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# A Smartphone App Survey to Encourage Sustainable and Healthy Travel Mode Choices

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**A Smartphone App Survey to Encourage Sustainable and Healthy Travel Mode Choices**

**by**

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## Abstract

The importance of understanding transportation from the perspective of carbon emissions and mode shift is paramount. Specifically, focusing within the transportation geography realm to highlight the carbon footprint of different transportation types [ie bus, car, carpool, subway, rail, bike, walk]. Survey methods are used in conjunction with smartphone sensor and a GPS mobile app. This app logs location, and speed of movement over the course of a week among other variables. The app outputs information concerning daily carbon footprint and health indicators – namely carbon emissions and avoidance, calories and fat burned, along with other locational information like speed and elevation. This data is gathered from respondents in an effort to understand whether daily information of carbon footprint and heath indicators influences their transportation choices. Survey techniques measure transportation tendencies in weekdays, and weekends, carbon emission differences between different transportation options, and willingness to shift transport mode based on app experience over the week.



**Keywords:** mode shift, mobile app, transportation, health, mobile sensors, mobile app, carbon emissions, New York

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## Introduction

Importance of Research

Transportation has been an integral part of a functioning society and will continue to be so as humanity embraces the digital age. Unfortunately, innovations developed during the industrial age have had unfortunate environmental consequences, particularly in the form of carbon dioxide emissions (EIA, 2016). The increasing amount of anthropogenic carbon emissions are the dominant driver of climate change and induced global warming (IPCC, 2014). In response, relevant resources and recommendations must be made available to the public in choosing how they cover the increasing distances modern society has enabled. While it is clear that new sustainable and energy efficient transport technologies can help stem the tide on runaway greenhouse gases (GHG) (Sims et al., 2014), there are many perfectly acceptable alternatives for the global citizen concerned about their carbon impact. Making changes to everyday behavioral decisions like commuting patterns can have significant overall impacts on the public's carbon footprint (Edenhofer O. et al., 2014). In addition, as mobile sensors like smartphones and GPS data become more widely available, and techniques to analyze these kinds of datasets more ubiquitous, local governments can begin to pursue behavioral change strategies more seriously. Increased public climate education should and can be invested in along with large scale infrastructural change. These types of interventions will aid in reducing carbon emissions, especially considering that the transportation sector is one of the biggest carbon polluters.

This research project will contribute to the growing body of research on sustainable transportation, sorely needed in today's changing climate and society. This research focuses on public empowerment through knowledge creation, specifically education regarding individual carbon footprint and health indicators. Along with promoting more sustainable mobility, public education can have other alternative benefits. For example, encouraging people to switch from private and sedentary modes like driving to mass transportation or active modes like biking and walking will support public health and foster positive health outcomes. Reducing private transportation (automobiles and other single occupancy transport modes) may reduce issues like traffic congestion. Finally, testing whether mobile apps like the one employed in this study can aid in changing environmentally relevant behaviors by citizens will have innumerable benefits in information-technology (IT) sectors, governmental applications, private enterprises, and grassroots initiatives.

## Influence of Transportation to Carbon Emissions

The transportation industry makes up a large part of global carbon emissions sources. The industry is responsible for about 23% of “total energy-related” carbon emissions globally, and is the most rapidly growing sector with emissions projected to double by 2050 (Creutzig et al., 2015, p. 911). The various sectors of society, predominately led by recommendations from academia and government, have drafted legislation and proclamations to reduce carbon emissions on a sectoral basis. Transportation is an integral part of these plans with disparate recommendations ranging from electric vehicles, energy efficient fuels, to more buildouts of public transport like rail. It is very likely that a combination of the many recommendations will play a part in reducing overall sectoral transport emissions. The International Panel on Climate Change Fifth Assessment Report notes that stabilization of transport sector carbon emissions at 2010 levels by 2050 is consistent with the agreed upon 2°C goal (Creutzig et al., 2015, p. 911). While the major driving force behind the reduction in transportation emissions is the mitigation of climate change impacts, there is considerable discussion as to which techniques should be prioritized. There is high confidence that behavioral change based techniques like modal shifts and avoided journeys, in conjunction with other recommendations like technology improvements, investment in infrastructure, and changes in the built environment have high mitigation potential (Sims et al., 2014, p. 603). While many techniques can be used in reducing the carbon emissions of transport this research will focus on behavioral options, specifically mode shift, and its ability to effect behavioral change in local often urban environments.

## Importance of Environmentally Pro Behaviors

Environmentally-positive behaviors, specifically transportation-related options like mode shift and avoided journeys can have a large impact on reducing overall emissions, and may often require less capital than alternatives such as building out new or retrofitting older infrastructure. Some of the scalability of behavioral solutions have been helped greatly by new technologies like GPS and widespread smartphone use. In addition, the availability of alternative lower carbon transport like bike sharing systems, as opposed to driving alone, have opened up new realms of behavioral research. It is here that society may find some low hanging fruit in efforts to reduce global emissions.

## Climate Change Influenced by Carbon Emissions

The global focus on greenhouse gas emissions overshadows the immense effects climate change will have on regional temperatures and urban areas. Global warming impacts not only sea levels, agricultural productivity, or sea ice cap extent, but coastal urban locations where some of the largest concentrations of humanity resides. Climate changes have been largely brought about by an increase in anthropogenic greenhouse gas emissions at levels not seen in the last 800,000 years (IPCC, 2014). Global emissions levels have been steadily increasing as a result factors like population and economic growth. According to the latest assessment report by the IPCC, anthropogenic greenhouse gas emissions had reached 49± 4.5 Gt $CO_2$ eq/yr (gigatons of $CO_2$ equivalent per year) (IPCC, 2014). Carbon emissions, along with other greenhouse gases are the primary driver of global climate warming, and it has been proven that observed GHG emissions along with other climate forcing's are anthropogenic in origin (IPCC, 2014). Urban areas especially are projected to experience increased environmental pressure due to climate change. Cities have become the economic engines of the developed and developing world and are increasingly the focal points of intensive climate study. Cities are also the nodes of many transportation networks and are therefore good places to study possibilities for mitigating transport-derived carbon emissions.

## Why Carbon Emissions and Climate Change are Important

The importance of reducing emissions globally as well those emitted by the transportation sector is paramount. Topics covered in this research on behavioral changes and technology can help address the impacts of climate change. The issues associated with climate change-induced global warming are primarily due to anthropogenic releases of carbon and methane releases:

> "human influence on the climate system is clear and recent anthropogenic emissions of greenhouse gases are the highest in history. Recent climate changes have had widespread impacts on human and natural systems" (IPCC, 2014)

Transportation emissions of greenhouse gases are widespread and largely ingrained in social and commercial actions and behavior. The transportation sector specifically has become particularly important in mitigating the influence of greenhouse gas emissions on overall climate change impacts. Transportation now makes up the largest share of carbon dioxide emissions from energy consumption by sector (see Figure 1. in References). According to the U.S Energy Information Administration's September 2018 Monthly Energy Review, in 1998 carbon dioxide emissions from transportation-related energy consumption surpassed industrial-derived energy consumption for the first time, the previous highest sector-specific source of emissions in the U.S. In 2016, transportation-derived emissions surpassed electricity generation-derived carbon emissions for the first time: increasing from 1848 million metric tons (mmt) $CO^2$ in 2015 to 1886 mmt in 2016 (EIA, 2018). Transportation has continued to be the dominant sector-specific source of emissions in the U.S. This only heightens the need for policy aimed at transport-derived emissions, along with an emphasis on behavior-based research and education.

## **Theoretical Structure of Thesis**

Research Rationale and Reasoning

This research attempts to bridge the gap between transportation behavior research and other more visible approaches to transportation-derived carbon emissions. More specifically, conclusions drawn would help broaden the discussion of what techniques society could use in reducing emissions in the transportation sector. In addition, while the importance of behavioral actions like modal shifts and trip avoidance in saving overall sectoral transport energy needs is clear (IPCC, 2014; Sims et al., 2014), to what degree can these changes provide non-climate benefits? While behavioral change like modal shift may seem negligible compared to major technological, fuel, or sector-wide shifts (Cruetzig, 2015), understanding why citizens make these kinds of choices is key to understanding how conclusions can be scaled across broader mitigation strategies. Moreover, highlighting the key talking points of positive-environment outcomes in transportation may diversify the available research on the subject. Contributing to the discussion can help society make informed choices in balancing environmental impact and the need for mobility. This technique lies fairly within the social geography and empowerment research lens. By giving subjects opportunities to learn through their experience with the mobile app, both technological development and co-knowledge production are being promoted. In this research topic lens, ideal results would indicate the transition to lower carbon footprint transport choices.

Broad Overview of Techniques and Research Questions

This research employs surveys and a mobile smartphone app in order to draw conclusions on the driving factors of environmentally positive transportation choices. More broadly, these techniques are used in order to gauge the effectiveness that access to personal environmental information has on pro-environmental transport behavior. Surveys are used to measure the amount of behavioral change before and after the use of a mobile app. Specifically, the mobile app outputs carbon emissions and health indicators like calorie and fat burn based on the subjects chosen transport mode decisions. The transit app uses these location tracking, mode detection, mobile sensing techniques in order to compose GPS paths, output carbon footprint and health data, and generate user daily trends. Using the transit app in conjunction with an opinion and behavioral survey gives the researchers more information on how interventions can influence behavior. Our question types behave much like an analytic survey, in which we want to know the “causes for characteristics” (Leung, 2001, p. 143). By combining rapidly developing mode detection and survey techniques, an ideal combination can be employed to provide additional context to data. Traditional travel surveys have been used to help measure how participants use available transportation and to answer research questions. However, by combining convenient online surveys with mobile app tech, ideally mobile sensing technology can be used to a fuller extent. This is a challenging task despite the wealth of literature on survey techniques, sampling, and mobile device based social studies.

**Literature Review:**

Traditional Enabling Technology, the Urban Environment, and Modern Refinements

This research attempts to utilize location-based mode detection, and survey techniques to measure and influence commuter behavior. There is a significant spatial concern involved in studying commuter patterns in large urban conglomerations. These concerns can include: urban canyon distortions with GPS due to tall buildings, data issues in a multi-modal transportation system, and even the increasing respondent burden associated with survey data collection. The goals of transportation-oriented studies often mirror efforts in transportation demand management (TDM). TDM-derived strategies seek to influence travel behavior by mode, time, location, and route (Barbeau, Labrador, Georggi, Winters, & Perez, 2009, p. 3). There is an established literature documenting attempts at monitoring transportation behavior. Previously, travel paper diaries required research participants to enter large amounts of locational and socio-demographic data (Chen, Gong, Lawson, & Bialostozky, 2010, p. 5). This large burden on respondents has been somewhat reduced with the advent of online computer-assisted data entry and GPS technologies. In previous cases, respondents would fill travel information into a web interface which includes entry options like lists, start / end options, addresses, origins, and destinations (Stopher, 2014, 317). GPS has completely restructured the possibilities of transportation use tracking. It can provide researchers, commuters, government, and other parties with reliable locational information in the form of 'paths' logged by the GPS unit. GPS units record these paths using time and geo-referenced points, along with variables such as latitude, longitude, time, speed, and heading (Chen et al., 2010, p. 830). GPS location paths are easily GIS translatable and offer a new range of digital information. Despite these benefits, they are still simply point logs with attributes, they cannot automatically infer more meaningful trip details.

