2.173	0.344
/cut2	0.558	1.131			-1.658	2.774
/cut2	2.010	1.163			-0.270	4.290
Model Statistics						
Number of Observations		50		Prob > c		0.0607
LR Chi2		7.38		Pseudo R		0.0688

5.3.11 Pet Supplies

Table 23 lists results for the model considering only pet supplies. The poor performance of this model may be linked to the small population that owns pets.

Table 23: Model Results, Pet Supplies

Levels:	More Likely = 1, Neutral = 2, Less Likely=3					
Variables	**Parameter**	**St.Error**	**t-stat**	**P-Value**	**95% Confidence Interval**	
age	0.034	0.020	1.69	0.091	-0.005	0.072
inc_low	-1.525	0.775	-1.97	0.049	-3.044	-0.007
inc_med	-1.414	0.651	-2.17	0.030	-2.689	-0.138
/cut2	-0.143	1.129			-2.356	2.069
/cut2	1.113	1.144			-1.129	3.355
Model Statistics						
Number of Observations		50		Prob > c		0.0349
LR Chi2		8.61		Pseudo R		0.0803

5.3.12 Sporting Goods

Table 24 lists results for the model considering only sporting goods.

Table 24: Model Results, Sporting Goods

Levels:	More Likely = 1, Neutral = 2, Less Likely=3					
Variables	**Parameter**	**St.Error**	**t-stat**	**P-Value**	**95% Confidence Interval**	
landsqmi	0.012	0.012	1.00	0.316	-0.012	0.037
age	0.056	0.023	2.47	0.014	0.011	0.100
inc_med	-0.786	0.562	-1.40	0.162	-1.888	0.317
grad	0.648	0.570	1.14	0.255	-0.468	1.765
/cut2	1.770	1.323			-0.823	4.362
/cut2	3.426	1.394			0.693	6.158
Model Statistics						
Number of Observations		50		Prob > c		0.0312
LR Chi2		10.62		Pseudo R		0.0994

The model for sporting goods is similar to that for clothing, but with fewer variables, considering only ZIP Code area, age, medium income status, and graduate degree status.

5.3.13 Toys

Table 25 lists results for the model considering only toys.

Table 25: Model Results, Toys

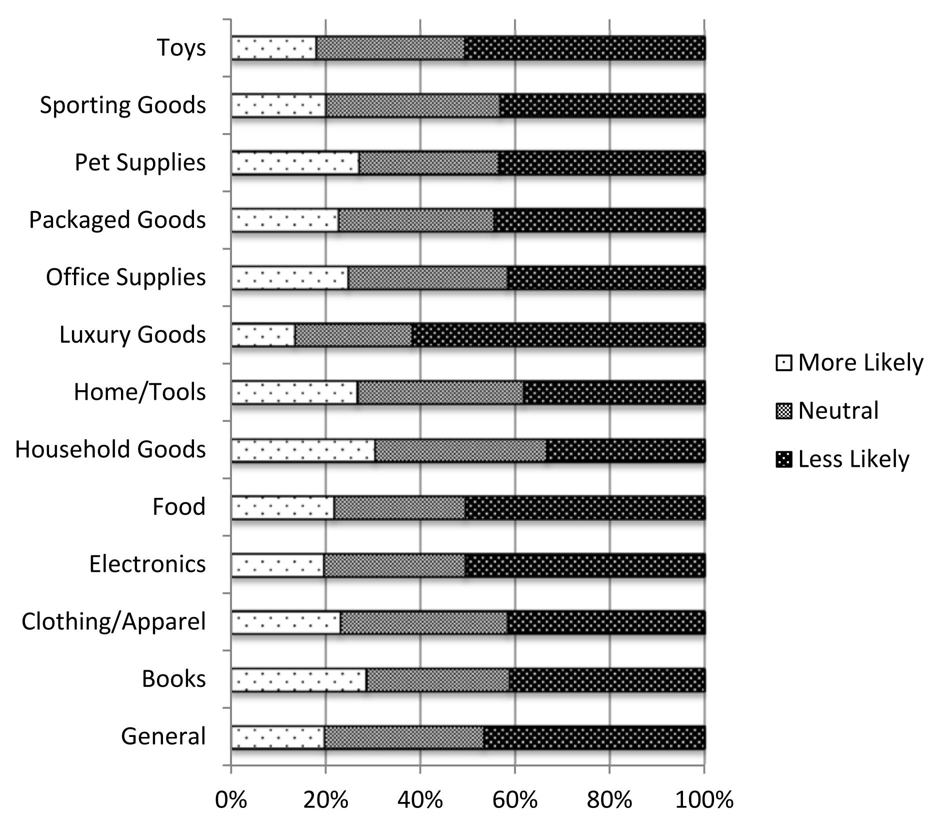
Levels:	More Likely = 1, Neutral = 2, Less Likely=3					
Variables	**Parameter**	**St.Error**	**t-stat**	**P-Value**	**95% Confidence Interval**	
age	0.056	0.021	2.59	0.01	0.014	0.098
inc_low	-1.022	0.775	-1.32	0.187	-2.540	0.496
inc_med	1.006	0.663	-1.52	0.129	-2.304	0.293
/cut2	0.783	1.174			-1.518	3.084
/cut2	2.278	1.216			-0.105	4.661
Model Statistics						
Number of Observations		50		Prob > c		0.0181
LR Chi2		10.06		Pseudo R		0.0971

This model is similar in structure to the models for office supplies, packaged goods, and pet supplies.

5.3.14 Predicted Probabilities

From model results, predicted probabilities were obtained using the average values of model variables. In general, is it predicted that crowd deliveries are likely to be accepted in approximately 20% of cases and not likely to be accepted in nearly 50% of cases. Some items, such as books, are much more likely to have accepted crowd deliveries, with this commodity having a predicted acceptance of 30%. Conversely, luxury goods have a predicted acceptance under 15%, which is linked to the high value of this commodity type. Figure 4 shows predicted probabilities for each commodity type and in general.

Figure 4: Predicted Probabilities



6. Adoption of Autonomous Vehicles

6.1 Data Description - Autonomous Vehicle Survey

In the autonomous vehicle subsection of the survey, respondents were asked about their opinions regarding autonomous vehicles and which autonomous technologies where present in their vehicles. 90.7% of survey respondents have a vehicle in the household. This is well above the state average of 70.6% households with at least one vehicle as estimated by the 2015 American Community Survey (*1*). Table 26 lists the travel modes used by respondents as part of their daily commutes. Note that respondents could select multiple modes, as many individuals in New York utilize multiple travel modes as part of each commute.

