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The Association between ICT-Based Mobility Services and Sustainable Mobility Behaviors of New Yorkers

Hamid Mostofi

Mobility Research Cluster, Department of Work, Technology and Participation, Technische Universität Berlin, 10587 Berlin, Germany; mostofidarbani@tu-berlin.de

Abstract: The energy consumption and emissions in the urban transportation are influenced not only by technical efficiency in the mobility operations but also by the citizens' mobility behaviors including mode choices and modal shift among sustainable and unsustainable mobility modes. Information and Communication Technologies (ICTs) can play an important role in the mobility behaviors of citizens, and it is necessary to study whether ICTs support sustainable mode choices like public transport and nonmotorized modes, which increase the total energy efficiency in the urban mobility and reduce traffic congestion and related emissions. This paper focuses on the two most popular ICT services in the urban transport, which are ATIS (Advanced Traveler Information Systems), and ridesourcing services. This study used the New York Citywide Mobility Survey (CMS) findings with a sample of 3346 participants. The associations between using these two ICT services and the mobility behaviors (mode choice with ATIS and modal shift to ridesourcing) are analyzed through a multinomial logistic regression and descriptive statistics, and the results are compared with similar international studies. The findings indicate that the respondents who use ATIS apps more frequently are more likely to use rail modes, bicycles, bus/shuttles, and rental/car sharing than private cars for their work trips. Moreover, the findings of the modal shift to ridesourcing indicate that the most replaced mobility modes by ridesourcing services are public transport (including rail modes and buses), taxis, and private cars, respectively.

Keywords: ICT-based mobility services; ridesourcing; ride hailing; ATIS advanced traveler information systems; mobility behaviors; sustainable urban transportation; modal shift; mode choice

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1. Introduction

The International Energy Agency (IEA, 2020) reported that transportation is still responsible for 24% of direct CO_2 emissions of fuel combustion in the world [1]. Transportation is one of the major energy consumption sectors, constituting 28% of total U.S. energy consumption in 2019 [2]. The second biggest source of CO_2 emissions is the road transport sector in the EU, which was around 25% of total emissions in 2016 [3]. Moreover, about 94% of the EU transport energy demands are covered by fossil energies [4]. According to the IEA report, there was a progress in the electrification of the road transport sector related to the increase of electric cars on the world's roads in 2019 (more than 7 million) and increase in the number of electric trucks and buses. However, the emissions of urban transport continued to increase in cities around the world, which is related to the inefficient energy consumption of road vehicles [1]. One of the technological solutions is the application of Information and Communication Technologies (ICTs) in urban transportation, which can improve the efficiency in energy consumption and decrease the environmental issues through reducing traffic congestion and the related pollutions [5]. UNESCO defines ICT as a technology-group which is applied to create, store, transmit, process, exchange, and exhibit information by electronic means [6]. The roles of ICTs in urban transportation can be categorized in two groups, which are the roles in improving operations of urban transportation and the roles in mobility behaviors of citizens. The roles of ICTs in the mobility operation include improving management, monitoring and integrating different transport platforms and processes in the operations [7] to contribute to the productivity and energy efficiency of the urban transport sector [5,8]. Moreover, ICTs have the potential to reinforce sustainable mobility behaviors by increasing connectivity, flexibility, and changing lifestyles [9–13] which might improve mobility mode choices [14]. The energy consumption and emissions in the urban transportation are influenced not only by technical efficiency in the mobility operations but also by the citizens' mode choices and modal shift among sustainable and unsustainable mobility modes. Therefore, the mobility behaviors of citizens have a substantial association with the energy efficiency level in the urban transportation. If the citizens choose sustainable mobility modes like public transport, and active modes more than private fossil fuel vehicles for their daily travels, then the city have a better energy efficient and sustainable mobility system. The term of sustainable mobility is defined as mobility that generates less emission and noise, less congestion, and efficiently consumes energy [15].

This paper tries to shed light on the impacts of two most popular ICT services on urban mobility behaviors, which are Advanced Traveler Information Systems (ATIS), and ridesourcing services (also known as ride-hailing, app-taxis) in New York. This paper studies associations between use of these ICT services and the mobility behaviors of New Yorkers including mobility mode choices and modal shift which influence energy consumption for daily urban travels. This study uses the results of an open-access survey in New York, which is called Citywide Mobility Survey (CMS) to answer two main research questions: what relationship are between the frequency use of ATIS apps and the mobility mode choices of New Yorkers by considering socioeconomic parameters? and which mobility modes have been replaced by ridesourcing services? The associations between the use of these two ICT service-groups and New Yorkers' mobility behaviors are analyzed through descriptive statistics and the multinomial logistic regression, and the results are compared with other international studies in this context.

1.1. Advanced Traveler Information Systems (ATIS)

Advanced Traveler Information Systems (ATIS), also known as navigation services, provide real-time information about temporal and spatial accessibility of different transport modes with online mapping and route optimization through the internet and mobile applications. Recently, the ATIS apps have replaced paper-based maps and timetables of mobility services worldwide. The ATIS apps are one of the most used smartphones-apps, like Google Maps, which is among the five most popular apps by the frequency of use and the download-numbers [16].

The ATIS platforms provide citizens real-time, accurate, and reliable urban traffic information, which improves the mode and route choices of their users to have less travel time, costs, and energy consumption. Consequently, The ATISs can improve traffic congestion, optimal urban transport infrastructure, and the overall productivity of urban transportation by energy saving and reduction of emissions [17–23]. Moreover, some studies indicate the emotional and psychological benefits of ATIS for their users by reducing the uncertainty of travel planning for different daily travel purposes [20,24]. Some studies analyzed the ATIS impact on route choice and travel behaviors by different survey methods and simulations [25–27]. Some researchers mentioned that the impact of ATIS on travel planning is associated with the socioeconomic factors of users, formats, costs, and the quality of disseminated information [28,29].