For example, while GPS units can get a detailed log of movement, they cannot detect the type of transport mode [i.e bus, carpool, biking, walking], distinguish users, or deduce trip purpose information (Barbeau et al., 2009, p. 5). In addition, there are some issues in relying solely on GPS availability. In New York City for example, the heavily built up areas are punctuated by tall buildings which cause ‘urban canyon effects’. These urban canyons distort GPS signal reception (Chen et al., 2010, p. 831). The spatial granularity of the city presents complex challenges to researchers investigating subjects using GPS location. However. it is possible to collect more information than just GPS paths using GPS-enabled mobile devices. Before widespread mobile phones, mobile sensing required specialized devices and tuned apps (Lane et al., 2010, p. 140). However, market forces have combined to allow researchers to take advantage of more accessible technologies. The inclusion of cheap sensor-embedded mobile devices, originally included in phones to improve user experience, has increased research application potential (Lane et al., 2010, p. 140). At the time of reporting the 2011 International Telecommunication Union Report projected almost 6 billion mobile phone subscriptions worldwide, making them the most popular personal device (as cited in Mavletova, 2013, p. 725). This translates into a huge amount of untapped diverse sensor types for a variety of social studies possibilities. Accelerometers for example were originally used to change the phone display orientation (Lane et al., 2010, p. 140). Now they can be used to measure aspects that GPS cannot. More expensive survey techniques are no longer required with the variety of sensors offered in modern mobile phones. These include: light and proximity sensors, cameras, GPS, Wi-Fi, Bluetooth radio, accelerometer, dual microphones, compass, and a gyroscope (Lane et al., 2010, p. 141). By using mobile devices researchers can avoid the complicated and uncertain data capture issues associated with travel surveys. Mobile devices used by subject will need to have multitasking and background processing capabilities (Lane et al., 2010, p. 146). Using the functions in a mobile phone system to conduct travel behavior surveys allows researchers to collect data digitally, reducing the large costs associated with traditional practices (Asakura & Hato, 2004, p. 6). By aligning the data capture abilities of GPS and information on transportation network and land use patterns, researchers can develop algorithms capable of detecting travel mode and trip purpose (Chen et al., 2010, p. 830).

Data collected for this purpose can be quite expansive and include significant geoprocessing. Transportation network information can include: geo-spatial layers representing different modes, roadway networks, bus routes and stops, subway routes, subway entrances and exits, and commuter rail routes and stops (Chen et al., 2010, p. 834). This information is useful for GIS analysis in conjunction with GPS paths and any alternate data. In Chen et al. (2010) the mode layers were spatially joined, then edited within the attribute table to resolve spatial connection, network merging, and spatial abstraction issues (p. 835). The resulting work included: a geodatabase that included line files of various modes, point files for rail stations, subway entrances and exits, bus stops, algorithm with multiple criteria enablement to reduce urban canyon effects, signal gaps, stops from trip segments, identification of mode change points, and the ability to distinguish spatially similar but different mode trip segments (Chen et al., 2010, p. 838). Once the underlying transport network database is completed the data and trip purpose identification can begin. This process includes: the division of trips into individual ‘trip segments’, and the identification of the travel mode (Chen et al., 2010, p. 835). ‘Trip segments’ are portions of each trip that are taken by a single mode (Chen et al., 2010, p. 835). These are particularly important because they provide more information for the researchers to confirm trip purpose, highlight commuting patterns, and improve the recognition capabilities of their analysis techniques.

Technology needs to keep up with the research demand for utilizing everyday gadgets. Some challenges to mobile phones include: the need for software to accommodate diverse device type and servers, adverse effects on phone performance, call and battery influences, and privacy concerns regarding position [location] (Barbeau et al., 2009, p. 6). The user can reduce some burden by initiating passive tracking, which runs operations in 'the background' separated from user view. However, passive tracking may impact cell performance, influence privacy, and phone functionality (Barbeau et al., 2009, p. 13).

Mobile phone sensing is effective for individual applications, social networks and other groups, and even entire communities i.e city populations (Lane et al., 2010, p. 142). The use of a mobile app to collect and display relevant information for respondents is ideal.

## Review of General Survey Techniques

While Leung (2001) highlights good sampling practices, along with tested and reliable techniques. They generally follow: clarification of purpose, definition of the study population, sampling and estimation of the sample size, deciding variables and information to collect, measurement of data gathered, collection of data, analysis and interpretation (Leung, 2001, p. 143). Some issues concerning sampling involve: the appropriate representation of the subject population, gathering a sufficient sample size, the clarification of questions intended to answer a research purpose (Leung, 2001, p. 144). These issues only increase when we move sampling into an internet-based and mobile device realm. A key challenge for online surveys is the lack of a discrete sampling frame (Mavletova, 2013, p. 726). In this case, internet users cannot simply be randomly selected in the same manner of phone number generation for telephone surveys (as cited in Mavletova, 2013, p. 726).

However, the issue can be raised that targeting mobile-only populations, and those with mobile internet access is limiting (Mavletova, 2013, p. 726). Mavletova (2013) sent emails and invitations with web links to the survey, and previously describes online questionnaires completed over PC, and cell phone (p. 726). Respondents can also be 'grouped' based on the survey presentation. Some respondents view questions in a different order, have different or decreased answer options, and denied 'don't know' type bypass options (Mavletova, 2013, p. 733).

## Influence of Survey Factors on Effectiveness

Many factors contribute to the effectiveness of survey techniques. Survey design plays a large part in the success of data capture. Answer length was measured against survey factors using OLS regression in one study. These survey factors included: mobile web usage experience, survey length, type of mobile phone, demographic variables, and place where respondent completed the questionnaire (Mavletova, 2013, p. 737). Despite the diversity of parameters, Mavletova (2013) found no impact regarding the questionnaire length, type of phone, and place (p. 737). Axhausen (2008) was helpful in using a study of social networks, locational choices, and travel. While Axhausen (2008) specifically looked at mobility tools owned¸ a breakdown list including residence, home ownership, household composition, income, and other variables (p.

986) were beneficial in designing a respondent profile survey section. Using methods like these help researchers understand how respondents respond to differently varied survey types.

Understanding trends in the established research would be critical in research design. Respondent bias could be an issue, especially in environmentally-focused studies. Public opinion while dramatically shifting in a favorable direction regarding climate change mitigation, may continue to be subject to opinion bias. At least respondents in interview settings in particular are more likely to give socially desirable answers, while less likely to give socially undesirable answers (as cited in Stern, Bilgen, & Dillman, 2014, p. 286). Recruitment is also an important part of sampling and survey techniques that needs review. Email recruitment techniques are quite popular for finding respondents. The feedback in the established literature can be mixed depending on the setting. In some cases, like Stern, Bilgen, and Dillman (2014) email contact has yet to achieve high response rate. This only heightens the importance of a well-designed survey. To judge whether the survey is informative it is key that survey responses “truly capture the agents unobserved beliefs” (Armantier, Bruine de Bruin, Topa, van der Klaauw, & Zafar, 2015, p. 507). A survey based in Australia included questions designed to assess whether the respondent would be willing to alter their travel behavior to improve air quality, or reduce greenhouse gas emissions (Golob & Hensher, 1998, p. 5). In this case, environmental attitudes play a large role and should be included as well.

## Health Influences as Additional Benefit

One aspect of travel that is of importance to commuters is health. Bicycle and walk modes are more physically intensive than more sedentary modes like driving. Does this mean that walking and biking contribute to health? de Sa, Parra, and Monteiro (2015) use variables like mode shift and distance to investigate active / non-active transportation behavior. However, they also find that active commuting like walking and biking could lead to health benefits. Increases in active transportation could lead to higher numbers of people reaching recommended physical activity levels (p. 186). In addition, other researchers have pointed to positive effects of active modes like walking or cycling, and even when using public transport (Ettema et al., 2116, p. 20). Health can be directly affected by the travel options groups like commuters choose. Switching from active modes or public transport to motor transport was correlated with an increase in BMI of 0.05 – 0.64 $kg/m^2$ (after adjustment) (Martin, Panter, Suhrcke, & Ogilvie, 2015, p. 4). Active modes are an integral part of maintaining health, but may not be the only option for those wishing healthier options. Even public transportation is correlated with reductions in BMI, over a 2 year study period (Martin et al, 2015, p. 4). So are the benefits associated with active commuting enough to prompt behavioral change?

Determining the Relationship between Mobility and Emissions: General Factors in Environmentally-Positive Behavior

Travel survey research has been extremely important in highlighting changes in commute behavior. While this survey includes individual commuter behavior, other studies focusing on household level granularity can offer good insights. For example, Xiao, Lenzer Jr., & Chai (2017) use Beijing as a case study for examining household travel carbon emissions (HTCEs) at a neighborhood level. Their data set was produced using a household activity diary reflecting typical neighborhood and community categories (Xiao, Lenzer, & Chai, 2017, p. 491). Surveys can diverge, with the Beijing case study using commuter patterns as a metric with demographic and socioeconomic factors (Xiao et al., 2017, p. 488). The general questions for the Beijing case study included family size, household income, age, car ownership while the travel diary included information on: activity type, timing, duration, trips taken for activity, travel modes, origins, and destinations (Xiao et al., 2017, p. 492). Additionally, the research analysis methodology is very helpful for understanding proper statistical investigation for variables. For example, distance to city center, age, residential composition, and other variables are listed for each neighborhood category, profile ranges are used for context at this neighborhood-level, and general statistics measures are generated (Xiao et al., 2017, p. 493). These data inferences can be applied to our own results.

Upham, Dendler, & Bleda (2011) also attempt to find whether the use of information in the form of carbon labeling in the UK can be considered a factor in consumer behavior. The results are slightly disconcerting for those of us in the transportation realm here in the U.S. Only 11% of UK citizens felt that environment and pollution were among their top factors affecting quality of life, with most instead choosing money, health, crime, jobs, neighbors, transport, and housing (Upham, Dendler, & Bleda, 2011, p. 351). They elaborate further that "growing awareness of environmental problems at an abstract or general level tends not to feed through to personally-relevant attitudes (Upham et al., 2011, p. 351). "Studies suggest a relatively low salience for climate change in individuals day-to-day choices and actions" (as cited in Upham, Dendler, & Bleda, 2011, p. 351).

The availability of information or experience is one factor of significant importance in determining travel behavior. Specifically, single-occupancy car users are able to switch modes based on information or experience. Thogersen (2009) found that the difference between switchers and non-switchers (from automobile mode to public transit mode) became larger after the research experience. This varies by occupation as well. Wang and Liu (2015) use framework analyzing mode choice behavior of commuters to University of Queensland. In this study, car modes are most popular with university staff, while public transport is more popular with students (p. 7). In other analyses like Ripplinger, Hough, and Brandt-Sargent (2009) the most popular mode for students commuting to campus was the car mode, followed by walking (p. 8).

Mode choice can be influenced by the availability of public transit and land use. More physically intensive trips called ‘active trips’ were defined by Mackenbach, Randal, Zhao, and Howden-Chapman (2016) as trips with an ‘active mode’ (biking, walking) with a duration of at least 10 minutes (p. 3). They found that higher housing density, higher walkability, and higher transit score (measure of useful transit routes in the immediate area) equated to a higher likelihood of active commuter trips (p. 8). In addition, bus frequency and a higher number of rail stops were both positively associated with higher likelihood of active commuter trips (p. 8). For example, proximity to a bike-path equipped bus mode is associated with large increases in active mode for residents up to 4km away (Heinen, Panter, Mackett, & Ogilvie, 2015, p. 6). These factors are particularly important as they influence the number of commuters by car. In one’s home area variables like a dense neighborhood, good walking routes, and good accessibility to transit can push commuters into active commutes (Mackenbach et al., 2016, p. 9). However, in destination areas a combination of transit options among other variables can ‘pull’ adults from car to active commuting (p. 10). However, distance and usage of transit specifically is negative correlated. As distance to transit access increases, the portion of users decreases (Phithakkitnukon et al., 2017, p. 17). Distance in particular is a key factor in many studies. Clark, Chatterjee, and Melia (2016) find that in addition to distance transport resources, specifically the opportunity of using a household car, have the strongest effects on switching active/non-active commuting (p. 102).