Table 26: Commute Modes

Mode	Percentage	Percentage Working Away From Home
Drive Alone	50.0%	79.4%
Carpool	3.7%	5.9%
Subway/Light Rail	9.3%	14.7%
Walk	3.7%	5.9%
Bus	1.9%	2.9%

Half of respondents and nearly 80% of those with a job outside of the home drive alone to work each day. 11.1% of respondents and 17.6% of those working outside of the home used some form of public transportation as part of their commute. Two respondents carpooled and two walked, with all walkers also using rail as part of the commute. Only one respondent uses the bus.

Table 27 lists the stated opinions of respondents regarding autonomous vehicles.

Table 27: Autonomous Vehicle Opinions

Opinion	Frequency
Extremely Positive	11.1%
Positive	27.8%
Neutral	35.2%
Negative	16.7%
Extremely Negative	9.3%

The median opinion regarding autonomous vehicles is located at “neutral”, followed in frequency by “positive” and “negative”. 79.6% of respondents had an opinion lying in one of the middle three categories, showing that few people have a particularly strong opinion regarding autonomous vehicles. Responses are skewed toward the “positive” end of the spectrum, with approximately 40% of respondents choosing one of the positive opinion levels, compared to 26% choosing one of the negative opinion levels. Prior to taking the survey, 3 respondents had not heard of autonomous vehicles. Half of all respondents indicated that their vehicle does not contain any form of autonomous technology, such as adaptive cruise control or automatic braking. 38.9% indicated that their vehicle had at least one autonomous technology and two indicated that they were unsure. The remaining 5 respondents do not have a vehicle at home. 51.9% indicated that they would pay any amount beyond the base cost of a vehicle in order to make it fully autonomous. Table 28 indicates the responses provided when survey recipients were asked what they would do while riding in a self-driving vehicle. Note that respondents could select multiple activities.

Table 28: Actions While Riding in Autonomous Vehicles

Activity	Frequency	People that would use autonomous vehicles
Watch road even if not driving	46.3%	78.1%
Talk/text with friends/family	31.5%	53.1%
Read	29.6%	50.0%
Do work	24.1%	40.6%
Sleep	20.4%	34.4%
Watch TV or play games	11.1%	18.8%
Other	1.9%	3.1%
Would not ride in a self-driving vehicle	40.7%	N/A

Nearly half of all respondents and a significant majority of those who would ride in an autonomous vehicle indicated that they would watch the road while in transit. Slightly over half of potential users would talk or text with other people when in motion and half indicated they would read. 40.6% of potential users would do work, approximately one-third would sleep and 18.8% would watch television or play games. One individual listed other activities they would partake in. 40.7% of all respondents indicated that they would not ride in an autonomous vehicle. For the purposes of this analysis, the “would not ride” option is considered to be exclusive of all activity options.

6.2 Methodology

In our survey, the main intent was to determine a person’s opinion regarding autonomous vehicles based on various factors. We determined that the most logical type of model to use for our dataset is an ordered probit model, since these rankings lend themselves to a 1-5 scale, with 1 representing “extremely negative” and 5 representing “extremely positive”.

The ordered probit model is defined as follows:

$$z = \beta X + \varepsilon$$

Where X is a vector of variables, β is a vector of coefficients,εis an error term and z is the unobserved variable in question. In our case, we have 5 levels of the likelihood variable y. For each observation, y is defined as follows:

$$y = 1\ (extremely\ unlikely) \qquad \text{if } z \leq \mu_1$$

$$
\begin{aligned}
y &= 2\ (unlikely) && \text{if } \mu_1 < z \leq \mu_2 \\
y &= 3\ (neutral) && \text{if } \mu_2 < z \leq \mu_3 \\
y &= 4\ (likely) && \text{if } \mu_3 < z \leq \mu_4 \\
y &= 5\ (extremely\ likely) && \text{if } \mu_4 < z
\end{aligned}
$$

The μ_i are thresholds that define bins of varying width corresponding to a certain value of y. The μ are estimated simultaneously with the β and the modeling simply becomes a problem of estimating the probability of specific ordered responses for each observation.

With the data we had collected, there were two other items we wanted to determine: what factors, if any, determine one's willingness to pay for autonomous technology or what they would do while riding in an autonomous vehicle? Willingness to pay is a simple "yes/no" that could be represented by a binary probit model. The probit model is defined as:

$$\Pr[Y = 1|X_i] = \Phi(z)$$

Where $z = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ki}$, X_i are variable values, βs are coefficients and Φ(.) is the standard normal distribution. Activities performed while in transit were not mutually exclusive (excluding the "will not ride" case), necessitating use of a multivariate probit model.

A multivariate probit model with three equations is used to analyze the choices of survey respondents regarding what they would do while riding in an autonomous vehicle. Each equation characterizes one of the potential in-transit activities: watching the road, doing work, and other non-productive activities (sleeping, talking with friends/family, etc.). Not performing any of these actions implies that one will not ride in an autonomous vehicle, as a response to the question was required. For respondent i, the response on action m can be specified as:

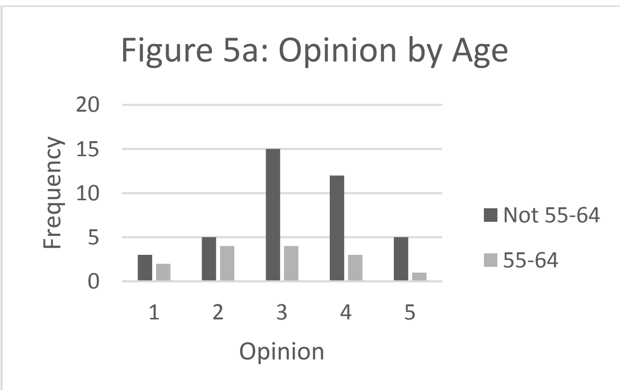
$$
\begin{aligned}
y_{im}^* &= \beta_m' x_{im} + \varepsilon_{im} \\
y_{im} &= 1\ if\ y_{im}^* > 0 \\
y_{im} &= 0\ if\ y_{im}^* < 0
\end{aligned}
$$

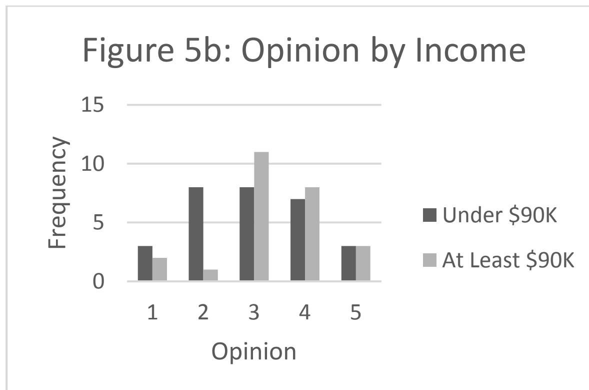
Where the term y_{im} denotes the respondent's response: 1 indicates that the respondent would perform an activity while in transit, 0 indicates they would not. The response is made based on latent utility y_{im}^*, which contains a deterministic part $\beta_m' x_{im}$ and a stochastic part ε_{im}. The deterministic part is composed of independent variables x_{im} and coefficients β_m. Independent variables x_{im} may vary across the M equations. The stochastic part ε_{im} is assumed to follow a multivariate normal distribution. Such an error term structure is able to analyze relationship among alternatives: two alternatives are complement when the covariance is positive and substitute when negative. Stata 14.2 is able to estimate these models with a maximum simulated likelihood estimated method by utilizing the mvprobit command (*2*).