The studies in the field of ATIS focused more on the impacts of ATIS on the optimal route choices of car drivers, traffic congestions, and their satisfaction of ATIS operators [30–33]. Some studies used stated preference (SP) and revealed preference (RP) survey methods [17–19] and simulation methods [20–22] to study the association between the ATIS use and mobility behaviors. Furthermore, some studies focused on the effects of ATISs on their users' mode choice behaviors, like public transport, and associations with multimodal mobility behaviors [18,34–36]. Guo (2011) indicated that regular public transport users had a significant tendency to use ATIS apps [37]. Moreover, Farag and Lyons (2012) analyzed how socioeconomic factors, travel attitudes affect the ATIS use for public transport travels for work and leisure purposes [38]. This paper studies the association between frequent use of ATIS services like Google Maps, MTA trip planner with the typically selected modes of New Yorkers for their work travels through a multinomial logistic regression by considering their socioeconomic parameters. This analysis gives an insight into the energy consumption behavior in the transport sector, whether the citizens who use more frequently ATIS apps are more likely to select energy-efficient modes like public transport and nonmotorized modes or unsustainable modes like private fossil-fuel vehicles for their daily work trips.

1.2. Ridesourcing

Ridesourcing is an ICT-based mobility mode, known as transportation network companies (TNCs), app-taxi, or ride-hailing, which connects passengers who request rides through smartphone-apps to their near available drivers by using GPS information and smart algorithms. The ridesourcing provides users real-time information about available drivers, waiting and travel time, different payment-methods, and rating systems, that passengers can assess the service quality of drivers [39]. Ridesourcing gained global successes in urban transportation by better service quality, more convenient door-to-door mobilities, and reasonable service fees than traditional urban transport modes like taxis. Some studies like in San Francisco indicated that ridesourcing services decrease deadheading distances compared to traditional taxis, which has a positive impact on energy efficiency and emission reduction [40]. Moreover, some studies mentioned that ridesourcing and online car-sharing might decrease household car ownership among citizens [41–44], which also positively impacts the sustainability of urban transport systems. Regarding the impact of ridesourcing on the mode choices of other sustainable modes like public transport, there are two effect-types, which are complementary and supplementary effects. The complementary impacts mean that citizens use ridesourcing integrated and connected with sustainable modes like public transport to fill temporal and spatial gaps in their infrastructure and service networks [45,46]. However, supplementary effects indicate that citizens replace sustainable modes with ridesourcing, which causes negative impacts on the sustainability of urban transportation by increasing vehicle-kilometers traveled (VKT), congestion volume, and consequently emissions [39,47]. The nonmotorized modes do not generate emissions, or public transport provides more energy-efficient and lower emissions by aggerating citizens' travels than ridesourcing services, which are based on car travels. Therefore, the modal shift from these modes to ridesourcing among citizens might offset the energy efficiency and sustainable impacts of ridesourcing when some other citizens shift from their private cars or traditional taxis to ridesourcing. This paper studies the percentage of modal shift from different mobility modes to ridesourcing services like Uber, Lyft, Via, and Juno in New York, and it compares with the international findings of other related studies.

1.3. The Modal Split in New York

New York City is known for its significantly higher share of public transport use in the urban modal share and the lower private car ownership than other American cities. The share of public transport use (excluding taxicabs) for the work travels in New York City is 58.5% of travel works which is higher than many American cities [48]. The Metropolitan Transportation Authority (MTA) provides 2.62 billion trips by buses, subways, and railroads each year to New Yorkers, which is around one-third of mass transit users in the USA [49]. Moreover, New York City has a higher population density than many American cities, with 2028 inhabitants per hectare, which is around two times bigger than that of compact cities like San Francisco (955 inhabitants per hectare) [50]. The modal split for work travels among New Yorkers includes 46% use the subway and railroads, 27% use cars (including driving alone and carpooling), 11.5% take the buses, 8.5% walk, 1.6% taxis, and 1.1% ride their bicycle to work [48]. NYC Department of Transportation (2019) reported a significant increase in For-Hire Vehicle (FHV) trips by around 90% since 2010, which is related to the increase in the use of ridesourcing services like Uber and Lyft [51].

2. Materials and Methods

2.1. Data Samples and Variables

This study used the results of the NYC DOT annual travel survey (New York City Department of Transportation) between May and June of 2019, which is open data and called Citywide Mobility Survey (CMS) [52]. The CMS gathered the data of travel behavior, preferences, and attitudes of New Yorkers. The CMS 2019 is the address-based sample, and totally 3346 citizens participated in the survey among ten city zones outlined by NYC DOT (around 300 residents per zone) [52]. The distribution of the participants across these ten zones is illustrated in Figure 1. The socioeconomic variables of this survey include age, gender, education, employment status, annual household income. The demography profile of the participants and their resident places are indicated in Table 1. The frequency-use of ATIS apps such as Google Maps, MTA trip planner, or other apps was driven by the question "How frequently do you use trip-planning apps, such as Google Maps, to plan your trips?". An ordinal variable is defined with eight measurement-levels which are 0: never, 1: less than monthly, 2: one-three days a month, 3: one day a week, 4: two-three days a week, 5: four days a week, 6: five days a week, and 7: six-seven days a week. The main mobility mode for work trips was asked by the question, "How do you typically travel to and from work?". Moreover, a sentence was added to clarify more this question: "If you use more than one method of transportation during the trip, select the method used for most of the distance". Furthermore, a replaced mode by ridesourcing services such as Uber, Lyft, Via, and Juno was asked by the question, "Before you began using smartphone-app ride services, how did you typically make these trips?". The multinomial logistic regression is applied to study the association between frequent use of ATIS apps and the main mobility mode for the work purpose, the multinomial logistic regression. Furthermore, the descriptive and inferential statistics (like Chi-square and Kruskal-Wallis tests) are applied to study the socioeconomic variables (income, gender) and the replaced mode by ridesourcing. The significant level is defined as a p-value < 0.05 for the coefficients in the multinomial regression and the inferential tests. Moreover, the p-values between 0.05 and 0.08 are regarded as marginally significant.