Evidence also indicates that many car commuters experience lower satisfaction with car transport after switching to public transport (Ettema et al., 2016, p. 21). Finally, environmental considerations also play some role. Willingness to protect the environment increases the likelihood of active commuting (Clark, Chatterjee, & Melia, 2016, p. 102).

Social networks also influence mode choice. The transport type that people use is heavily influenced by the modes that those in their social network choose (Phithakkitnukon et al., 2017, p. 18). However, this association decreases depending on distance. Phithakkitnukon et al. (2017) finds that social connections which are geographically closer influence mode choice more than those farther away (p. 17). In fact, a large number of factors can influence decisions to shift typically used modes. Mode choice can also be influenced by age, socio-economic status, geographical constrains, social influences, awareness of environmental damage, and time of commute (Phithakkitnukon et al., 2017, p. 19). Geographical constrains may be a more influential factor. Employment or residential relocations that alter commute distances are a strong influence on switching to/from active commuting (p. 102). Finally, mode habits themselves influence choice. Automobile drivers for example may not switch to public transit modes due to old transport habits (Thøgersen, 2009, p. 342). This assertion is affirmed in the literature. Martin et al. (2015) conducts a study analysis on the health impacts of mode switches, but yields excellent insights on the precursors. For example, car access was more prevalent among participants who switched from active transport to the car mode in their original sampling.

Determining the Relationship between Mobility and Emissions: Mode Switch Based on Change

Transport mode choices can be flexible based on changes in available infrastructure. Clark et al. (2016) in their study investigating change in commute mode, found that commuters living close to new transit infrastructure were more likely to increase walking and cycling mode share, while reducing car mode use (p. 91). Pucher & Buehler (2008) find a number of factors that influence biking rates: safe and continuous cycling facilities, and strict land use policies that favor compact mixed use developments and short bikeable trips (as cited in Mackenbach, Randal, Zhao, & Chapman, 2016, p. 2).

In shifting transport types, commuters can feel differently regarding previously relied upon modes. For example, car commuters when switching to public transport can experience lower satisfaction with car travel (Ettema, Friman, Garling, & Olsson, 2016, p. 21). Lingering feelings regarding mode shift can influence future choices. For example, if experience with public transport is positive, commuters are likely to keep using it, but may forget this experience after time (Ettema et al., 2016, p. 21). More active modes have been proven to have a correlation with public transport modes in the case of switching. For example, the probability of willingness to change to public transport for regular trips increases if one relies on bike mode travel (van der Waerden, Timmermans, & Berenos, 2008, p. 6). Thøgersen (2009) investigated commuter behavior based on opportunity, in the form of free access to bus transit. Discussion points indicated that commuters – specifically car mode users – are more likely to use public transportation after interventions aimed at initiating shifts – particularly price promotions (p. 342).

Klockner and Friedrichsmeier (2011) in their survey outlined mode choice students took to standard trips like their university, work, and favorite shop or leisure place (p. 266). The students completed a travel diary for a period of one week following their completion of the survey questionnaires (p. 266). Pre-existing attitudes also play a major role in behavioral outcomes. The results of their study while enlightening, serve to outline mode choice and purpose as key attributes in transportation questionnaires. They found that car use was closely correlated to leisure, shopping, and work (p. 272). In addition, strong intentions aimed at using alternative modes of transport [besides car use] reduces the correlation of 'shopping' with car use (p. 272). Aside from trip purpose they also measure duration or length of trip as related to transportation mode. Trip duration was also found to be a strong influence on car use, which found that trips undertaken by car tend to be shorter (p. 273). Similar results were found in the German travel survey INFAS & GIW (2004) (as cited in Klockner & Friedrichsmeier, 2011). However, whether or not this can be replicated in the United States remains to be seen. How is transport mode choice influenced by external factors? Location and spatiality are key influences. Individuals who prefer to cycle, walk or use public transport may locate themselves within denser environments to take advantage of land-use diversity (Buehler, 2011, p. 645). Gleeson & Low (2001) develop a theory of 'ecosocialization' which indicates cultural change towards sustainability and sustainable modes of transport generally [as cited in (Buehler, 2011, p. 647). Other researchers have highlighted the attributes of a shift like ecosocialization to include more concern about the externalities of car use (as cited in Buehler, 2011, p. 647). Golob & Hensher (1998) concluded that drive alone commuters are less willing to reduce distance driven, and are less supportive of environmental sustainability through their travel behavior (p. 16). Will this manifest itself in willingness to alter travel behavior in those that drive? Past studies have identified factors that influence car alone drivers. Distance seems to be key among these. Zhou (2012) used an online travel survey of UCLA students to investigate mode choices in a highly car dominant setting. Some conclusions were correlated to distance, indicating that commute distance was positively correlated with behaviors like carpooling (p. 1026). This type of analysis highlighted distance as another key factor in travel diary / questionnaire research. However, Collins and Chambers (2005) sample of Australian university students concluded that transport mode preference was driven by what respondent believe is the effect on themselves, not environmental or other transport considerations (p. 656). Individuals travelling on public transport are more likely to meet weekly physical activity guidelines (Mackenbach et al., 2016, p. 10). In addition, access to and frequency of public transport in a neighborhood can facilitate active travel (Mackenbach et al., 2016, p. 11). Collins & Chambers (2005) also noted that the perception of control was an additive influence on pro-environmental behavior, which was supported in the literature (p. 656). In this case, respondents will see the pro-environmental outcomes in the fluctuations of carbon footprint levels directly correlating to their transport choices.

In conducting a travel survey it is important to place the ‘most active’ time-period of travel, in order to obtain diverse results. This tendency has been replicated in the literature. Mathez, Manaugh, Chakour, El-Geneidy, and Hatzopoulou (2013) investigates greenhouse gas emissions from the transport sector in Montreal, and samples McGill University students in travel-related emissions, seasonality, and alternative mode shift. Seasonality is a key consideration, and has not been discussed at length in previous studies. Mathez et al. (2013) find that users of active transportation increased during the fall, with a corresponding decrease in public transit in the same time frame (p. 135). They explained this increase by associating it with an increase population that cycled and walked during the fall instead of driving and using transit (p. 135).

Determining the Relationship between Mobility and Emissions: Information and the Causation of Action

In composing research involving environmentally relevant behavior it is important to understand the existing literature regarding the environmental attitudes of the public, and highlight work with similar designs.  These efforts allow for checking the relevance of survey questions. For example, with questions regarding environmental attitudes and understanding between the carbon emissions output of different modes, looking at public energy surveys was critical. One survey found that 12.9% of survey participants in the U.S thought curtailment actions [of inefficient modes] were the single most effective action they could take in conserving energy in automobile use (Attari, DeKay, Davidson, & Bruine de Bruin, 2010, p. 16055). However, participants may not be so knowledgeable about how different modes confer carbon benefits or penalties. Ripplinger et al. (2009) found that only 40% of survey respondents directly stated that the one of the benefits of riding mass transit was helping the environment (p. 10).

Armantier et al. (2015) asks this very same question in their analysis of respondent attitudes to 'financially incentivized investments'. Particularly, do consumers "act" on the expectations and beliefs they report in the survey (Armantier et al., 2015, p. 506)? Their analysis corresponded to a close comparison of reported expectations to experimental choices. This is important because they concluded that there is a "tight correspondence" between stated beliefs and behavior in their particular experiment (p. 533). This is insightful in the travel survey realm as well. They conclude that while nothing can guarantee that surveys capture the true beliefs of the respondent, by proving that reported attitudes are connected to informative consideration of consequences – financial consequences in this study - the analysis was supportive of their brand of surveys (p.

533). This is helpful in conducting a transportation survey in which attitudes will be connected to informative consideration of consequences, though non-financial in nature.

These types of assertions as to the connection between belief and behavior is supported by the academic literature in environmental studies as well. Polonsky, Vocino, Grau, Garma, and Ferdous (2012) perform an analysis of how environmental knowledge and attitudes influence behavior and perspective. They reference various authors asserting that environmental knowledge has been noted as a precondition to environmental attitudes, while environmental attitudes have been found as precursors to 'pro-environmental behavior' (p. 242). This gives credence to the idea that information and awareness brought about by that information, can lead to behavioral change. This also applies to the transportation realm as well. Past studies have linked environmental attitudes with specific behaviors including pro-environmental transport considerations like the use of fuel efficient vehicles, and voluntary reduction in transportation-related CO2 footprints [as cited in (Polonsky et al., 2012, p. 244)]. Information in these cases are key to possible change. Overall results suggested that as consumers integrate new knowledge into their general attitudes, it is possible more information will result in consumer action (Polonsky et al., 2012, p. 254). This consumer action would likely manifest as a modification of behavior to have a smaller environmental impact (Polonsky et al., 2012, p. 254). Some researchers have reported an increased willingness to pay for premium 'green' products (Vanclay et al., 2011, p. 154), which indicates that behavior change is possible when interventions are undertaken.

Behavior change can be better effected through increased access to environmental indicators, information, and citizen-directed awareness projects. It has been documented that consumers can often become confused when trying to integrate carbon considerations into their behavior.

Polonsky et al. (2012) notes that given the complexity of carbon issues and offset programs, consumers have difficulty in integrating carbon issues into their consumption and decision making processes, largely because of incorrect knowledge surrounding carbon claims and offset programs (as cited in Polonsky et al., 2012, p. 239). Providing data about carbon impact would naturally lead better access to information and raise awareness. This causation is reflected in many industries where the availability and recognition of target environmental information led to increased pro-environmental actions. For example, in carbon labeling on goods, or consumer products related to environmental impact like fruit beverages. Labeling raised awareness and encouraged people to think more carefully about [purchasing] decisions, including price, quality, and environmental footprint (Vanclay et al., 2011, p. 158). In the case of sustainable wine consumption, the more consumers knew about environmental  knowledge related to the industry, the greater their overall attitude to general environmental issues (Barber, Taylor, & Strick, 2009, p. 69). In these cases, more information did lead to behavioral change. More information - in the form of an expanded, well-organized knowledge framework - strongly influences attitudes (as cited in Barber, Taylor, & Strick, 2009, p. 68). This suggest that voluntary reductions in 'domestic emissions' are possible, especially with the additional collaboration of price and carbon signals (Vanclay et al., 2011, p. 159).