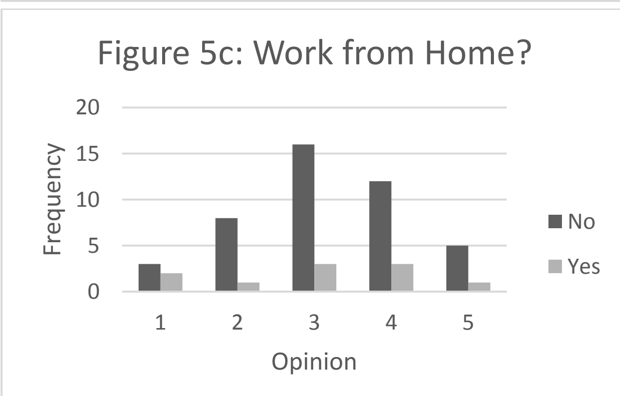
6.3 Results Analysis

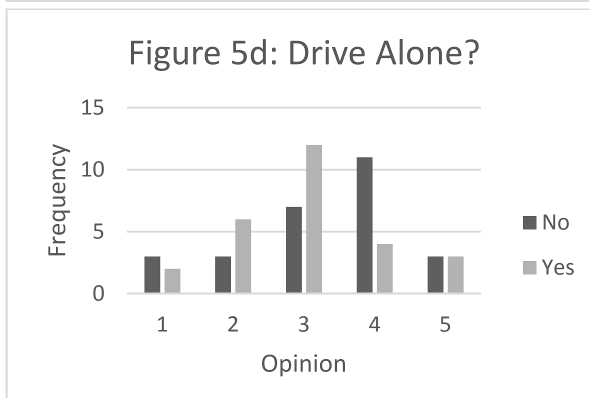
<u>6.3.1 Autonomous Vehicle Opinions</u>

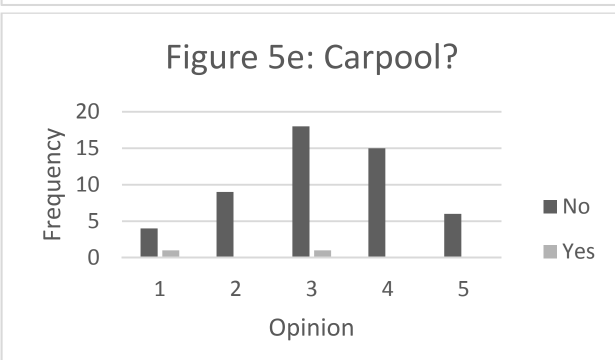
A 2-dimensional cross-tabulation analysis was performed on each of the binary independent variables contained in the final model. Figures 5a through 5i contains the results of this analysis. Figure 5a shows that the opinion of people outside of the 55-64 age range peaks at “neutral”, while that of people between the ages of 55 and 64 plateaus between “negative” and “neutral”. As indicated by Figure 5b, virtually no respondents with high household incomes have a negative opinion of autonomous vehicles, compared to the relatively symmetric distribution for lower incomes. In Figure 5d, it can be seen that opinions of people who drive alone to work peak at “neutral”, while those of people who do not drive alone to work peak at “positive”. There is not enough data to analyze Figures 5c, e, f and g, but these figures indicate that the overall opinion distribution is symmetric.

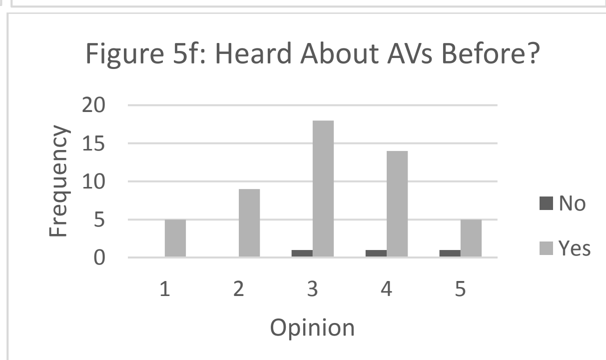


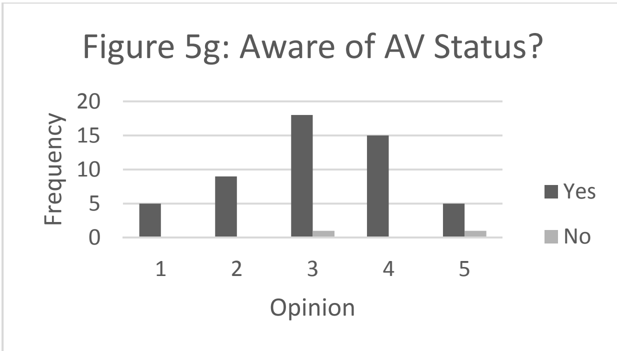












Several ordered probit models were created in Stata 14.2. The variables contained in the final model are listed in Table 29. Generally, gender was insignificant, as was age unless the respondent was between the ages of 55 and 64, inclusive. Household income was significant, as was whether or not a person works from home. Commute mode was insignificant unless the respondent specified that they drove alone or carpooled, as was whether or not a person's current vehicle has autonomous technology. Yet, a person not knowing if their vehicle has autonomous technologies was significant, as was knowing about autonomous technology before the survey. Surprisingly, a person's unwillingness to ride in a self-driving vehicle had no effect on opinion. Table 30 lists results of the estimated model.