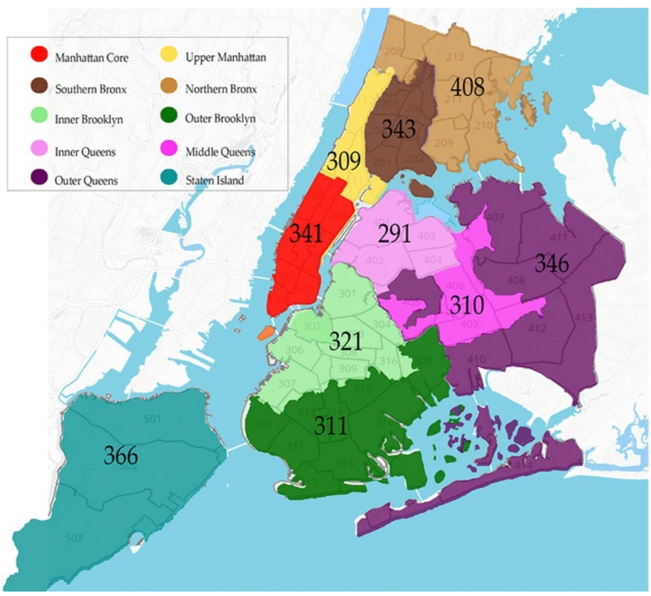

Figure 1. Distribution of participants based on their residential place [52].

Table 1. Demographic profile of the participants.

		N	%
Gender	Female	1806	55.6%
	Male	1440	44.4%
Age	18–24	253	7.6%
	25–34	749	22.4%
	35–44	664	19.8%
	45–54	612	18.3%
	55–64	555	16.6%
	65–74	361	10.8%
	75–84	125	3.7%
	85 or older	27	0.8%
Education	Less than high school	123	4.1%
	High school graduate/GED	307	10.2%
	Some college	454	15.0%
	Vocational/technical training	58	1.9%
	Associate degree	201	6.7%
	Bachelor's degree	1003	33.2%
	Graduate/post-graduate degree	874	28.9%
Employment	Employed full-time (paid)	1735	51.9%
	Employed part-time (paid)	315	9.4%
	Primarily self-employed	239	7.1%
	Not currently employed (e.g., retired, looking for work)	984	29.4%
	Unpaid volunteer or intern	73	2.2%
Annual household incomes	Under 15,000 $	259	9.0%
	$15,000–$24,999	250	8.7%
	$25,000–$34,999	224	7.8%
	$35,000–$49,999	290	10.1%
	$50,000–$74,999	489	17.0%
	$75,000–$99,999	407	14.1%
	$100,000–$149,999	462	16.0%
	$150,000–$199,999	243	8.4%
	$200,000–$299,999	171	5.9%
	$300,000 or more	84	2.9%
Resident zone	Inner Brooklyn	314	9.4%
	Inner Queens	298	8.9%
	Manhattan Core	301	9.0%
	Middle Queens	310	9.3%
	Northern Bronx	416	12.4%
	Northern Manhattan	315	9.4%
	Outer Brooklyn	312	9.3%
	Outer Queens	361	10.8%
	Southern Bronx	346	10.3%
	Staten Island	373	11.1%

2.2. Multinomial Logistic Regression

The multinomial logistic regression is used to model the association between the nominal (categorical) dependent variable, which is the main mobility mode for work travels, and the log odds of the independent variables, which are frequency use of ATIS apps, and variables annual household income, age, gender, and binary variable of the workplace in Manhattan. The multinomial logit model is an extension of binary logistic regression for the independent variable with more than two categories. The maximum likelihood estimation is applied to evaluate the odds of categorical membership relative to the reference group in the logit model. The multinomial logit model contains k-1 models, where k is the number of categories of the dependent variable and one category is chosen as the reference group [53]. In this model, the private vehicle is selected as the reference group for the model. The equation of the multinomial logistic regression is mentioned below, where $\boldsymbol{P_h}$ is the probability of using each mode, $\boldsymbol{P_{ref}}$ is the probability of using private vehicle (reference group), $\beta_{\mathbf{0}}$ is the constant, and $\beta_{\mathbf{jh}}$ is the coefficient related to each explanatory variable in the logit model of the given mode relative to the reference group.

$$\boldsymbol{ln}\left(\frac{\boldsymbol{P_h}}{\boldsymbol{P_{ref}}}\right) = \beta_{0\mathbf{h}} + \beta_{1\mathbf{h}}\mathbf{X_1} + \beta_{2\mathbf{h}}\mathbf{X_2} + \ldots + \beta_{\mathbf{jh}}\mathbf{X_j}$$

where k is the number of categories, **h** is 1 to k−1, j is the number of predictors.

Each exponentiated coefficient of a given estimator is the odds ratio, indicating the multiplicative change in the odds of using a specific mode relative to private vehicles (reference group) per a unit increase in the estimator, by holding other estimators constant. Long and Freese explained that the Exp($\beta_{\mathbf{jh}}$) is mentioned as the odds ratio because the multinomial logit model is considered as the simultaneously estimating binary logits for all comparisons among the different categories of dependent variable and the reference group [53].

An odds ratio greater than 1 for an estimator in a logit model of a specific mode suggests that the odds of using this specific mode relative to using private vehicles increases, when the given estimator increases. It means that using this specific mode is more likely than using private vehicle (the reference group). An odds ratio less than 1 means that by an increase in the given estimator, the odds of using the specific mobility mode relative to using private vehicles decreases. In other words, using private vehicles (the reference group) is more likely than using this specific mode. If the odds ratio is 1 for an estimator, it indicates that a change in this estimator does not change the odds of using the mobility mode relative to private car.

It is necessary to check the assumption of no multicollinearity between independent variables to use multinomial logistic regression. For this assumption, the correlation matrix and the variance inflation factor (VIF) are checked. If the correlation matrix shows a correlation more than 0.90, it indicates a high risk of multicollinearity [54,55]. Moreover, Hair et al. mentioned that if the variance inflation factor is bigger than 5.0, it indicates a high probability of multicollinearity between independent variables [55]. Both methods were applied to check the assumption of no multicollinearity, and the results did not show this risk. The values of VIF for the logit model are below 3.0 for the mentioned independent variables, and the correlation matrix does not show a correlation above 0.7 which indicates that there is no risk of multicollinearity.