## Carbon Emissions Values by Mode

Emissions differ by transportation mode, an assertion that the environmentally informed can likely deduce. The exact numbers however vary in space, scale, and local realities. In Montreal, Mathez et al. (2013) measured average greenhouse gas emissions for employee/student by mode, and sample size. For example, students and employees who only used transit modes averaged around 750 grams per person over the study period. This measure of ‘transit’ alone respondents was the highest sample number among tested modes, with the lowest non-negligible greenhouse gas emitter (walking and biking modes are considered carbon negligible). This indicates that taking transit alone can serve more people with some of the lowest greenhouse gas output than using other modes. The results are equally enlightening looking at ‘drive only’ persons [as explicitly distinguished from carpool/taxi modes] in which carbon emissions are the highest among modes at almost 4100 g / person (Mathez et al., 2012, p. 143). This indicates that while car alone is widely relied upon many people – it was the second most used mode behind transit - the emissions quotient is very high. Lowe, Aytekin, and Gereffi (2009) discuss the differences between transport modes, particularly buses and cars. The data is closely linked with some automobile and bus indicators like miles per gallon efficiency, ‘passenger’ miles per gallon, and the number of occupants. For example, Lowe et al. (2009) note that a passenger car carrying one person [single occupancy] emits 89 pounds of $CO_2$ per 100 passenger miles, while a fully occupied bus emits only 14 pounds in the same distance (p. 3). Similarly, when carpooling two or more people travel together in the same private vehicle, reducing the number of single-occupied trips (Neoh, Chipulu, & Marshall, 2017, p. 424). A fully occupied bus [70 occupants] achieved up to six times the fuel economy per passenger mile as a single occupancy passenger car (p. 4). So, if a passenger car gets 25 passenger miles per gallon (pmpg), a transit bus operating even below capacity at 11 people [out of 70 spaces] will still equal the car’ fuel economy. Occupancy also plays a large role in carbon emissions outcomes. While it is true that single occupancy buses emit much more carbon than single occupancy cars, this carbon poundage is more than equaled once the bus reaches 11 passengers (p. 4). Different transport modes have very different $CO_2$ emissions, which are influenced by certain factors. Kennedy

(2002) included as parameters: mode type, fuel or electricity use, number of commuters [occupancy], and energy use per person (p. 477). According to Kennedy (2002), automobiles emit 101 grams of Carbon / person / kilometer (g C/person -km) for a base fuel of 15 L / 100km; 11 g C/person-km for a diesel bus for a base fuel of 56L/100 km; 11 g C/person-km for a base electricity use of 2.61kWh/km (p. 477). Other publications have found similar distributions. The U.S Department of Transportation FTA (2010) found that per passenger mile private auto (SOV) emits 0.96 pounds of $CO_2$, bus emits 0.64 pd, heavy rail 0.22 pd, light rail 0.36 pd, and van pooling 0.22 pd (Hodges, 2010, p. 2). This changes when considering occupancy rates. A single occupancy trip via automobile incurs 0.96 pounds per passenger mile, which decreases to 0.24 pounds in a 4 person carpool (p. 3). In addition, bus transit in 'average occupancy' decreases from 0.64 to 0.18 in full occupancy; heavy rail decreases from 0.23 to 0.11, light rail from 0.36 to 0.14, commuter rail from 0.33 to 0.10, and van pool from 0.22 to 0.12 (p. 4). These figures are important as single occupancy car trips accounted for 76% of all work commutes (McKenzie & Rapino, 2009). Do commuters understand these differences? Energy efficient cars are viewed favorably by 80-90% among 4 countries: the U.S, UK, Sweden, and Japan (D. Reiner et al., 2006, p. 4). In addition, almost 80% of U.S respondents thought that cars contributed to increasing levels of carbon dioxide in the atmosphere (D. M. Reiner et al., 2006, p. 2094).

## **Literature Review: Discussion and Dialogue**

Distance plays a large role in influencing mode choice and time behavior. Distance as an objective measure helps remove some subjective bias in logging travel behavior. In surveying UCLA students Zhou (2012) provides some insights into distance. In regards to this survey we specifically highlight distance in logging weekend mode choices. Willingness to switch to public transit modes is lower in the case of work commuters, as compared to other purposes (van der Waerden et al., 2008, p. 6). As work commutes normally take place during the weekday, it will be interesting to see the results for weekday – weekend mode choice survey responses.

Can we compare the sample number – emissions findings of past studies? Mathez et al. (2013) uses a similar mode breakdown of drive only [car], transit [subway or bus], carpool, bicycle, and walk [given]. It would be pertinent to compare the spatiality of Montreal to New York City, as we deduce how behavior, mode change, and carbon interrelate. If the survey results are similar it could give credence to the methodology, and potentially highlight parallels between urban conglomerations.

### Question Answer Options and Effectiveness

In this case, Mavletova (2013) hypothesized that respondents 'activated' the skip option by using the 'next page' radio button. The results indicated that there was no statistically significant difference in response length between mobile devices as: feature phones vs. smartphones; touchscreen phones vs. non-touchscreen phones (Mavletova, 2013, p. 737). Therefore, smartphones are an ideal medium for tracking data for this type of research. In addition, the survey allows participants to skip most questions, thereby contributing to a more fluid survey design.

The questionnaire seeks to understand commuter behavior from the perspective of knowledge being a precursor to behavioral change. Does this assume that participants will actively understand, and integrate new knowledge? As discussed, the main goal of the travel survey is to discover whether awareness through personal carbon footprint information yields changes in behavior. More generally, does more information incentivize potentially disrupting changes in commuting patterns?

Will the inclusion of a ‘weeks ahead’ mode switch section in the questionnaire prompt behavioral change after the research is done? As Abou-Zeid and Ben-Akiva (2012) found, the differences between switchers and non-switchers (from car to public transport modes) increasing after the experiment supports that mode change as possible, if not likely. The experiences of car mode users when trying public transit often prove to be better than they had anticipated, but this insight is often forgotten after some time (Abou-Zeid & Ben-Akiva, 2016, p. 21).

Measurements of carbon footprint for research participants will help give objective information. While the extent to which mode transport choices influence overall global warming exceeds the scope of this study, but empowering the public to make more informative decisions would assist in mitigating the issue. Experience with mode switching is key in promoting behavioral change. For example, Fujii and Kitamura (2003) completed a small-scale study analyzing the travel behavior of car users after giving them a free one-month bus pass. They found that although their sample size was not large enough to draw statistical measure, the frequency of bus use increased immediately during the study, and remained higher than before the mode switch after the study was completed (p. 92). They concluded that structural changes in transport mode decisions do not have to be permanent to induce behavioral change (p. 92). Ettema et al. (2012) notes that ‘positive’ experience with public transport may be forgotten over time, and that car commuters experience lower satisfaction with the car mode after switching to public transport. How can the potentiality of those future mode shift be measured? Since car commuters may experience lower satisfaction with car commuting after a mode switch, will they be more likely to preserve public transport habits? Other studies like Thogersen (2009) seen in research literature show car mode users’ reluctance to switch. Other studies, notably Ripplinger (2009) note the use of dominant mode patterns by populations within the academic sector. Specifically, can the conclusions of staff and student modes be replicated in a study involving CUNY Hunter students, staff, and faculty?

**Methodology: Support Points for Research Design Based on Literature Precedent**

The design of this research project correlated with established precedent in the academic literature surrounding transport behavior and mode shift. Many researchers have emphasized the use of GPS for recording tracks using georeference points, and variables like speed (Chen et al. 2010; Gong, Chen, Biolostozky, and Lawson 2012). The need to automatically detect transport mode through GPS is very important, often incorporating techniques like travel mode detection algorithms (Barbeau et al. 2009) and agglomerated transport network geo-spatial layers (Chen et al. 2010). Recruitment methods have been drawn from similar studies concerning transport behavior, and often in an academic environment. Recruitment through emails and survey web links has been a novel way to find and enroll participants in research; bypass questions also provide increased choice to survey respondents (Mavletova, 2013). Making contact – methodology – with respondents may overcome issues of low response rates observed in email recruitment projects, as well as potential issues with self-administered surveys [(Armantier, Bruine de Bruin, Topa, van der Klaauw, & Zafar, 2015; Stopher, FitzGerald, & Xu, 2007). Incentives can also play an important role in garnering interest for participating in research. Research burden can influence whether incentives may be desirable or not. Considering the use of research incentives for participants, it was inferred that a week of daily mobile app use, as well as two survey's constituted reasonable research burden. There is precedent in the transport survey literature of offering incentives where potential high respondent burden exists (Auhausen, 2008). Axhausen's (2008) breakdown of the survey model was helpful in our decision to include mobility modes [bicycles, motorcycles, cars, vans, etc..], preferences in transport mode, and workplace status (Axhausen, 2008, p. 986).

The temporal aspect of survey design is highly important. Specifically, mode choices change during work days and weekends. To capture these changes, the experience with the app was determined to be one week, encompassing weekend and week day times.

Health indicators are an important part of understanding the impact of mode choices. For example, Mackenbach et al. (2016) work on understanding physical activity quotas in relation to use of public transit modes. Health indicators are included in the app and survey in order to grasp the influence of each variable on overall mode shift behavior. Preferably, one week of app activity is ideal, considering Fujii & Kitamura (2003) conclusion that temporary interventions may be enough to bright about permanent behavioral change (Fujii & Kitamura, 2003).

Research design for this project has been heavily drawn from the established literature concerning survey-based methods and sampling, GPS app tracking and app use, mode shift and environmental factors, travel modes, and general research design. Survey methods often vary considering sample size, topic, resources available to researchers, and considerations like target population. Among these researchers are limited specifically by the time, money, and personnel available to them (Montello & Sutton, 2013, p. 167). Sampling methods are never a perfect representation of the aspects being studied, but do often give opportunities for describing the population at large.

The mobile phone app used in this research was provided by Prof. Gong in the Geography Department at Hunter College.  The iPhone and Android apps send GPS and other data to a cloud server that uses the mode detection algorithm based on the work by Gong, Chen, Bialostozky & Lawson (2012), in particular, tracking and determining transport modes. The underlying multi-modal database included data like street centerlines, bus routes and stops, subway lines, station entrances, commuter rail lines and stations, and other relevant sets (Gong, Chen, Bialostozky, & Lawson, 2012). Although the mode detection technique was refined later, much of the initial work on mode detection was included in this earlier publication, in addition to the Chen et al. (2012) publication.

## Sampling, Recruitment, and Survey Design

When planning the research methodology it is helpful to reference established literature on similar topics in order to verify the efficacy of certain techniques. In this particular instance, while simple random sampling of Hunter College students (at the City University of New York) was preferred, the timing and design of the assignment warranted relying more on a modified quota sampling system. This is where drawing on established sampling and survey participant recruitment methods along with taking specific project design parameters into consideration was the most important. In composing the questionnaire it was important to understand survey methodology in relation to newer technologies. While the travel survey relies on a mobile app to predict transport mode and automate the data gathering process, typical issues come into play. For example, how to structure questions towards dual variables like environmental attitudes and health indicators, but still yield meaningful data on the respondent, and their habits. Widespread participation of the entire Hunter College campus was encouraged, with the department system acting as a way to delineate quota groups. In particular, each department in the various schools were contacted, and posters advertised in the main connecting hallways.

General research work may involve the use of survey's involve such decisions as to establish incentives for research tasks, and how to organize messages to research participants. Email blasts in particular have been shown to be effective. Recruitment through emails and survey web links has been a novel way to find and enroll participants in research; bypass questions also provide increased choice to survey respondents (Mavletova, 2013). Other factors are likely to have project specific outcomes. However, in the previous case questionnaire length, type of mobile device had less impact on overall outcomes (Mavletova, 2013). This is ideal considering the limitations on recruitment specifically to iPhone and Android users. To this end, the use of email blasts for recruitment and messaging was somewhat effective. Email recruitment messages can capture the interest of a portion of the target population, but may not be sufficient to convince potential participants of the merits of the research proposal. Making contact – methodology – with respondents may overcome issues of low response rates observed in email recruitment projects, as well as potential issues with self-administered surveys (Armantier, Bruine de Bruin, Topa, van der Klaauw, & Zafar, 2015; Stopher, FitzGerald, & Xu, 2007). Contact with the research may be ideal considering the large amount of research tasks. It is reasonable to infer that self-administered surveys would suffer from the lack of an interviewer (Stopher, FitzGerald, & Xu, 2007, p. 724). This type of endeavor was put into practice by sending in an IRB revision, requesting that meeting with participants to assist with the completion of research tasks, be allowed.