Table 29: Opinion Variable Definitions

Variable	Definition
OpinAV	Ordinal opinion regarding autonomous vehicles, ranging from 1 to 5
Bt55to64	Respondent is between the ages of 55 and 64
AtLst90K	Respondent has household annual salary of at least $90,000
WorkHome	Indicator for respondent working from home
DriveAlone	Respondent drives alone for a portion of their commute
Carpool	Respondent carpools for a portion of their commute
HeardAV	Indicator for respondent hearing about autonomous vehicles before survey
DKATech	Indicator for respondent not knowing if their vehicle has autonomous technology

Our model results indicate that respondents between the ages of 55 and 64 (baby boomers) are less likely to have a high opinion of autonomous vehicles. Wealthier respondents tend to have a higher opinion of autonomous vehicles while people who work from home have a lower opinion. Respondents who drive alone have a lower opinion of self-driving vehicles, but being part of a carpool has a larger negative effect on opinion. People who have heard of autonomous vehicle technology before the survey have a lower opinion and people who are unaware if their vehicle features any form of autonomous technology have a much higher opinion.

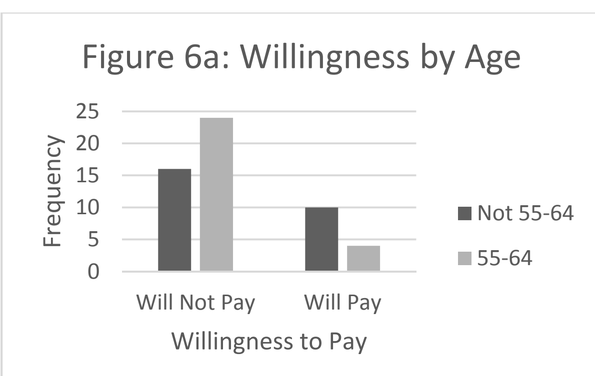
Table 30: Opinion Model Results

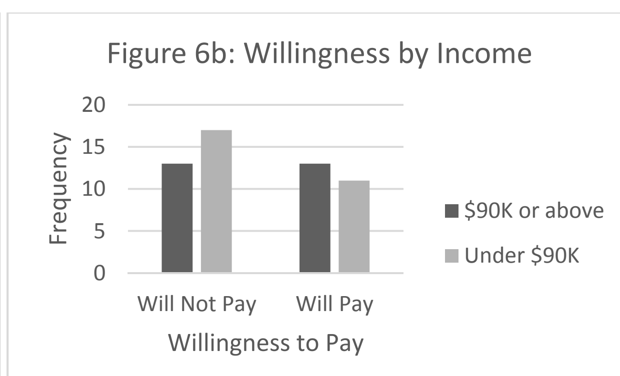
Variable	Coefficient	Std. Err.	95% Conf Interval	
Bt55to64	-0.8575*	0.3821	-1.6065	-0.1085
AtLst90K	0.8622**	0.3231	0.2290	1.4954
WorkHome	-1.2908**	0.4969	-2.2648	-0.3168
DriveAlone	-1.0255**	0.3692	-1.7491	-0.3019
Carpool	-1.8594*	0.9233	-3.6690	-0.0499
HeardAV	-1.4966*	0.6925	-2.8540	-0.1393
DKATech	1.8426*	0.9029	0.0729	3.6123
1-2 Boundary	-3.6833	0.8369	-5.3236	-2.0431
2-3 Boundary	-2.8042	0.7937	-4.3598	-1.2486
3-4 Boundary	-1.6007	0.7455	-3.0618	-0.1395
4-5 Boundary	-0.4710	0.7309	-1.9035	0.9615
Chi Squared	21.65			
Prob. > Chi 2	0.0029			
Pseudo R2	0.1349			
Log Likelihood	-69.4425			

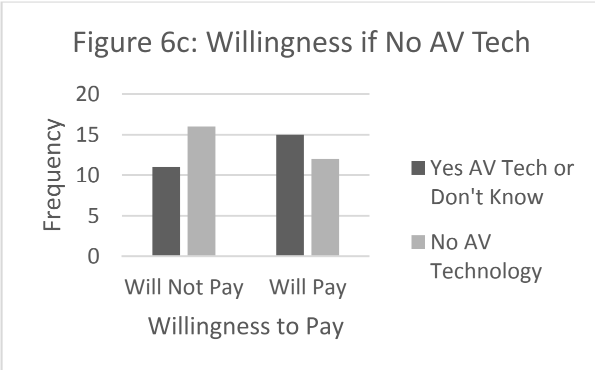
NOTE: * = significant at 5% level, ** = significant at 1% level

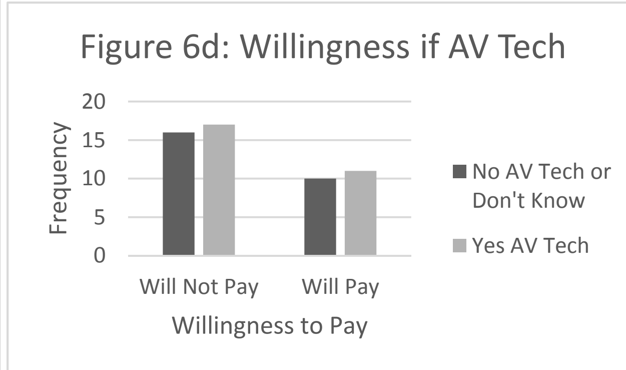
6.3.2 Willingness to Pay for Autonomous Technology

A 2-dimensional cross-tabulation analysis was performed on each of the binary independent variables contained in probit model for willingness to pay. Figures 6a through 6d contain graphs showing the results of this analysis.









Individuals between the ages of 55 and 64 are less likely to pay for autonomous technology than other age groups. While respondents with a household income above $90,000 are equally likely to be willing to pay or not willing to pay, respondents making less than $90,000 are less likely to pay for the technology. Figure 6c indicates that people with no autonomous technology in their vehicle are less likely to pay for a fully self-driving car, while Figure 6d indicates that knowing one has autonomous technology present in their vehicle makes little difference in likelihood to pay. While Figures 6c and d appear similar, a "do not know" response was possible and selected by more than one respondent.

Several binary probit models were created in Stata 14.2 for detailed analysis, with variables contained in Table 31.