3. Results

3.1. The Association between the ATIS Frequency Use and Mode Choices

2175 out of 3346 participants in this survey replied to the question about the main mobility mode for their work trips including rail modes, ferry, bicycle, bus/shuttle, rental/carsharing, private vehicles, walking, and taxi/ride hailing. Figure 2 shows the frequency use of ATIS apps by participants who select each mobility mode as their main mode for work trips.

The multinomial logistic regression is used to study the association between the frequency use of ATIS and the major mobility mode for work trips. As it is mentioned, the dependent variable in this logit model is the main mobility mode for work trips, and independent variables are frequency use of ATIS and variables gender, age, annual household income. As the Manhattan zone is the main employment center in New York with the high volume of work trips which affects mobility behaviors, a binary variable is defined as the workplace in Manhattan (Yes = 1, No = 0).

Private vehicle is selected as the reference group of the categorical variable of "main mobility mode". The Omnibus test indicates Chi-square = 531.567 and p-value < 0.001, which shows a significant difference between the log-likelihoods of the baseline model (without independent variables) and the model with independent variables. The Nagelkerke R-square and Cox and Snell of the model are 0.275 and 0.259, respectively.

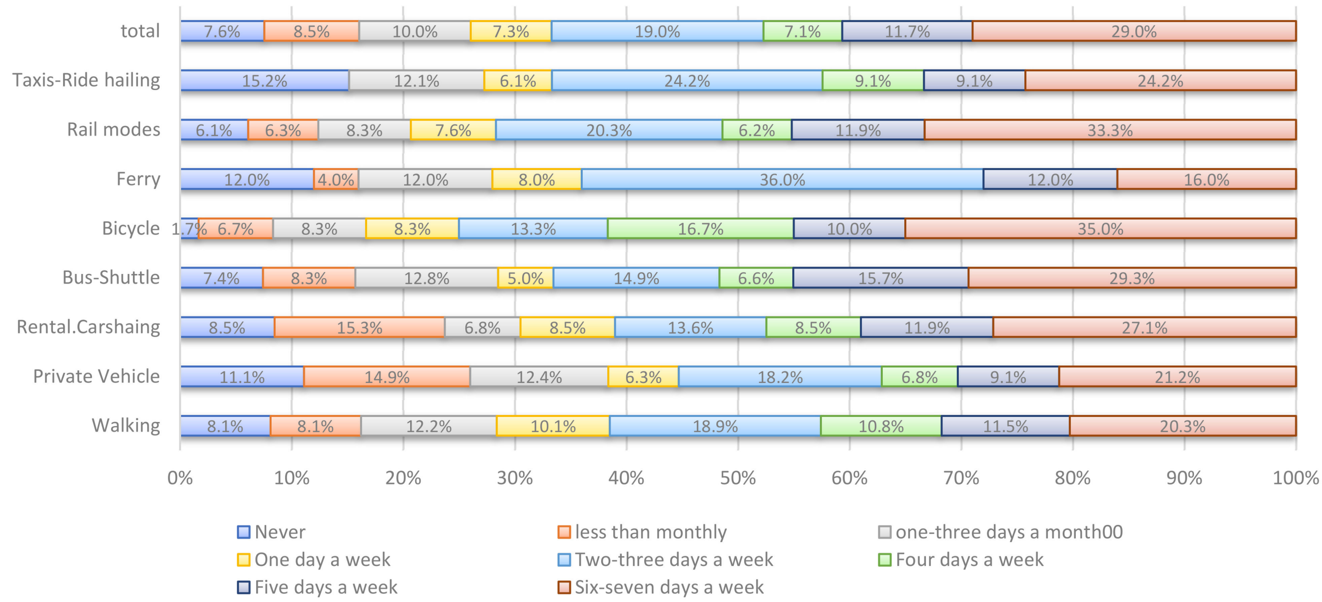

Figure 2. Frequency use of ATIS apps of participants for each main mobility mode.

Table 2 shows seven models for each main mobility mode for work trips, including walking, rental/carsharing, bus/shuttle, bicycle, ferry, rail modes (subway, train, light rail), and taxi/ridesourcing. Each model indicates the odds of using one of these modes relative to using private cars. As it was mentioned, the Exp(β) for each estimator in Table 2 is the odds ratio, and its amount indicates the multiplicative change in the odds of using specific mode relative to private vehicles. If it is greater than 1 in a given model, it indicates that one unit increase in this estimator (as a continues estimator) or a group change in the categorical estimator, increases the odds of using the given mode relative to the private vehicle. In other words, using this given mode is more likely than using the private vehicle. However, if it is less than 1, one unit increase in the given continues estimator or a group change in the categorical estimator, decrease the odds of using this mode relative to the private car, and in this case, using the private car is more likely than using this mode.

Table 2. Multinomial logit model for the main mobility mode for work trips.

Main Mobility Mode for Work Trips		B	Std. Error	Wald	Sig.	Exp (B)
Rental/Carshaing	Intercept	−0.846	0.926	0.836	0.360	
	Frequency use of ATIS apps	0.107	0.059	3.280	0.070	1.112
	Annual household income	−0.147	0.073	4.090	0.043	0.864
	Age	−0.110	0.123	0.805	0.370	0.896
	Gender (Female = 1, Male = 0)	−0.393	0.313	1.583	0.208	0.675
	Workplace in Manhattan (Yes = 1, No = 0)	1.204	0.417	8.327	0.004	3.333
Bus/Shuttle	Intercept	−1.606	0.593	7.345	0.007	
	Frequency use of ATIS apps	0.131	0.036	13.367	<0.001	1.139
	Annual household income	−0.286	0.045	40.367	<0.001	0.751
	Age	0.150	0.074	4.112	0.043	1.161
	Gender (Female = 1, Male = 0)	0.930	0.196	22.556	<0.001	2.535
	Workplace in Manhattan (Yes = 1, No = 0)	2.571	0.255	101.959	<0.001	13.072