Incentives were used in order to alleviate the potentially high respondent burden, especially considering the large number of research tasks. Considering the use of research incentives for participants, it was inferred that a week of daily mobile app use, as well as two survey's, constituted reasonable research burden. There is precedent in the transport survey literature of offering incentives where potential high respondent burden exists (Axhausen, 2008).

Some trends emerge when analyzing the transport habits of different groups. For instance, the popularity of the car mode followed by walking for students (Ripplinger, Hough, and Brandt-Sargent, 2009) was particularly interesting. What is the scalability of this analysis to other research environments? Do students, or other groups as a whole commute similarly? It is very likely that spatial and temporal elements come into play in this case. New York City is a commuter city largely reliant on public transit, so it may be unlikely that car modes are dominant in the Hunter College student population. In general, are commuters more likely to shift to modes like public transit after targeted interventions? If so that may explain the similarities between different research studies, or future mode shifts chosen by survey respondents. Question design attempts to take into consideration these questions by allowing student / faculty, and staff labels, along with tracking how mode shifts differ temporally (weekday, weekend, observed – planned shifts). Weekday trips likely constitute traveling from base – Hunter College campus, and therefore outer borough to Manhattan direction. This likely acts as a proxy for 'commuting trips'. While classes also take place during weekends, the "longest distance" question design for capturing primary mode was required to capture general weekend trips.

Questions topics on the survey included the general information on their occupation (student, faculty, or staff), location of residence (i.e Manhattan, other NYC boroughs, New Jersey, Pennsylvania, etc), their understanding of carbon emissions by transportation types, and whether they have used citi-bike, along with various environmental questions. Question are designed to measure whether the mobile app had an impact on their transport choices on week days and weekends, carbon footprint understanding [between different transport types], and their willingness to alter and plan for changes in transport tendencies. The questionnaires, along with consent form and sampling of recruitment scripts can be found in Appendix, Figure 4 – 5. Likert scale questions like those loaded into SurveyMonkey are ideally suited to measuring existing knowledge, degree of change, and mode shifts.

This research involves the usage of a GPS-use mobile app that outputs carbon emissions, and health information of individual trips to the survey participants. We expect that by knowing their carbon emissions/carbon avoidance and fat/calorie burnt results displayed on a smartphone app, survey participants would consider switching from driving alone to more environmentally friendly and healthy travel modes such as walking, public transit, or car-pool.  Many researchers have emphasized the use of GPS for recording tracks using georeference points, variables like speed, and augmenting that with transport network data (Chen et al. 2010). Considering the widespread usage of smartphones, mobile phone sensor related studies are relatively available to researchers looking to study urban – transport based issues. Studies relying on mobile sensing can often be scaled up depending on the application (individuals, social networks, even communities) (Lane et al., 2010). By having a relatively modest subject pool <35 persons we can shift the application scale variability from individuals to groups, and eventually with opportunities for communities in future research.

Carbon emissions specifically are a very important area in mitigating the effects of climate change. Interventions aimed at educating the public about their carbon inputs toward global emissions via transport decisions are immensely important. Commuters may not understand transport decisions in the frame of environmental stability. As only 40% of the respondents in the Ripplinger et al. (2009) study affirmed that mass transit benefits the environment, education / intervention methods become increasingly imperative. Using a mobile app to output carbon and health information via transportation decisions is precisely one type of education / intervention method. Health information in this case constitutes a secondary benefit, and therefore was included in the research project goals. Public transit access facilitates active travel, and helps individuals meet weekly physical activity guidelines (Mackenbach et al., 2006). Mode switches may be sustained after interventions, which may bolster further research in the area. To measure these types of experiences and -after-intervention behavior, the 2-week mode question was included.

## Methodology Section – Data Analysis Techniques

Much of the survey data was downloaded via SurveyMonkey into Excel format. SurveyMonkey provides a basic level of analysis in the downloaded file, like percentage of the study population who chose each question response, graphics to visually represent answer breakdowns, and basic numeric values indicating number of answers or skipped answers. While basic conclusions can be drawn from this 'in-house' analysis, a more statistical means was required to draw deeper conclusions from the dataset. For example, what was the measure of change between first round and second round survey respondents? Was there a measurable and statistically significant difference between pre and post-app survey respondents? Finally, were measured and planned mode shifts particularly relevant – more specifically were shifts observed to low or high carbon options? In order to better answer these questions a reliance on the Mann Whitney U test was ideal. Using the Mann Whitney U requires a way to assign the ranking structure to the mode options like those on the mobile app.

## Analysis of Data

Assigning rankings to the data involved finding the number of responses (n), and assigning rankings to transport modes via carbon emissions hierarchy. For example, bike and walking would receive the lowest rankings (indicating ideal carbon outputs), while higher footprint modes like ‘car’ use would receive the highest rankings (indicating non-ideal carbon outputs). Other modes like rail, bus, and subway receive modest rankings from hierarchy (from lower footprint to higher footprint: subway, rail, bus) according to their average carbon outputs. A full ranking hierarchy of low footprint to high would be walk and bicycle (both equally low), subway, rail, bus, carpool, and car mode use. The rankings can be found with their respective weights on Table 3 in the Appendix. The n in the analysis of weekday mode use to weekend mode use is 22, which indicates 1-22 full rankings. Carpool was included on this list to capture that mode as well in the surveys, and is included under car in carbon hierarchy.

## **Results**

Discussion of First Round Analysis Results

The survey took a wide variety of information from respondents, anonymously using vague, or otherwise random usernames instead of identifying information, at the discretion of the respondent. First round responses can be found in the Appendix, Table 4. Data trends can be referenced from Table 4, Table 4a. The majority of the survey pool was based in the outer boroughs of New York City, Brooklyn, Queens, the Bronx, or Staten Island. In addition, an overwhelming majority of the survey pool (81.8%) used the public transit system subways as their primary travel mode on weekdays. Because weekend trips can often include a number of modes and non-commuting trips, the provision for longest distance was used to highlight primary mode on the weekend. The high reliance on subways as the primary mode for weekdays – and therefore more commuting use – declines significantly on weekends (54.5%). Instead, respondents demonstrate more likelihood to use car modes with car and carpool as 31.8% of overall trips.

It was ideal to include carbon and health information on the app, as two variables that could potentially influence commuting and trip mode decision patterns. In particular, according to Question 11 [survey questionnaire found in Appendix] results of the pre-app - beginning of the week - survey, 50% of respondents noted that they would be willing to alter their commute to reduce their individual carbon footprints, with 13.6% not willing, and 36.3% remaining neutral on the issue.

In addition, bike modes have remained a popular alternative for those looking to lead an active life and lower their carbon footprints (Blondel, Mispelon, & Ferguson, 2011; Chapman et al., 2018). Over 90.9% of respondents hadn't tried the NYC public biking system 'CITI-Bike'.

Discussion of First Round and Second Round Knowledge Shifts

Both the first and second round of the surveys included carbon footprint knowledge evaluation questions, as the beginning section. This was in order to gauge the impact of the mobile app, specifically on respondents' understanding of relationships between carbon emissions and transportation. As the app provides relevant carbon footprint data based on various travel mode usage, respondents would be able to note result changes based on their commute or trip decisions. For instance, does the average respondent understand the carbon differences between driving alone and carpooling, or using public transit like buses, subways, and rail?

Between the first and second round survey, 18.1% (4 of 22 full responses) of respondents indicated a change in their car vs. carpool carbon knowledge. Of these, 3 noted a change from 'Neutral' to 'Agree' on whether driving alone increased one's carbon footprint more than carpooling.

Between the first and second round survey, 13.6% (3 of 22 full responses) of respondents indicated a change in their car vs. public transit carbon knowledge. Of these, 2 noted a change from 'Neutral' to 'Agree' on whether driving alone increased one's carbon footprint more than using public transportation.

Between the first and second round survey, 22.7% (5 of 22 full responses) of respondents indicated a change in their motorized vs. non-motorized carbon knowledge. Of these, 3 noted a change from 'Neutral' to 'Agree' on whether using motorized transport increased one's carbon footprint more than using non-motorized transport, with 1 disagree – agree, and 1 agree to neutral.

Discussion of Second Round Analysis Results: Recorded Mode Shifts

Analyzing the second round involved using the Mann Whitney U test to compare observed mode shift data compiled during a week of using the mobile app. Respondents indicated a wide variety of mode shifts. 12 respondents out of the 22 that submitted full responses to the second round survey indicated at least one mode shift during their app experiences. Early rankings of results showed a significant change from higher carbon modes towards lower carbon modes, specifically walking. As shown from the Appendix – Table 1, ranking totals between from / to mode shifts were 199 and 101. This is a fairly large difference between ranked groups, indicated that from / to shift were largely not equal. This result, is quite similar to theoretical ranking totals for the most difference between groups, 222 and 78, further indicating that from / to shifts groups have a larger difference than similarity. The ranking sum suggested that the null hypothesis can be rejected (H0) – that the groups are not equal.

Early ranking results showing a large reliance on walking as a 'to' shift, indicates that much of this difference is from high to lower carbon transport modes. This is in stark contrast to a theoretical equal grouping calculation, in which the ranking totals are 144 – 156, and the test statistics are 78 and 66.

Calculating the main test statistic yielded ($U_{1,}$ $U_2$) of 23, and 121, of which the final test statistic was 23. In the Mann Whitney U test the theoretical test statistic range from most difference to most equality in groupings was 0 to 66. The overall test statistic for the observed data was 23, which indicates that the data populations are more likely to be **not equal** than equal. In this case, H1 is more likely to be true, that the groups are not equal.

The Mann Whitney U testing requires a critical value based on the n of both groups. At a statistically significant confidence level of 5% the critical value is 37, and at 1% is 27. The observed test statistic of 23 is less than both values. Therefore, the groups are statistically significantly different, at a confidence level of 5%, and 1%. Additionally, since most of the low rankings are clustered in the ‘to’ – mode groups – as evidenced by a lower R2 (rank sum) value, a test statistic much lower than n1 * n2, a test statistic closer to the most difference theoretical range, and a statistically significant rejection of the H0 null hypothesis – many of the observed mode switches were to lower carbon modes.

10 of the 22 respondents that submitted full responses to the second round survey indicated that they did not undertake any mode shifts during / after the mode experience. Some users among these reported that they already used public transport and did not anticipate making any major mode shifts, or had difficulties using the app and getting reliable data. This may explain some of the instances where mode changes were not undertaken.

Discussion of Second Round Results: Potential Mode Shifts

Analyzing the second round involved using the Mann Whitney U test to compare potential mode shifts after a week of using the mobile app. Respondents indicated a number of planned mode shifts in the 2 weeks after they completed the second round survey, presumably based on their experience with the app. 15 respondents indicated future planned mode shifts, out of the 22 that submitted full responses to the second round survey. Initially, early group rankings suggested an overall switch to lower carbon footprint transport modes, specifically walking. The switch to walking modes accounts for the large number of low ranks. Looking specifically at group differences, the rankings sums – from 316.5 to 148.5 – indicates a significant difference between groups. These ranking sum values yielded test statistic values of 28.5, and 196.5 respectively, of which 28.5 being the lesser, is the observed U value. Theoretical rankings for the most group difference, and the most equality between groups were calculated. The theoretical most group difference yielded r values of 345 to 120, which resulted in U values of 0 and 225. The theoretical least difference group – most equality – yielded r values of 225 to 240, which resulted in U values of 120 and 105. Therefore, the theoretical U value of most difference to most equality between groups is 0 – 105. Because the observed test statistic of 28.5 is closer to the 0 value of most difference, it is likely that the mode shift from – to groups are more different than similar. According to the Critical value chart for the Mann Whitney U, two n's of 15 constitute a critical value of 64 at 5% confidence, and 51 at 1% confidence. Since the observed test statistic of 28.5 is ≤ both of these values, the groups show a statistically significant difference at a 5% and 1% confidence. Additionally, since most of the low rankings are clustered in the 'to' – mode groups – as evidenced by a lower R2 (rank sum) value, a test statistic much lower than n1 * n2, a test statistic closer to the most difference theoretical range, and a statistically significant rejection of the H0 null hypothesis – many of the observed mode switches were to lower carbon modes.