Table 31: Willingness to Pay Variable Definitions

Variable	Definition
PayAV	=1 if respondent would pay for a fully-autonomous vehicle, else =0
Bt55to64	Respondent is between the ages of 55 and 64
Un90K	Respondent has household annual salary below $90,000
NoATech	Indicator for respondent not having autonomous technology in their vehicle
YesATech	Indicator for respondent having autonomous technology in their vehicle

Only three factors were found to be significant: age, income and presence of autonomous technology in one's current vehicle. Age was significant if the respondent is between the ages of 55 and 64, inclusive. Income was significant if household income is below $90,000. Both the "yes" and "no" responses to having autonomous technology in one's vehicle were significant, leaving "don't know" as the base. Table 32 lists results of the estimated model. As with the opinion model, baby boomers are less likely than other age groups to be willing to pay for fully-autonomous technology, while respondents with lower incomes were less likely to be willing than those with high incomes. Knowing whether or not one has autonomous technology has a negative effect on likelihood to pay, but not possessing autonomous technology in a current vehicle has a larger negative effect than having autonomous technology in a current vehicle. The "no autonomous technology" variable has a larger negative effect on willingness to pay than any other factor, with this being the only factor that will put one's likelihood to pay below 50% if combined with a positive result for just one other factor.

Table 32: Willingness to Pay Model Results

Variable	Coefficient	Std. Error	95% Conf. Interval	
Bt55to64	-1.3406**	0.4967	-2.3141	-0.3671
Un90K	-0.7154†	0.3975	-1.4944	0.0636
NoATech	-1.8099*	0.7531	-3.2860	-0.3338
YesATech	-1.3260†	0.7373	-2.7711	0.1191
Constant	2.1421**	0.7880	0.5977	3.6865
Chi-Squared	12.94			
Prob > chi2	0.0166			
Pseudo R2	0.0173			
Log Likelihood	-30.9226			

NOTE: † = significant at 10% level, * = significant at 5% level, ** = significant at 1% level

6.3.3 In-Transit Activities

A 2-dimensional cross-tabulation analysis was conducted for each of the three activity variables. Results of this analysis are in Figures 7a through 7i.

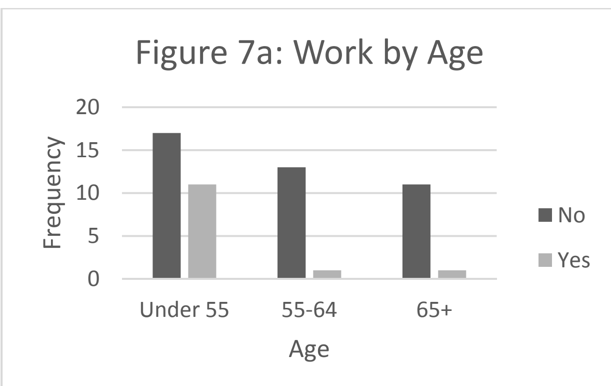


Figure 7a: Work by Age

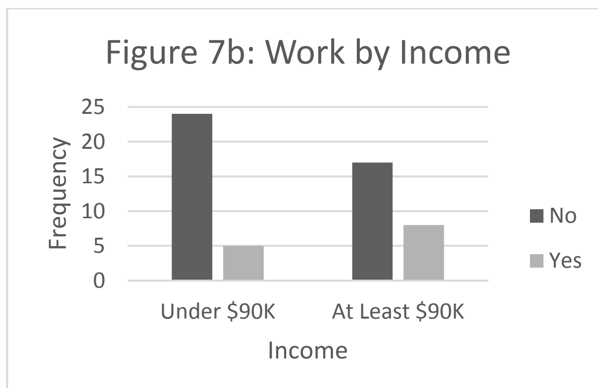


Figure 7b: Work by Income

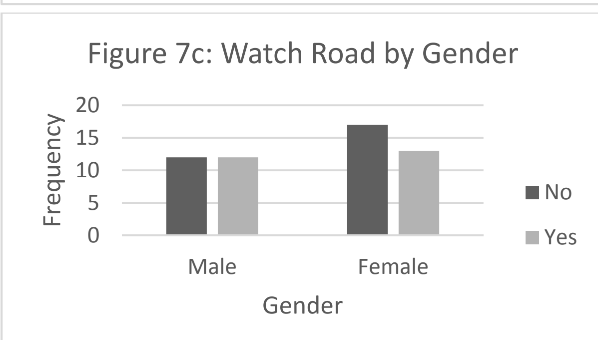


Figure 7c: Watch Road by Gender

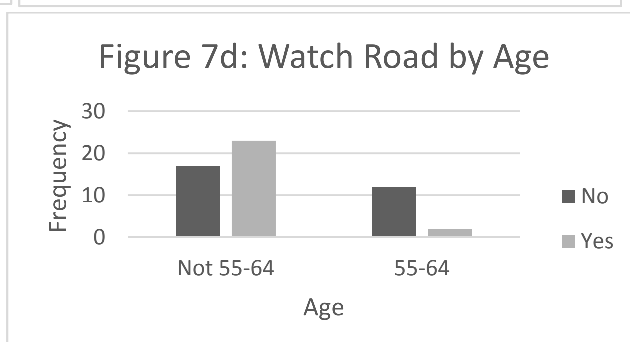
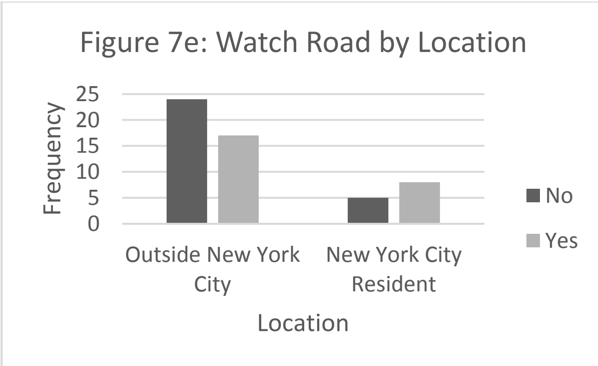
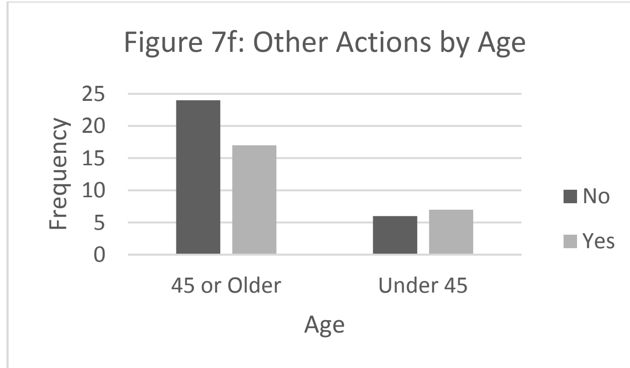
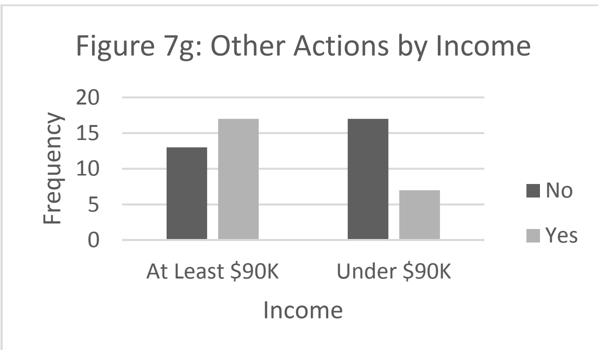