Table 2. *Cont.*

Main Mobility Mode for Work Trips		B	Std. Error	Wald	Sig.	Exp (B)
Walking	Intercept	1.096	0.638	2.957	0.085	
	Frequency use of ATIS apps	0.036	0.041	0.792	0.374	1.037
	Annual household income	−0.246	0.051	23.374	<0.001	0.782
	Age	−0.238	0.086	7.619	0.006	0.788
	Gender (Female = 1, Male = 0)	0.260	0.213	1.484	0.223	1.297
	Workplace in Manhattan (Yes = 1, No = 0)	2.387	0.278	73.854	<0.001	10.884
Bicycle	Intercept	−0.874	0.978	0.798	0.372	
	Frequency use of ATIS apps	0.168	0.061	7.636	0.006	1.182
	Annual household income	−0.138	0.073	3.557	0.059	0.871
	Age	−0.227	0.129	3.113	0.078	0.797
	Gender (Female = 1, Male = 0)	−1.230	0.363	11.444	0.001	0.292
	Workplace in Manhattan (Yes = 1, No = 0)	2.991	0.359	69.572	<0.001	19.910
Ferry	Intercept	−3.569	1.541	5.362	0.021	
	Frequency use of ATIS apps	−0.060	0.093	0.413	0.520	0.942
	Annual household income	0.165	0.125	1.731	0.188	1.179
	Age	−0.056	0.186	0.090	0.764	0.946
	Gender (Female = 1, Male = 0)	−1.165	0.573	4.127	0.042	0.312
	Workplace in Manhattan (Yes = 1, No = 0)	2.420	0.505	22.979	<0.001	11.248
Rail modes	Intercept	1.213	0.439	7.632	0.006	
	Frequency use of ATIS apps	0.132	0.027	23.385	<0.001	1.141
	Annual household income	−0.151	0.034	19.251	<0.001	0.860
	Age	−0.154	0.057	7.353	0.007	0.858
	Gender (Female = 1, Male = 0)	0.334	0.143	5.463	0.019	1.397
	Workplace in Manhattan (Yes = 1, No = 0)	−3.017	0.216	194.240	<0.001	20.430
Taxis-Ridesourcing	Intercept	−0.538	1.178	0.209	0.648	
	Frequency use of ATIS apps	0.019	0.077	0.064	0.800	1.020
	Annual household income	−0.296	0.095	9.684	0.002	0.744
	Age	−0.183	0.161	1.295	0.255	0.832
	Gender (Female = 1, Male = 0)	0.439	0.408	1.156	0.282	1.551
	Workplace in Manhattan (Yes = 1, No = 0)	2.297	0.465	24.414	<0.001	9.942

The model of rental/car sharing relative to private cars includes two significant estimators at 99% and 95% confidence level for variables workplace in Manhattan and annual household income, respectively. Moreover, the model reveals a marginal-significant coefficient for frequency use of ATIS apps with p-value 0.07. The odds ratio of frequency use of ATIS suggests that each unit increase in the frequency use of ATIS apps raises the odds of using rental cars/carsharing relative to using private cars by 11.2% when other estimators are held constant. It means that people who use more frequently ATIS apps are more likely to use rental cars or carsharing than private cars. The odds ratio of being workplace in Manhattan indicates that the odds of using rental cars or carsharing relative to using private cars for citizens working in Manhattan are 3.33 times greater than these odds for citizens working in other zones when other estimators are constant. Therefore, people who work in Manhattan are more likely to use rental cars or carsharing instead of private cars than those working in other zones. Moreover, each unit increase in annual household incomes decreases the odds of using rental cars/carsharing compared to private cars by 14%. The model bus/shuttle suggests four significant coefficients at 0.001 level for frequency use of ATIS, annual household income, gender, and being workplace in Manhattan. Furthermore, the coefficient of age is significant at 0.05 level. Each unit increase in frequency use of ATIS apps and age increases the odds of using bus/shuttles relative to private cars raises by 14% and 16%, respectively, when other estimators are constant.

Moreover, every unit increase in annual household income decreases the odds of using bus/shuttles compared to private cars by 25%. The odds ratio of gender indicates that the odds of bus/shuttles compared to private cars for women are 2.53 times greater than these odds for men. The odds ratio of the binary variable "being workplace in Manhattan" is 13.07, which indicates that people working in Manhattan are significantly more likely than those working in other New York zones to use bus/shuttles instead of private cars.

The model walking indicates three significant estimators at significance level 0.05, which are age, annual household, and being workplace in Manhattan. Every unit increase in age and annual household decreases odds of walking relative to using private cars by 21% and 22%, respectively. The frequency use of ATIS apps does not have a significant odds ratio in this model. The model of bicycle suggests a significant odds ratio for the frequency use of ATIS apps at 0.05 level, indicating that each increase in frequency use raises the odds of using bicycles compared to private cars by 18% when other variables are constant. Moreover, the odds of using bicycles relative to cars for women are 71% less than for men. The model of ferry does not suggest a significant odds ratio for the frequency use of ATIS apps, and it indicates two significant odds ratios which are 0.31 and 11.25 for gender and workplace in Manhattan, respectively. The model of rail modes (subway, train, light rail) suggests five significant estimators at 95% confidence level. Every unit increase in frequency use of ATIS increases the odds of rail models relative cars by 14% by holding other variables constant. Moreover, every unit increase in age and annual household income decreases the odds of using rail modes compared to private vehicles by 14%. Moreover, these odds for women are 1.4 times greater than men. The model of taxi/ridesourcing does not indicate a significant odds ratio for the frequency use of ATIS apps. However, it suggests two significant odds ratios for annual household income and being workplace in Manhattan. Each unit increase in annual household decreases odds of using taxi/ridesourcing services compared to private cars by 26%.

3.2. Modal Shift to Ridesourcing Services

The question "Before you began using smartphone-app ride services, how did you typically make these trips?" was asked to study the modal shift from different mobility modes to ridesourcing services like Uber, Lyft. 1927 participants in this survey answered this question. The results are illustrated in Figure 3.