### Discussion of Second Round Results: Reasoning for Mode Shifts

Respondents indicated a wide variety of answers as to their main motivations for observed or planned mode changes. Out of the 22 respondents who submitted full responses to the second round survey, 9 affirmed that both carbon footprint and health considerations like calorie and fat burn were motivations for mode shifts. 3 respondents specifically highlighted the carbon footprint consideration, while 3 others noted health indicators as primary in mode shift decisions. 6 respondents did not answer the motivation questions, while 1 other found that observed changes were random due to app operation difficulties.

In addition, respondents were questioned on their willingness to petition local officials for more public bike share locations, specifically the NYC iteration ‘Citi-Bike’. 7 respondents expressed unwillingness to do so, while 15 others said they would indeed be willing to do so.

## Discussion of Results

New York City with its multiple transportation systems affords residents with many mode options for those undertaking commuting / non-commuting trips. Respondents were based in many different parts of the city, with available patterns as traveling inter-borough, to Manhattan – likely to Hunter College throughout the week, or other non-commuting weekend trips. The data suggests that respondents would be more likely to rely on higher carbon modes like subway, bus, or possibly even car / carpool in their base – campus commuting trips. Weekday and weekend questions are well designed to capture overall mode use for each weekday / weekend time period. Additionally, the majority of respondents were beginning their trips in the outer boroughs of the city. This may explain the reliance on higher carbon subway mode use.

From the beginning of the analysis of survey results, it was apparent that the vast majority of respondents relied on the public transit system – particularly the subway mode - for daily weekday transportation. This was less apparent for weekends where the car and carpool modes were noted more often, than during weekdays. This makes the resulting reliance on lower carbon modes after the app use more striking. Despite needs of higher modes for longer distance trips on weekends and a reliance on the subway mode for weekday trips, respondents still moved toward low carbon modes after the experience with the app. Admittedly, health concerns like calorie and fat burn played a large part in those decisions. While over half of the respondents were willing to initially alter their commute, 40.9% (9 of 22) found that both carbon footprint and health considerations were motivations for any mode shifts.

Respondents demonstrated an initial attitude towards altering their transport behaviors that was largely parallel to the research project goals. There was a fair proportion (40.9%) of respondents that were initially willing to change their behaviors to reduce their carbon footprint, a model situation for studying the important influencers of environmentally relevant behavior. Additionally, most of the respondents correctly noted the different average carbon outputs of various modes. Between roughly 13 – 18% of respondents changed their responses from neutral to agree to correct statements about carbon outputs of certain transport modes. This shows that experience with mobile devices which aim to provide information about the environmental impact – specifically carbon emissions – of various transport modes can effectively serve to educate people about mode differences. Ideally, this would suggest that more broadly, access to information about environmental impact can meaningfully influence public knowledge and awareness. More realistically, measured and statistically relevant data shows this more forcefully to be the case. Respondents were required to outline undertaken and planned mode shifts during and after their experience with the app respectively. During the scrutiny of survey results, it is clear there was a degree of change after respondents had experience with the app. In particular, analyses have shown a statistically significant difference – at 5% and 1% confidence - between respondent mode behavior before and after their experience with the app. In addition, respondents noted statistically significant differences in their planned mode shifts. In mode shift 1 – where respondents outlined a shift they planned to undertake in the 2 weeks following their completion of the study – the shift was to different modes than originally planned, and largely to lower carbon options.

## Limitations: to be Considered Along Study Conclusions

This study involved a high reliance on survey methods, the completion of numerous research tasks by participants, and the use of a mobile app. While these techniques were necessary to draw relevant deductions concerning the questions being studied, conclusions should be taken with research applicability and scope in consideration. For example, survey techniques by their very nature often provide imperfect knowledge of the population being studied, and therefore limit the researchers' ability to interpret conditions.

The mobile research app used in this study had not been previously used in conjunction with surveys. The mobile app was tested repeatedly for practical accuracy, ideal app user interface design, and to craft accompanying instructions. Despite this, having participants learn and interact with the mobile app, the experience of which would determine some survey responses, presents a unique environment for researchers conducting studies in transportation. In some cases, participants reported difficulties in app operations, or setbacks in following the schedule of research tasks – most particularly using the app consecutively over the study period. While all users were required to complete 7 full days of app use to receive an incentive – submitting valid data and receiving at least one valid response from the app per day – these may not be consecutive due to reported difficulties. A recognition that this may have influenced observed survey responses in the second round is recommended. Therefore, their ability to retain information regarding app experiences may have been limited.

A monetary incentive was provided to help support recruitment and participant retainment over the course of the research. This amount was in the form of a $50 Amazon gift card. Considering experiences in recruiting participants, high participant research burden, and noted participant difficulties in following the research schedule it is likely a higher incentive would've been more suitable to lessening these difficulties. Participants reported similar sets of complications in app usage or consistent usage. While app usage concerns stem largely from inexperience with the new app, a higher incentive to faithfully complete research tasks would be ideal considering high research burden.

Financial limitations stemming from the provisions of incentives, funds to maintain the cloud computing resources, and to a lesser extent survey platform fees constrained the number of research participants that could ultimately participate in the study. While non-parametric tests were faithfully used, considerations regarding conclusions must recognize low power in the survey sample. Related to this, the inherent strength for description of populations with non-parametric tests may be considered substandard to parametric tests in some applications.

This study relies on a modified quota sampling scheme, specifically drawing on the design of Hunter College's department system. Quota sampling is uniquely suited to working with subgroups of people. Recruitment techniques were based on previous knowledge surrounding the department system of the researcher, and were designed to help ensure a wide and diverse distribution of the different branches. Hunter College's department system was deemed the only viable way to reach the most diverse representation of students, faculty, and staff. This sample strategy was modified quota sampling due to the inconsistent numbers of participants from each department in the school. Participation from every department at Hunter College was encouraged. Despite this, while all departments were given an opportunity to participate, because the confidentiality and privacy concerning the participants were of highest priority, no information was collected as to what departments they were affiliated. In addition, the various department listservs were in some cases unavailable to student researchers, or contact persons unresponsive. For this reason, while listserv email blasts were effective, listservs are not always the most secure method to reach the intended population. Therefore, an affirmation of equal representation among departments cannot be reasonably expected.

Since this research was designed with the intention of using Hunter College participants based in New York City, conclusions may not be faithfully transferred to other urban locales. Each geographical place is different, owing partly to the unique dynamics of the city environment. Therefore, the transferability to other research settings must be carefully considered for those wishing to effect broader transportation mode shift locally.

## **Conclusions and Future Research**

Having a reliable base of information in the research community regarding the impact of technology on environmentally-relevant behaviors is particularly important in current scalable efforts to reduce greenhouse gases emissions. Providing evidence that technology is effective in promoting environmentally-pro behaviors will contribute to providing citizenry with more options in managing their overall impact. With the current data points showing a statistically relevant shift from high to lower carbon modes after app-based interventions, it would be ideal for the public and parties interested in managing society's overall carbon impact, to take advantage of these techniques. Additionally, many participants found that health considerations like calorie or fat burn were important in their consideration of transport changes. Therefore, it is important to recognize that adding or providing additional benefits other than purely carbon emissions considerations can be a powerful incentive for citizens to make mode shift decisions.

Alternative benefits like health considerations in the use of transportation systems should be a prime options in efforts to promote mode shift decision making. Aspects of transport design can provide sensible conclusions drawn from the data. As the reliance on public transport decreased, and car / carpool modes increased for long-distance trips on weekends, transportation policy generation could be well off designing services more easily accessible on weekends. As half of respondents were initially willing to alter their commutes to reduce their footprint, more policy submissions to make that transition easier would be ideal. In addition, as 36.3% of respondents were neutral, and 13.6% initially unwilling, policy makers may consider education and participant opportunities to learn more about the interconnections between transport, health, and environmental impact. That an overwhelming majority of respondents had not tried opportunities like NYC bike sharing (Citi-Bike), and that nearly two third expressed willingness to petition elected officials for more bike share locations only strengthens the need for additional programs.

That observed and planned mode shifts were largely to lower carbon modes, and that there was a clear significant difference between transport decisions after the app experience demonstrates the efficacy of app technology education influences, specifically in dealing with transport mode shifts. Future research could ideally improve operation procedures, incentives, and participant-researcher interactions to help decrease the number of participants that did not conduct any observed or planned mode shifts. Finally, since New York City has many outer boroughs – from which the majority of participants originated from - distance may be a factor on just how much the current transportation system can accommodate mode shifts.

More research needs to be pursued so that supplementary evidence can be provided as to the possible benefits of providing mobile app environmental and health information on developing mode shift behavior. This would naturally include exploring other possible pathways that could provide information regarding environmental impact. Technology can be effectively used to guide human decisions, in a way that is accessible to average members of the public. The widespread availability of smartphones in high carbon emissions per capita societies heightens the need for research and science-guided approaches to reducing emissions in a way that is empowering to the public citizenry. In view of using technology to this end, a focus on data and information empowerment while conducting behavioral shift and educations programs is paramount. To accomplish these goals, more research will be needed. Behavioral change-based programs employing techniques like technology and education to promote environmentally-pro actions show much promise. While the limitations outlined in this study do limit the scalability to which data conclusions can drive transport-industry or public decision making, more research concerning the diversification of options available to society to limit environmental impact and climate change broadly are immensely important in a public debate largely dominated by industrial-scale technology companies and business-as-usual incremental changes.