Figure 7d: Watch Road by Age







For comparison purposes, a cross-tabulation analysis was conducted on the base "will not ride" case utilizing each of the independent variables, with results contained in Figures 8a through 8d. Respondents under the age of 55 were significantly more likely to work in an autonomous vehicle than those that are older. Wealthier respondents are significantly more likely to express an interest in working while in transit. Men are more likely to watch the road than women. Less than half of respondents between the ages of 55 and 64 would watch the road even if not driving, but over half of respondents of another age would watch the road. Residents of New York City are more likely to watch the road than those living elsewhere. Respondents under the age of 45 are more likely than older individuals to do non-productive activities, such as read or sleep, while in transit, as are those making at least $90,000. People in high-income households are much more likely to be willing to ride in autonomous vehicles, while men are generally more willing to ride than women. New York City residents are more willing to ride than residents of other regions of the state. A majority of people under the age of 45 and 65 or older are willing to ride in an autonomous vehicle, while the 55-64 age group has a majority of respondents unwilling to ride.

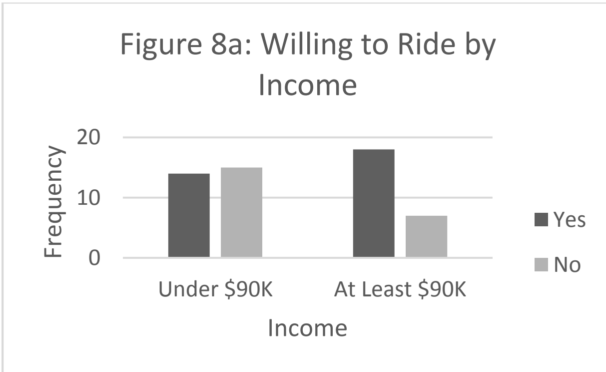


Figure 8a: Willing to Ride by Income

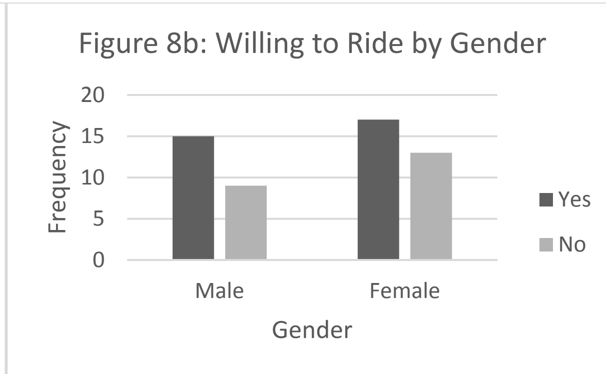


Figure 8b: Willing to Ride by Gender

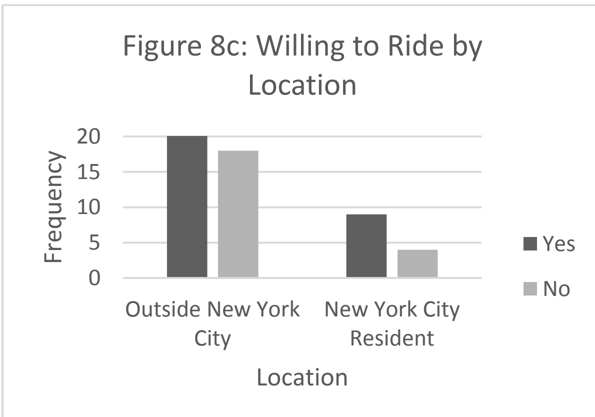


Figure 8c: Willing to Ride by Location

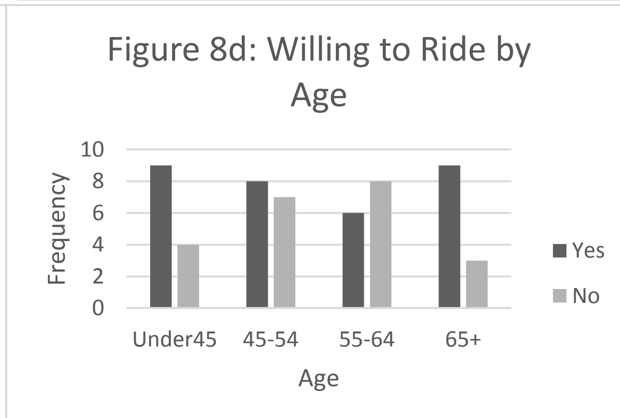


Figure 8d: Willing to Ride by Age

The mvprobit command in Stata 14.2 was used to generate a multivariate probit model for the in-transit activities, using each of the three activity categories as dependent variables. Table 33 lists the variables used in these models. Not all variables were used for all dependent variables. Table 34 lists the results from the multivariate probit model.

Table 33: Activity Variables

	Variable	Definition
Dependent	Work	Respondent would work while riding in an autonomous vehicle
	Watch	Respondent would watch the road while in an autonomous vehicle
	NonProd	Respondent would do other non-productive activities (read, sleep, etc.) while in an autonomous vehicle
Independent	Female	Respondent is female
	Under45	Respondent is under the age of 45
	Bt55to64	Respondent is between the ages of 55 and 64 (inclusive)
	Over65	Respondent is at least 65 years old
	Un90K	Respondent's household income is under $90,000/year
	AtLst90K	Respondent's household income is over $90,000/year
	NYC	Respondent lives in New York City
	CommDist	Commute distance in miles

Table 34: Activity Model Results

	Variable	Coefficient	Std. Error	95% Conf. Interval	
Work	Bt55to64	-0.9600*	0.3898	-1.7240	-0.1960
	Over65	-1.7593***	0.4374	-2.6167	-0.9020
	AtLst90K	0.7645**	0.2639	0.2292	1.2637
	Constant	-0.5980*	0.2492	-1.0865	-0.1095
Watch Road	Female	0.4672**	0.1785	0.1173	0.8171
	Bt55to64	-1.1144***	0.3089	-1.7199	-0.5090
	NYC	0.4568*	0.2220	0.0217	0.8920
	Constant	-0.2604†	0.1560	-0.5661	0.0454
Non-Productive Activities	Under45	0.8804**	0.2597	0.3715	1.3894
	Un90K	-1.2179***	0.1921	-1.5946	-0.8413
	CommDist	-0.0229**	0.0087	-0.0399	-0.0058
	Constant	0.2863*	0.1435	0.0050	0.5675
Correlations	Work-Watch	0.9742***	0.0317	0.7397	0.9977
	Work-NonProd	0.9660***	0.0199	0.8947	0.9893
	Watch-NonProd	0.8895***	0.0686	0.6503	0.9682
Model Statistics	Chi-Squared	78.12			
	Prob > chi2	0.0000			
	Log Likelihood	-69.2831			