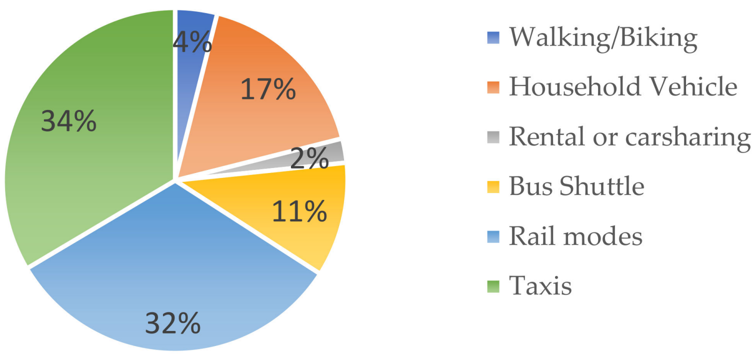

Figure 3. The percentage of modal shift to ridesourcing services.

The results indicate that the most replaced mobility modes by ridesourcing services, including Uber, Lyft, Via, and Juno are taxis and rail modes by 34%, 32%, respectively. The private car is in the third place by 17%. The Kruskal-Wallis test is used to study whether there is a significant difference in the distribution of annual household incomes among citizens who replaced different mobility modes with ridesourcing services. Figure 4 illustrated the boxplot of annual household incomes per each replaced mobility mode by ridesourcing.

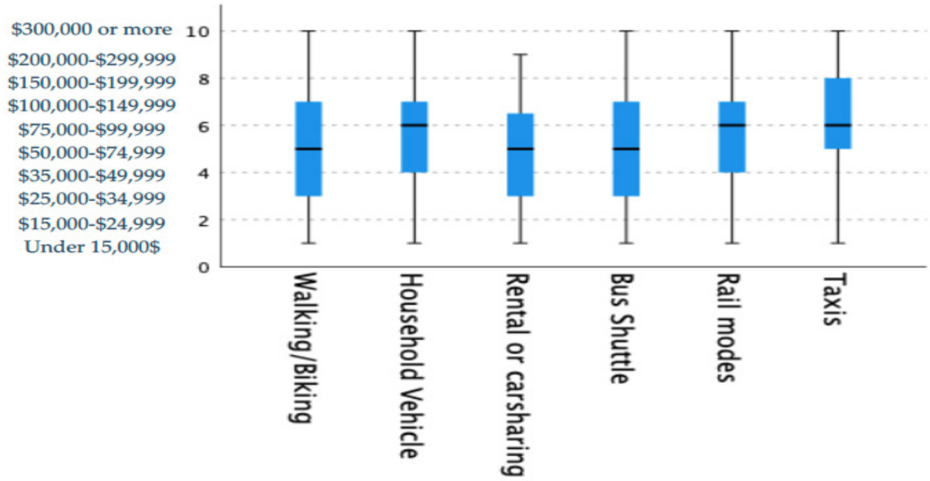

Figure 4. Boxplot of annual household incomes per each replaced mobility mode.

Figure 4 indicates that the medians of annual household incomes of people who replaced walking/biking, rental cars/carsharing, and bus shuttles are less than people who replaced taxis, private cars, and rail modes by ridesourcing. Table 3 indicates the Kruskal-Wallis test results for pairwise comparison in the distributions of household income among replaced modes by ridesourcing.

Table 3. Kruskal-Wallis test for pairwise comparison of household incomes among mobility modes.

Sample 1-Sample 2	Test Statistic	*p*-Value
Walking/Biking-Rental or carsharing	−3.215	0.974
Walking/Biking-Bus Shuttle	−7.208	0.917
Walking/Biking-Rail modes	−126.313	0.044 *
Walking/Biking-Private vehicle	−184.811	0.005 **
Walking/Biking-Taxis	−259.425	<0.001 **
Rental or carsharing-Bus Shuttle	−3.994	0.964
Rental or carsharing-Rail modes	−123.099	0.135
Rental or carsharing-Private vehicle	181.596	0.032 *
Rental or carsharing-Taxis	−256.210	0.002 **
Bus Shuttle-Rail modes	−119.105	0.005 *
Bus Shuttle-Private vehicle	177.603	<0.001 **
Bus Shuttle-Taxis	−252.216	<0.001 **
Rail modes-Private vehicle	58.498	0.104
Rail modes-Taxis	−133.111	<0.001 **
Private Vehicle-Taxis	−74.614	0.037*

* confidence level 95%, ** confidence level 99%.

The Kruskal-Wallis test suggests significant differences in the distributions of annual household income between people who replaced walking or bicycle by ridesourcing with the median (5th income level: 50 k$–74,999 $) and people who replaced rail modes, private cars, and taxis with the median (6th income level: 75 k$–99,999 $) at 95% confidence level. Also, this test indicates a significantly different distribution of household incomes among commuters who replaced rental car or carsharing by ridesourcing with the median (5th income level: 50 k$–74,999 $) and those who replaced private cars and taxis with the median (6th income level: 75 k$–99,999 $) at significance level 0.05. Furthermore, the distribution of household incomes between people who replaced rail modes and those who replaced bus/shuttles and taxis are significantly different at 95% confidence level.

Figure 5 illustrates the percentages of replaced modes by ridesourcing among female and male respondents in this survey. The Chi-square test of independence is applied to study whether there is an association between categorical variables of replaced modes by ridesourcing and gender. The result of this test indicates the Chi-square 19.140 with a *p*-value 0.002, which suggests a significant association between the variable of replaced modes by ridesourcing and gender at 99% confidence level. Figure 5 indicates that women replaced mostly taxis by 34.6%. However, the most replaced mode by ridesourcing among men was rail modes by 33.8%.