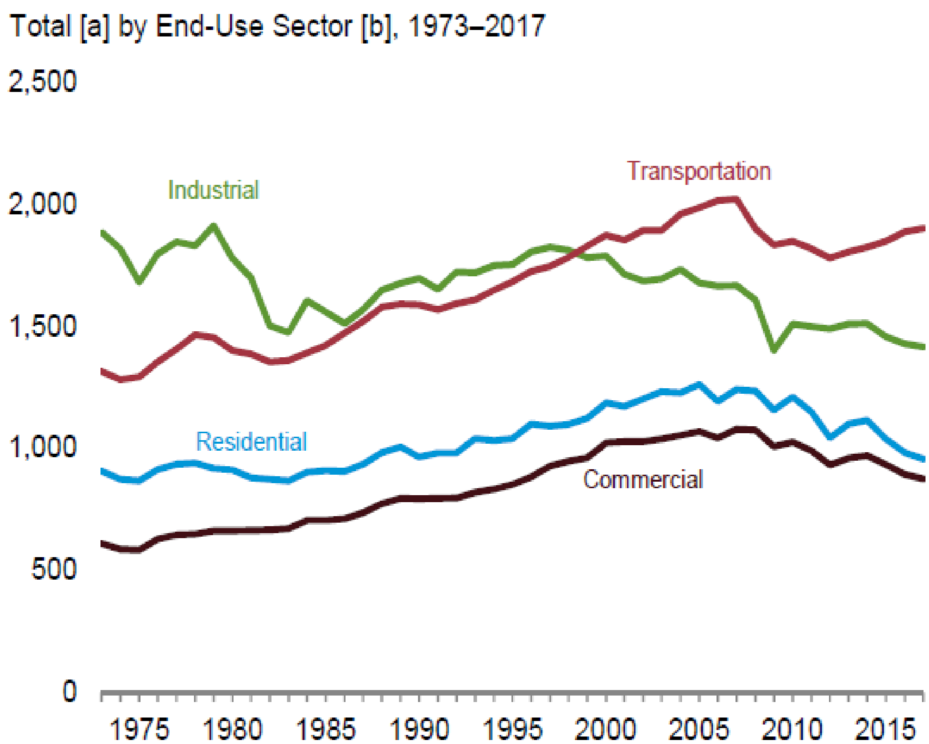
Future work on this setting would ideally involve higher power in the study population and a reliance on parametric tests. Asking survey questions specifically to detail trip purpose – as commuting vs non-commuting– would provide more information that delineating weekday vs weekend trips for this information. This would likely result in an increased ability to draw observations as to the differences between populations at different times of the week. Moving from a local or relatively small environment like Hunter College, to a large study population would be ideal. This would move the scalability of observations from those found at Hunter College as a proxy for the larger urban area, to direct observations of the larger NYC environment. In addition, it would be interesting to see if mode shift behavioral changes differ between a city environment than more rural areas. The availability of public transportation would be an ideal independent variable for regression in this case.

In addition, it would be interesting to see if willingness translates into action. This survey project collected information as to the willingness of survey respondents to alter their commute to reduce their carbon footprint. This could be related to direct action during and after the research period – using data like observed and potential mode shift responses. The willingness variable could be measured and coded, and along with observed and planned mode shifts could be compared in a regression analysis to judge the relationship between intent and action. This was not feasible in the current project due to low power, but would be ideal in a parametric test analysis setting.

## Appendix: Figures and Base Data Tables

**Figure 1.**

Carbon Dioxide Emissions from Energy Consumption by Sector




Citation: (EIA, 2018, p. 210)

**Figure 2.**

Questionnaire for SurveyMonkey Surveys

<u>Questionnaire – beginning of week</u> - *consent questions account for questions 1-3

Question 1: Are you age 18 or over?

{Yes / No}

In the event of 'No' – Thank you for your interest, but this study is open only to individuals 18 and over, and CUNY Hunter College students, faculty, and staff.

Question 2: Are you currently a CUNY Hunter College student, faculty or staff member?

{Yes / No}

In the event of 'No' - Thank you for your interest, but this study is open only to individuals 18 and over, and CUNY Hunter College students, faculty, and staff.

Question 3: Please create a vague, anonymous unique ID and retain it in your records, you will use it in the second round of the survey

<u>Respondent Profile</u>

Question 4: What is your current occupation?

{Faculty or Student / Staff}

Question 5: Where do you live as of today?

{Manhattan, the outer boroughs (Brooklyn, Queens, Bronx, and Staten Island), Long Island (Nassau, Suffolk), New Jersey (for example, Newark, Jersey City), the rest of New York State (for example, Westchester), Connecticut (for example, Stamford, New Haven), Others.

Question 6: What is the primary travel mode that you use to commute during weekdays?

{Car, Carpool, Bus, Subway, Rail, Ferry, Walk, Bicycle}

Question 7: What is the primary travel mode that you use for the longest-distance trip during weekends?

{Car, Carpool, Bus, Subway, Rail, Ferry, Walk, Bicycle}

<u>Environmental Knowledge</u>

Question 8: Using cars alone increases your carbon footprint more than carpooling.

{Agree, Neutral, Disagree}

Question 9: Using cars for transport has a higher carbon footprint than using public transit [subway, bus, rail, ferry].

{Agree, Neutral, Disagree}

Question 10:

Using motorized transport (for example, car, subway) has a higher carbon footprint than non-motorized transport (for example, walk, bike)

{Agree, Neutral, Disagree}

<u>Attitudes & Behavioral</u>

Question 11: I am willing to alter my commute to reduce my carbon footprint.

{Agree, Neutral, Disagree}

Question 12: I have used the NYC bike sharing program 'Citi-Bike'

{Yes / No}

<u>Questionnaire – end of week</u>

Question 1: Please enter your unique username ID (the same username you created when completing the first round) { }

<u>Environmental and Physical Attitudes</u>

Question 2: Using cars alone increases your carbon footprint more than carpooling.

{Agree, Neutral, Disagree}

Question 3: Using cars for transport has a higher carbon footprint than using public transit [subway, bus, rail, ferry].

{Agree, Neutral, Disagree}

Question 4: Using motorized transport (for example, car, subway) has a higher carbon footprint than non-motorized transport (for example, walk, bike)

{Agree, Neutral, Disagree}

<u>Attitudes & Behavioral</u>

*dropdown options indicated by { } include: Car, Carpool, Bus, Subway, Rail, Ferry, Walk, Bicycle

Question 5: Over the past week have you shifted your travel mode differently from your experience before the app?

| | Travel Mode from | Travel mode to |
|---|---|---|
| Mode Shift: | { } | { } |
| | { } | { } |
| | { } | { } |

Question 6: Out of your possible trips for the next 2 weeks, do you plan to change your travel mode?

| | Travel mode from | Travel mode to |
| --- | --- | --- |
| Mode Shift 1 | { } | { } |
| Mode Shift 2 | { } | { } |
| Mode Shift 3 | { } | { } |

If no change is intended indicate here: ‘No’

{}

Question 7: What were your motivations for the attitude and behavior change in question 5-6?

{Carbon footprint, health, both, other (please specify below)}

Question 8: Are you willing to petition local officials for more Citi-bike locations?

(Yes/No)

Question 9: Thank you for completing this survey. If you have any feedback or final thoughts please specify below:

{-}

**Table 1.**

*In this table, Question 5 [end of the week survey] measuring mode “shift” was answered with the same response in two instances. Hence, although these from / to responses are not a “shift” from one mode to another, they constitute the original data.

Tables for Observed Mode Shift – Calculating Mann Whitney U Test

Table 1. Detecting Mode Shift Direction Using Mann Whitney U - Statistical Test

| Original Data | | Sorted Data | | Rankings | | Theoretical Ranking: Most Difference | | Theoretical Ranking: Most Equal | |
|---|---|---|---|---|---|---|---|---|---|
| Mode Shift 1 - Travel mode from | Mode Shift 1 - Travel mode to | MS1 From | MS1 To | From Rank | To Rank | From | To | From | To |
| Bicycle | Bicycle | | Walk | | 1 | | 1 | 1 | 2 |
| Subway | Subway | | Walk | | 2 | | 2 | 3 | 4 |
| Subway | Walk | | Walk | | 3 | | 3 | 5 | 6 |
| Subway | Walk | | Walk | | 4 | | 4 | 7 | 8 |
| Subway | Walk | | Walk | | 5 | | 5 | 9 | 10 |
| Subway | Walk | | Walk | | 6 | | 6 | 11 | 12 |
| Bus | Walk | | Walk | | 7 | | 7 | 13 | 14 |
| Bus | Walk | Bicycle | Bicycle | 8.5 | 8.5 | | 8 | 15 | 16 |
| Carpool | Bus | Subway | Subway | 13 | 13 | | 9 | 17 | 18 |
| Car | Walk | Subway | Subway | 13 | 13 | | 10 | 19 | 20 |
| Car | Carpool | Subway | | 13 | | | 11 | 21 | 22 |
| Car | Subway | Subway | | 13 | | | 12 | 23 | 24 |
| | | Subway | | 13 | | 13 | | | |
| | | Bus | Bus | 18 | 18 | 14 | | | |
| | | Bus | | 18 | | 15 | | | |
| | | Carpool | Carpool | 20.5 | 20.5 | 16 | | | |
| | | Car | | 22 | | 17 | | | |
| | | Car | | 23 | | 18 | | | |
| | | Car | | 24 | | 19 | | | |
| | | | | 199 | 101 | 20 | | | |
| | | | | R1 | R2 | 21 | | | |
| | | | | | | 22 | | | |
| | | | | | | 23 | | | |
| | | | | | | 24 | | | |
| | | | | | | 222 | 78 | 144 | 156 |
| | | | | | | R1 | R2 | R1 | R2 |
| | | | | | | 0 | 144 | 78 | 66 |
| | | | | | | U1 | U2 | U1 | U2 |

-

Table 1a. Information and Checks

| | |
|---|---|
| n | 24 |

| | |
|---|---|
| N1 | 12 |
| N2 | 12 |

| Sum of Ranks |
|---|
| Included on Table. |

| Checks on Ranks | | |
|---|---|---|
| n(n+1)/2 | | |
| | 300 | |
| | 300 | |
| Check | | √ |

| Calculating the Test Statistic | | |
|---|---|---|
| U1 | | 23 |
| U2 | | 121 |
| | | |
| Observed U Value | | 23 |
| | | |
| Check for U Test Statistic | | |
| U1 * U2 | | 144 |
| N1 * N2 | | 144 |
| Check | √ | |

| Theoretical Test Statistic | |
|---|---|
| Most Difference | 0 |
| Most Equality | 66 |

**Table 2.**

Tables for Planned Mode Shift – Calculating the Mann Whitney U Test

Table 2. Detecting Direction for Planned Mode Shift - Using Mann Whitney U - Statistical Test

| Original Data | | Sorted Data | | Rankings | | Theoretical Ranking: Most Difference | | Theoretical Ranking: Most Equal | |
|---|---|---|---|---|---|---|---|---|---|
| Mode Shift 1 from | Mode Shift 1 to | MS1from | MS1to | From Rank | To Rank | From | To | From | To |
| Bicycle | Walk | | Walk | | 5.5 | | 1 | 1 | 2 |
| Subway | Walk | | Walk | | 5.5 | | 2 | 3 | 4 |
| Subway | Walk | | Walk | | 5.5 | | 3 | 5 | 6 |
| Subway | Walk | | Walk | | 5.5 | | 4 | 7 | 8 |
| Subway | Walk | | Walk | | 5.5 | | 5 | 9 | 10 |
| Bus | Walk | | Walk | | 5.5 | | 6 | 11 | 12 |
| Bus | Walk | | Walk | | 5.5 | | 7 | 13 | 14 |
| Bus | Walk | | Walk | | 5.5 | | 8 | 15 | 16 |
| Car | Walk | | Walk | | 5.5 | | 9 | 17 | 18 |
| Car | Walk | | Walk | | 5.5 | | 10 | 19 | 20 |
| Subway | Bicycle | Bicycle | Bicycle | 11.5 | 11.5 | | 11 | 21 | 22 |
| Subway | Subway | Subway | Subway | 16.5 | 16.5 | | 12 | 23 | 24 |
| Car | Subway | Subway | Subway | 16.5 | 16.5 | | 13 | 25 | 26 |
| Car | Carpool | Subway | | 16.5 | | | 14 | 27 | 28 |
| Car | Carpool | Subway | | 16.5 | | | 15 | 29 | 30 |
| | | Subway | | 16.5 | | 16 | | | |
| | | Subway | | 16.5 | | 17 | | | |
| | | Bus | | 21 | | 18 | | | |
| | | Bus | | 22 | | 19 | | | |
| | | Bus | | 23 | | 20 | | | |
| | | | Carpool | | 24 | 21 | | | |
| | | | Carpool | | 25 | 22 | | | |
| | | Car | | 26 | | 23 | | | |
| | | Car | | 27 | | 24 | | | |
| | | Car | | 28 | | 25 | | | |
| | | Car | | 29 | | 26 | | | |
| | | Car | | 30 | | 27 | | | |
| | | | | 316.5 | 148.5 | 28 | | | |
| | | | | R1 | R2 | 29 | | | |
| | | | | | | 30 | | | |
| | | | | | | 345 | 120 | 225 | 240 |
| | | | | | | r1 | r2 | r1 | r2 |
| | | | | | | 0 | 225 | 120 | 105 |
| | | | | | | U1 | U2 | U1 | U2 |