NOTE: † = significant at 10% level, * = significant at 5% level, ** = significant at 1% level, *** = significant at 0.1% level

Based on the model, respondents 55 or older were less likely to work than younger respondents, with the over 65 age group least likely. Respondents from high-income households are more likely to express an interest in working while riding in an autonomous vehicle. Women are more likely to watch the road than men, as are residents of New York City. The 55-64 age group is less likely to watch the road while in a self-driving vehicle. Respondents under the age of 45 are more likely to perform non-productive activities, as are higher-income respondents. The likelihood to participate in non-productive activities decreases as commute distance increases. All activity types are highly correlated, but watching the road and non-productive activities have a lower correlation than the other two combinations.

7. Discussion and Conclusions

This project studies the effect of various new trends in transportation on residents of New York State. Three recent and growing trends, namely delivery lockers, crowd delivery, and autonomous vehicles, and their impact on New York residents are analyzed. While the survey response was small and biased toward older residents, New York residents were generally wary of these trends. New Yorkers tended to have a neutral opinion regarding delivery lockers, an unwillingness to use crowd delivery, and an unwillingness to pay any additional cost for autonomous technologies in a vehicle. Unsurprisingly, residents of New York City were more willing to join the new trends, possibly due to increased prior experience with the technologies or the difficulty of using private vehicles in a dense urban environment. It must be noted that, at the time of the survey, fully autonomous vehicles were illegal in New York.

Future studies can study these trends in further detail. Different survey strategies may be able to retrieve the opinions of a much larger population. In the 17 months since the survey was administered, several supermarket chains in New York, notably Price Chopper/Market32 and Wegmans, have begun to offer grocery delivery using the crowd delivery service Instacart. This development has meant that a significantly larger population has access to and reason to use crowd delivery services. New vehicles are incorporating more and more autonomous technologies, with many of these becoming standard. Amazon and other companies continue to deploy delivery lockers, with most of the state's population having access to at least one. For each of the three trends analyzed here, recent developments have meant that the public has had much more exposure, almost certainly changing opinions and usage patterns.

8. References

[1] *Household Size by Vehicles Available.* Publication B08201, 2015.
[2] Cappellari, L., and S. P. Jenkins. Multivariate probit regression using simulated maximum likelihood. *The Stata Journal,* Vol. 3, No. 3, 2003, pp. 278-294.

Appendix I: Survey Questionnaire

Demographic Information

1. What is your gender?
    a. Male
    b. Female
    c. Prefer not to answer
2. What is your age?
    a. 18-25
    b. 26-34
    c. 35-44
    d. 45-54
    e. 55-64
    f. 65-74
    g. 75 or older
    h. Prefer not to answer
3. What is the 5-digit ZIP code for your home address?
4. What is your annual household income (in US dollars)?
    a. $9,999 or less
    b. $10,000 - $29,999
    c. $30,000 - $49,999
    d. $50,000 - $69,999
    e. $70,000 - $89,999
    f. $90,000 - $109,999
    g. $110,000 - $129,999
    h. $130,000 - $149,999
    i. $150,000 - $169,999
    j. $170,000-$189,999
    k. $190,000 or higher
    l. Prefer not to answer
5. What is the highest level of education you have completed?
    a. Less than high school graduate
    b. High school graduate
    c. Technical/vocational training
    d. Some college
    e. Completed Associate's Degree
    f. Completed Bachelor's Degree
    g. Completed graduate degree
    h. Prefer not to answer

Shopping Behavior

6. Within the past 12 months, have you purchased an item online?
    a. Yes (Skip to Question 8)
    b. No
7. Why not? (Skip to Question [-] afterward regardless of answer)
    a. I do not have a credit card
    b. I do not like to use a credit card
    c. I like to see the actual product before I buy it
    d. I do not trust courier services
    e. Other (please specify)
8. Approximately how often do you buy physical items online?
    a. Once every three months or less
    b. Once every two months
    c. Once a month
    d. Twice a month
    e. Three times a month
    f. Once a week
    g. Twice a week
    h. Three times a week
    i. Four or more times a week
    j. Other (please specify)
9. What types of items do you buy online?
    a. Books
    b. Clothing/Apparel
    c. Electronics
    d. Food/Groceries
    e. Household Goods
    f. Home/Tools
    g. Luxury Goods
    h. Office Supplies
    i. Packaged Goods
    j. Pet Supplies
    k. Sporting Goods
    l. Toys
    m. Other (please specify)
10. Are you a member of Amazon Prime?
    a. Yes
    b. No
11. Are you a member of an online shopping subscription service or "subscription box" service, such as an Amazon subscription service, Dollar Shave Club, Blue Apron, or Book of the Month Club?
    a. Yes

b. No (Skip to Question 13)

12. What types of goods do you get from subscription services?
    a. Books
    b. Clothing/Apparel
    c. Electronics
    d. Food/Groceries
    e. Household Goods
    f. Home/Tools
    g. Luxury Goods
    h. Office Supplies
    i. Packaged Goods
    j. Pet Supplies
    k. Sporting Goods
    l. Toys
    m. Other (please specify)

Delivery Lockers

This is a delivery locker used by Amazon. Delivery lockers provide a central, secure and free drop-off point for parcel carriers to leave packages if requested by a customer. In many cases, customers can pick up their packages at any hour, meaning that one does not have to wait at home for a package to arrive. Delivery lockers may be located in public spaces, as seen here, or residential buildings for resident use. Delivery lockers can reduce the time required to ship items and reduce congestion and pollution in residential areas by removing delivery vehicles from the streets.