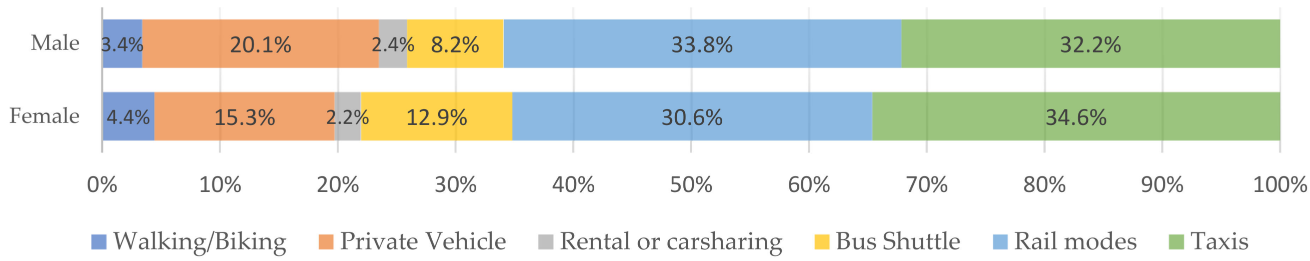

Figure 5. Replaced mobility mode by ridesourcing among female and male respondents.

Furthermore, the other big different percentages of replaced modes by ridesourcing among men and women are private cars and bus/shuttles. Men and women reported that they had replaced private cars by ridesourcing by 20.1% and 15.3%, respectively. The percentage of men and women who replaced bus shuttles by ridesourcing are 8.2% and 12.9%, respectively.

4. Discussion

The first part of findings indicates the association between the frequency use of ATIS apps and New Yorkers' mode choice behaviors for their work trips. The second part of the findings includes the modal shift from different mobility modes to ridesourcing services among participants in the CMS survey in New York City.

4.1. Frequency Use of ATIS Apps and Mobility Mode Choice

The multinomial logit model was used to study the relationship between frequency use of ATIS apps and mobility mode choice for work trips by controlling socioeconomic parameters. The model contains seven logit models which indicate the association between the odds of using each mobility mode relative to private cars and the frequency use of ATIS by holding the socioeconomic variables constant. The odds ratio of the frequency ATIS use is significant in the models of rail modes, bicycle, bus/shuttles, and marginally significant in the model of rental cars/car sharing. These findings indicate that by holding the socioeconomic parameters constant (like age, gender, annual household incomes), the New Yorkers who use ATIS apps more frequently are more likely to use rail modes than private cars for their work trips. This is also the same result for the mobility modes: bicycle, bus/shuttles, and rental/car sharing, which high-frequent users of ATIS apps are more likely to use these modes than their private vehicles for work trips. This finding of the association between ATIS use and mode choice is similar to the finding of Guo (2011), that reported a significant positive association between the public transport use and the tendency to use ATIS apps [37]. The impact of ATIS apps on the sustainability of urban mobility systems depends on how their released information affects citizens' mobility behavior by considering other factors like socioeconomic and urban forms of the cities. Moreover, some studies indicated that the socioeconomic parameters, traffic information types, and urban forms could more affect mobility behaviors and route choice of ATIS users [56–61]. Chorus et al. (2006) indicated that the influence of ATIS information on public transport mode choice is low when the users have more preference for car trips [62]. They mentioned that even if ATIS provides reliable information of public transport and encourages users to take public transport, its impact on mode choices of public transport is low and users tend to use cars because of their general preference for car travels. Furthermore, Farag and Lyons reported similar findings that the impact of ATIS on mode choice is affected by the overall tendency of users to public transport rather than achieving information through ATIS [38,63]. Therefore, positive attitude, experiences of public transport have a stronger association with the choice of public transport. In the case of New York City, which has the higher share of public transport use in the urban modal split than many American cities, the mode choice of public transport might be more related to other parameters. These parameters are socioeconomic factors [64,65]; urban forms and spatial parameters [66–69]; and qualitative factors, such as comfort [70,71].

However, the significant positive association between frequent use of ATIS apps and using sustainable mobility modes like public transport and bicycle rather than private cars indicates that ATIS apps have a potential to foster and reinforce sustainable mobility behaviors among New Yorkers. Because information is an important role in optimizing the commuters' choice for using sustainable modes like public transport [72,73]. Moreover, Kammerlander et al. explained that one of the barriers for shifting from private cars to sustainable modes like public transport is a cognitive dissonance which includes a sense of uncertainty or discomfort when commuters are used to car travels [74]. Therefore, ATIS apps can reduce this uncertainty by providing high-quality and reliable information about the optimized time plan and routes for sustainable modes like bicycle, public bus, and rail modes. Furthermore, some studies emphasized the role of gamification in ATIS apps to engage users effectively and encourage them to use active modes and public transport. [75,76]. Moreover, providing some personalized services in ATIS apps for sustainable modes, like user customization, highlighting the advantages of active and sustainable modes in daily life, and getting feedback are influential factors to foster sustainable mobility behaviors. Therefore, it is recommended to improve active ATIS apps and platforms in New York by gamification methods and provide more user-friendly interfaces to reinforce sustainable mobility behaviors.

4.2. Ridesourcing Services and Mobility Behaviors

To understand whether ridesourcing services have sustainable or unsustainable impacts on the urban transport of cities, it is necessary to analyze which mobility modes are replaced by ridesourcing. If the users of ridesourcing services shift more from sustainable modes like public transport or nonmotorized modes rather than private cars, then ridesourcing has negative effects on the sustainability of cities. Because nonmotorized modes and public transport are more energy-efficient and environment-friendly than ridesourcing services, which are mostly based on fossil fuel vehicles.

The impact of ridesourcing services on mode choice behaviors can be studied through the counterfactual questions like "which mobility mode would interviewees have used if ridesourcing had not been available?" which were applied in some studies [39,47,77–80]. The interviewees imagined a manipulated situation to answer this type of question. Some studies applied other approaches to understand how the tendency of frequent ridesourcing users is toward nonmotorized modes [81,82] and public transport mode [83] by asking a think-forward question from regular users of ridesourcing in the present tense like "how often do you make travels by nonmotorized modes/public transport?".