-

| Table 2a. Information and Checks | |
|---|---|
| n | 30 |
| N1 | 15 |
| N2 | 15 |

| Sum of Ranks |
|---|
| Included on Table. |

| Checks on Ranks | |
|---|---|
| n(n+1)/2 | 465 |
| R1 + R2 | 465 |
| | |
| Check | √ |

.

| Calculating the Test Statistic | |
|---|---|
| U1 | 28.5 |
| U2 | 196.5 |
| | |
| Observed U Value | 28.5 |

| Check for U Test Statistic | |
|---|---|
| U1 + U2 | 225 |
| N1 * N2 | 225 |
| Check | √ |

| Theoretical Test Statistic | |
|---|---|
| Most Difference | 0 |
| Most Equality | 105 |

**Figure 3.**

Formulas for Mann Whitney U Test

Test Statistic for MHU Test

$$U_1 = n_1 n_2 + \frac{n_1(n_1 + 1)}{2} - R_1$$

$$U_2 = n_1 n_2 + \frac{n_2(n_2 + 1)}{2} - R_2$$

**Table 3.**

Simple Breakdown on Mode Shift Hierarchy for Mann-Whitney U Ranking Calculations

Mann Whitney U Ranking Hierarchy - by Mode Type

| Mode Type | Ranking Grade |
|---|---|
| Walk | Lowest Carbon |
| Bicycle | Lowest Carbon |
| Subway | Low |
| Rail | Moderate |
| Bus | High Moderate |
| Carpool | High |
| Car | Very High |

**Figure 4.**

Copy of Research Consent Form

HUNTER
The City University of New York

**THE CITY UNIVERSITY OF NEW YORK**
*CUNY Hunter College*
*Department of Geography*

**CONSENT TO PARTICIPATE IN A RESEARCH STUDY**

| | |
|---|---|
| **Title of Research Study:** | A Smartphone App Survey to Encourage Sustainable and Healthy Mode Choices |
| **Principal Investigator:** | Paul Rivers, B.A; M.A Candidate<br>Graduate Student |
| **Faculty Advisor:** | Hongmian Gong, B.S; M.S; M.A; PhD<br>Professor |

---

You are being asked to participate in a research study because you are a staff member, faculty member, or student of CUNY Hunter College and are age 18 and over.

**<u>Purpose</u>:**

This research study is intended to measure the impact that health and environmental information has on citizens' transportation behavior. It seeks to ask: Does empowerment through knowledge lead to behavior change? Do people care more about carbon footprint information or health (calorie burn, fat burn) when making their transport choices? The information you provide will contribute to understanding travel behavior, and aid the cause of increased public access to and awareness of carbon footprint and health information.

**<u>Procedures:</u>**

If you volunteer to participate in this research study, we will ask you to do the following:

- Meet with the researcher at the faculty advisor's office to complete eligibility questions, a first round survey, and have the app downloaded to your phone. Our geo-enabled app will track your location, speed of movement, period of time in a place (minutes). The user will enter: weight, number of persons in a car, and primary mode of transport every time a new track is started. The app will give you daily updates on your carbon footprint ['cemissions' in KgCO2], carbon avoidance, light bulb energy, fat and calories, speed, distance, elevation, and other indicators. For Android users, the app is downloaded by email. For Apple users the app is installed manually via computer wire connection.
- You will be expected to use the app for one week, starting the day after the app is installed.
- You will be sent a reminder email every 3 days from the app installation date if you have not started using the app. We will send 3 reminders at most.
- Complete the second round survey online within 3 days of finishing your app week. You will be sent a reminder email every 3 days if you do not complete it. We will send 3 reminders at most.

Questions on the survey will include topics like: where do you live (i.e the Bronx, Jersey City, New Haven, etc); your occupation (student, faculty or staff); the differences between transport types (i.e car, bus, bike, etc) in carbon footprint; your willingness to change your travel route; your resulting change after using the app.

If reminders are not responded to, you will receive a 'Withdrawal from Study' email, notifying you that if a response is not sent, your data will be deleted at the end of the research study period.

**<u>Time Commitment:</u>**

Your participation in this research study is expected to last for a total of 7-10 days depending on how quickly you complete the research tasks.

Downloading the app should take 3 minutes. Each round of the survey should take 5 minutes to complete.

There are only 2 rounds of the survey, both online, and only one office visit. You will complete the first-round survey online at the office visit, and the second-round on your own.

**<u>Potential Risks or Discomforts</u>:**

- There is the small possibility that the server containing the GPS location data from the mobile app could be viewed by unauthorized parties, such as computer hackers. The researcher has attempted to reduce this risk by not collecting any identifying information through the app, having the server password protected, and reducing the number of authorized persons with access to the server.

- There is the small possibility that the master list containing the participant email, identity, username, and dates to complete research tasks could constitute a breach of confidentiality. To alleviate this risk the researcher will password protect the file and encrypt the storage drive. Only the PI will have access to the master list.

- You will be using a username, not your real identity for the app and survey. Only the researcher will know your identity and username. This username-identity information will be password protected and encrypted. The username helps ensure the researcher knows whether you consent to having your survey and app data stored and / or shared.

- *You may refuse to answer any questions that you do not want to answer and still remain in the study. If you do not wish to answer a question, you can skip it and go on to the next question.*

**Potential Benefits:**

- You will receive daily updates of your carbon footprint and health indicator information. This information will contribute to data empowerment, in which the participant is informed about the environmental and health influences of their daily transport decisions.

**Costs**

- Using the app is free. However, as the app must access the server to calculate statistics. This may involve typical phone data charges which vary based on your cellphone data plan.

**Payment for Participation:**

- Participants will be given a $50 Amazon card via email once they complete the full study. You will be asked for an email address to send the Amazon card to within 3 days of completing the second round survey.

**New Information:**

You will be notified about any new information regarding this study that may affect your willingness to participate in a timely manner.

**Confidentiality:**

We will make our best efforts to maintain confidentiality of any information that is collected during this research study that may identify you. We will disclose this information only with your permission or as required by law.

Your app and survey data will be logged under a username. We will password protect the file list that connects your username with your actual name and email. Additionally, the drive that the file is stored in will be encrypted.

**Participants' Rights:**

Your participation in this research study, or your request to withdraw from it, will not affect your grades, academic standing, employment, or any other status with CUNY.

You can decide to withdraw your consent and stop participating in the research at any time, without any penalty. If at ANY time you would like location tracking to stop, you may do so in the app settings. To restart tracking later, please see app settings.

**Questions, Comments or Concerns:**

If you have any questions, comments or concerns you can contact:

Principal Investigator: Paul Rivers, (347-701-9405) or paul.rivers28@myhunter.cuny.edu

If you have questions about your rights as a research participant, or you have comments or concerns that you would like to discuss with someone other than the researchers, please call the CUNY Research Compliance Administrator at 646-664-8918 or email HRPP@cuny.edu. Alternately, you can write to:

CUNY Office of the Vice Chancellor for Research

Attn: Research Compliance Administrator

205 East 42nd Street

New York, NY 10017

**Store and/or Share Data for Future Research**

On the checklist below, please indicate if you would permit the researcher to store and/or share your survey and app data for future research.

____ I agree to allow my survey and app data to be stored for future research by the researcher of this study.

____ I agree to allow my survey and app data to be shared with other researchers for future research.

____ I do not agree to allow my app and survey data to be stored or shared for future research.

**Signature of Participant:**

I have read the consent form and agree to participate in this research study, please sign and date below. You will be given a copy of this consent form to keep.

_______________________________________________________

Printed Name of Participant Date

_______________________________________________________

Signature of Participant Date

**Signature of Individual Obtaining Consent**

___________________________________________________

Printed Name of Individual Obtaining Consent Date

_______________________________________________________

Signature of Individual Obtaining Consent Date

**Figure 5.**

Script for Recruitment – Listserv Use

Subject Line: CUNY Hunter Geography, Request for Email Distribution

Body:

Hello Mr. Ms. …, my name is Paul Rivers. I am a graduate student at CUNY Hunter Geography. I am currently working on a graduate research project involving the study of transport behavior of CUNY students, staff, and faculty. In an effort to find research participants I wanted to request that you distribute an 'interest' email throughout your listserv. This project has been approved by CUNY UI-IRB.

The project involves having participants download and use a new mobile app called GPS Tracks Hunter (Apple iPhone Version) or My Tracks (Android Version) that outputs carbon footprint information, and health indicators like calorie and fat burn based on one's transport choices. In addition, they will take an online survey twice over the course of one week measuring topics like: the degree to which participants understand the carbon footprint differences between transport types (car, bus, subway, ferry, etc), their willingness to change their transport tendencies, and the resulting change over the course of a week based on their experience with the app.

I hope that you would consider distributing the email to your listserv members. The experience should familiarize them with environmental terminology, and contribute to a positive experience in actively participating in carbon awareness and empowerment efforts. Thank you so much for your consideration in the aforementioned matter.

**Table 4.**

Supporting Data Tables for First Round Survey Responses, Results, and Analyses

Table 4. Responses for Geography and Primary Mode for First Round Survey Respondents

| Geographic Origin | Weekday - Primary Mode | Weekend - Longest Distance Trip |
|---|---|---|
| the outer boroughs | Subway | Bicycle |
| Manhattan | Subway | Car |
| the outer boroughs | Subway | Car |
| the outer boroughs | Subway | Rail |
| the outer boroughs | Subway | Subway |
| the outer boroughs | Subway | Subway |
| the outer boroughs | Subway | Subway |
| the outer boroughs | Subway | Subway |
| Manhattan | Walk | Walk |
| the outer boroughs | Bus | Car |
| the outer boroughs | Subway | Subway |
| the outer boroughs | Subway | Subway |
| the outer boroughs | Subway | Car |
| the outer boroughs | Subway | Car |
| the outer boroughs | Subway | Car |
| the outer boroughs | Subway | Carpool |
| Manhattan | Subway | Subway |
| the outer boroughs | Subway | Subway |
| the outer boroughs | Subway | Subway |
| the outer boroughs | Subway | Subway |
| Manhattan | Bicycle | Subway |
| Manhattan | Walk | Subway |
| | n = 22 | |

Table 4a. Results of First Round Responses

| Aspect of Data | Percent of Survey Pool |
|---|---|
| Outer Borough Residents | 77.3 |
| Manhattan Residents | 22.7 |
| Subway as Primary Mode - Weekdays | 81.8 |
| Subways as Longest Distance Trip - Weekend | 54.5 |
| Car and Carpool Modes as LDT - Weekend | 31.8 |

Table 4b. Statistical Significance of Results - with Confidence Level

| Variable | Statistically Significant Difference? | At Confidence Level 5%? | At Confidence Level 1%? |
|---|---|---|---|
| Recorded Mode Shifts - before | Yes | √ | √ |

| | | | |
|---|---|---|---|
| and after app use | | | |
| Potential or Planned Mode Shifts<br>- after app use | Yes | √ | √ |

Note: See Limitations for discussion of applicability and scope of data conclusions.

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