13. Have you ever, in person, seen a delivery locker of any brand, such as the one shown here?
    a. Yes
    b. No (Skip to 18)
14. Have you ever used a delivery locker?
    a. Yes
    b. No (Skip to 18)
15. Why did you decide to use a delivery locker? Select whichever choices apply.
    a. The locker is close to where I work
    b. I wanted to try using one
    c. I was unavailable for delivery at home
    d. I did not want my package left on my doorstep
    e. I cannot accept deliveries at work
    f. The delivery locker is on my way to/from work/school
    g. The locker is close to where I live
    h. My residential building/complex uses them for receiving packages
    i. Other (please specify)
16. Which companies have the delivery locker(s) you used belonged to?
    a. Amazon (Amazon Locker)
    b. FedEx (FedEx Ship&Get)
    c. Luxer One
    d. Package Concierge
    e. Parcel Pending
    f. UPS (UPS Access Point)
    g. I don't know
    h. Other (please specify)
17. How many times have you used a delivery locker within the last 12 months?
    a. 0
    b. 1
    c. 2-5
    d. 6-10
    e. 11-20
    f. 21 or more
18. How likely are you to consider using a delivery locker? Keep in mind that they generally incur no additional cost to you.
    a. Extremely likely
    b. Likely
    c. Neutral
    d. Not likely
    e. Extremely unlikely

19. How likely are you to use a delivery locker if there is a shipping or subscription cost discount for using one?
    a. Extremely likely
    b. Likely
    c. Neutral
    d. Not likely
    e. Extremely unlikely
20. What is the furthest distance you would travel from your home or daily routine in order to use the nearest delivery locker?
    a. More than 20 miles
    b. 20 miles
    c. 10 miles
    d. 5 miles
    e. 3 miles
    f. 2 miles
    g. 1 mile
    h. ½ mile
    i. ¼ mile
    j. Less than ¼ mile
    k. I would not use a delivery locker

Commute Information

21. Do you have a car?
    a. Yes
    b. No
22. Are you currently employed?
    a. Yes
    b. No (Skip to 29)
23. Do you work from home?
    a. Yes
    b. No (Skip to 29)
24. Approximately how long is your commute to your primary job in minutes?
25. Approximately how long would it take to travel to your job if there is no congestion at all?
26. How much would you be willing to pay to avoid this congestion?
27. Approximately how far is your primary job from your home?
28. Now thinking about your daily commute, which of the following describes your usual means of commuting to work each day? Please check all that apply.
    a. I drive alone
    b. I carpool
    c. I take a bus

d. I take the subway/light rail
e. I take commuter rail
f. I take a ferry
g. I walk
h. I ride a bicycle
i. I ride a motorcycle/scooter
j. Other (please specify)

Crowd Deliveries

Crowd Deliveries (also known as Crowd-Sourced deliveries) are a new trend of deliveries that enable buyers (whether online or in store) to have different shipping options in a cheap and efficient way. This model uses the crowd as potential drivers and it would provide options to the buyer according to distance, desired vehicle characteristics and their willingness to pay for the delivery service. This model is similar to Uber or Lyft, but for delivering merchandise instead of passengers.

29. Based on the description provided above, do you understand what crowd deliveries are?
    a. Yes
    b. No
30. How likely are you to use crowd deliveries as an alternative delivery service?
    a. Extremely likely
    b. Likely
    c. Neutral
    d. Not likely
    e. Extremely unlikely
31. How likely are you to use crowd deliveries based on type of product? (check one per row)

	Extremely Likely	Likely	Neutral	Not Likely	Extremely Unlikely	N/A
Books						
Clothing/Apparel						
Electronics						
Food/Groceries						
Household Goods						
Home/Tools						
Luxury Goods						
Office Supplies						
Packaged Goods						
Pet Supplies						
Sporting Goods						

Toys						

32. Consider a situation where you had to buy a book or a small package, how much more would you be willing to pay (in US Dollars) for a crowd delivery service if your package is guaranteed to arrive: [short answer for each]
    a. The same day
    b. The next day
    c. Within a week
    d. After a week
33. Are there any reasons why you would not use crowd deliveries? Please check all that apply.
    a. Because I do not trust other people handling my goods
    b. I prefer a courier service because it is more reliable
    c. I do not like trying new things
    d. I can't think of a reason for not using crowd deliveries
    e. Other (please specify)

Participating as a driver in Crowd Deliveries

34. Would you be interested in becoming a driver for Crowd deliveries?
    a. Yes
    b. No
35. Based on each scenario, how likely are you willing to make a delivery? (select one per row)

	Extremely Likely	Likely	Neutral	Not Likely	Extremely Unlikely	N/A
Pick up at a warehouse/postal office/store (in the city) and the delivery is located on your way to work or back from work.						
Pick up/deliver in your local neighborhood						
Pick up/deliver in another neighborhood in your city						
Pick up/deliver in another city						

36. How much would you charge (in US Dollars) for your service as a driver for crowd deliveries? [short answer for each]
    a. Per Mile
    b. Per Hour

Autonomous Vehicles

Autonomous vehicles are those in which at least some aspects of a safety-critical control (such as steering, throttle, or braking) operate without direct driver input. Vehicles that provide safety warnings to drivers (for example, a forward-crash warning) but do not take control of the vehicle are not considered autonomous.

Autonomous vehicles may use on-board sensors, cameras, GPS, and telecommunications to obtain information in order to make decisions regarding safety-critical situations and act appropriately by taking control of the vehicle at some level. Examples of autonomous-vehicle technologies range from those that take care of basic functions such as cruise control, to completely self-driving vehicles with no human driver required.

37. Had you ever heard of autonomous and/or self-driving vehicles before participating in this survey?
    a. Yes
    b. No
38. What is your general opinion regarding autonomous and self-driving vehicles? Even if you had never heard of autonomous or self-driving vehicles before participating in this survey, please give us your opinion based on the description you just read.
    a. Extremely positive
    b. Positive
    c. Neutral
    d. Negative
    e. Extremely Negative
39. Which of the following autonomous-vehicle technologies, if any, do you have on the vehicle(s) that you own or lease? Autonomous vehicle technologies include adaptive cruise control, lane departure systems, automated braking, collision avoidance, advanced parking assistance, blind spot monitoring, or speed alert systems.
    a. My vehicle does not have any of these technologies
    b. My vehicle does have one or more of these technologies
    c. I do not know if my vehicle has any of these technologies
    d. I do not currently own or lease a vehicle
40. How much extra would you be willing to pay for technologies to make a car FULLY self-driving (i.e., without driver control)?
    a. $0
    b. $1 - $1000
    c. $1001 - $3000
    d. $3001 - $7000
    e. $7001 - $10000
    f. $10000 or more
41. If you were to ride in a completely self-driving vehicle, what do you think you would use the extra time doing instead of driving? Please check all that apply.
    a. Text or talk with friends/family

b. Read
c. Sleep
d. Watch movies/TV or play games
e. Work
f. Watch the road, even though I would not be driving
g. I would not ride in a completely self-driving vehicle
h. Other (please specify)

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