In this approach, first, the group of regular ridesourcing users is clustered among interviewees regarding their frequency use, and then their tendency to different sustainable modes is compared with non-regular users. This approach is based on the theory that the frequent use of one transport mode influences general mobility behaviors to use other transport modes [84]. In this survey, the Citywide Mobility Survey (CMS) 2019, the participants were asked the direct question, "Before you began using smartphone-app ride services, how did you typically make these trips?". This question gives insight into the modal shift from different modes to ridesourcing services like Uber, Lyft, Via, and Juno. If we consider the percentage of replaced rail modes and bus together as public transport by 43%, then the public transport is the first and taxi by 34% is the second most replaced mode by ridesourcing services among the New Yorkers in this sample. This result is the same as the findings of Gehrke et al. in Boston [85]. However, the studies in other American cities reported that taxi is the first most replaced mode in California by Alemi et al. [79], and separately in San Francisco by Rayle et al. [39]. Moreover, in other countries, it was reported that taxis and public transport were the first and second most replaced modes by ridesourcing, respectively, like Chinese cities by Tang et al. [86], Brazilian cities by Souza Silva et al. [87] and in Santiago (Chile) by Tirachini and Gomez-Lobo [88].

The third replaced mode is private cars by far lower percentage 17%. This finding is different from Henao and Marshall's finding in Denver that reported the same percentage for private cars and public transport as the most replaced mode by ridesourcing [89]. However, the other studies reported similar findings of this study that public transport is more replaced than private cars [39,86–88]. If citizens replace their car travels by ridesourcing services, this modal shift has a positive effect on the urban environment because ridesourcing services have better efficiency of energy consumption by increasing passengers per car trips and cause to reduce traffic congestions. However, if the citizens replace public transport by ridesourcing, which are mainly based on fossil-fuel cars, it causes negative impacts on the urban environment and transport systems. Public transport modes including rails modes and public buses are more energy efficient than private vehicles through aggregating individuals' travels. Therefore, the modal shift from public transport to ridesourcing raises VKT (vehicle kilometers traveled) and the traffic volume, while public transport is much more efficient energy-consumer and generates lower emission than ridesourcing services. Graehler et al. indicated that the modal shift from public transport to ridesourcing causes to decrease annually in the use of buses by 1.7% and heavy rail by1.3% in the 22 big American cities [90]. Lewis and MacKenzie indicated that this type of modal shift increased air pollution in Seattle [91]. The finding of this survey shows that the share of modal shift from nonmotorized modes was 4%, including walking and biking. Although the findings indicate that nonmotorized modes were replaced less than taxis, private cars, and public transport, this type of modal shift has significant negative impacts on the overall energy-efficiency of urban transportation and the environment. Because this modal shift induces more energy demands for mobility systems, which can be done by nonmotorized and zero-emission modes like walking and biking. Therefore, it is essential to avoid this type of modal shift by improving the infrastructure and conditions of nonmotorized modes.

Furthermore, the Kruskal-Wallis test suggests a significant difference in the distribution of the annual household of the participants who replaced nonmotorized or buses and those who replaced taxis, private cars by ridesourcing services. These groups of participants have lower median household income. Therefore, there is a potential that by imposing price-policies, for example, special charges on short-distance ridesourcing trips, the citizens are encouraged to make their short-distance trips by nonmotorized modes or buses, which are more environmentally friendly modes. Moreover, this special charge for short-distance ridesourcing trips can be spent to improve the conditions of bike lanes and pedestrian paths which increase the tendency of citizens toward nonmotorized modes. Furthermore, the policymakers could encourage ridesourcing companies to offer incentives or discounts to the commuters who use ridesourcing in connection with sustainable mobility modes like public transport and public bikes [46,92].

The gender differences in the modal shift to ridesourcing indicate that women replaced bus/shuttles and nonmotorized modes more and private cars less than men by ridesourcing services. One reason for this difference might be related to the different perceptions of safety and security among women and men on public buses and private cars. One solution to improve the positive impacts of ridesourcing on urban sustainability is developing and increasing the availability of shared ridesourcing services like the uberPool and Lyft line in New York, which increase the passenger per car travels decrease VKT (vehicle kilometers traveled) and traffic congestion. However, there might be some social and cultural barriers for shared ridesourcing, like the preference for privacy, or women might not prefer to share their ridesourcing services with strangers [46,87,93], which should be considered to develop these mobility services.

5. Conclusions

The energy efficiency and sustainability in the urban mobility sector are influenced by the citizens' mobility behaviors. This paper tried to shed light on the impact of two ICT services on the urban mobility, including Advanced Traveler Information Systems (ATIS), and ridesourcing services. This paper analyzed the associations between use of these ICT services and the mobility behaviors in New York including mobility mode choices and modal shift which affect the energy consumption in daily urban travels. This study used Citywide Mobility Survey (CMS) results, which was conducted by the New York department of transportation in 2019. The multinomial logit model results suggest that by holding the socioeconomic parameters constant (like age, gender, annual household incomes), high-frequent users of ATIS apps are more likely to use rail modes than private cars for their work trips. Moreover, these users are more likely to make their work travels by bicycle, bus/shuttles, and rental/carsharing than the private vehicles. The significantly positive association between frequency use of ATIS and using modes like bicycle and public transport rather than private cars indicates that ATIS apps have a potential to reinforce sustainable mobility behaviors among New Yorkers which improve the overall energy efficiency in the urban transport sector. ATIS apps reduce the uncertainty of traveling by bicycles, public transport, and shared vehicles by providing reliable information about the optimized time plan and routes.

The modal shift to ridesourcing from different modes indicates that public transport (including rail modes and buses) is the first, and taxi is the second most replaced mode by ridesourcing services among the New Yorkers in this sample. The third replaced mode is private cars by far lower percentage. The modal shift from public transport might cause negative effects on the total energy efficiency in the urban transport sector and urban environment by increasing VKT and traffic volume. Therefore, it is essential to avoid modal shift from sustainable modes by improving the infrastructure and conditions of these modes. Moreover, it is suggested to encourage citizens to use ridesourcing in connection with sustainable mobility by imposing price-policies, like offering some incentives and discounts to the commuters who use ridesourcing integrated with public transport and city-bikes. Furthermore, special charges can be imposed on ridesourcing fees for short-distance trips to avoid the modal shift from nonmotorized modes, which has a negative impact on the sustainability of urban transportation.

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