Planning Like It's 2099: The Use and Distribution of Smartphone Transit Applications in Chicago, Illinois

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Abstract

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Jonathan Feakins

Public transit provides an indispensable service to many of those who make major cities their home. At the same time, smartphones have become a commonplace but powerful piece of consumer technology, whose relevance to its users' daily lives only promises to increase in the years to come. I describe the intersection of these two fields, in the form of smartphone applications that provide real-time transit information. I gather data via the server logs of two real-time transit applications, AnyStop and TreKing. I present an analysis of transit application users in Chicago, Illinois, and compare these users to the overall ridership of public transit in Chicago to determine if they are analogous. Using a combination of internet surveys and aggregate travel planning data, I attempt to illustrate overall patterns in how and why smartphone users utilize their smartphones to navigate public transit. Using log odds ratio and scatter plots, I specifically demonstrate how these two groups of users ride transit in markedly similar manners, both in space and time: smartphone users demonstrate classic usage peaks during both morning and evening rush hours, and their ridership across one hundred and thirty transit routes parallels overall transit usage with 70-86% accuracy. I also suggest variables that may account for any discrepancies in transit ridership between these two populations, and find that smartphone usage demonstrates negative correlation to factors such as total hours of service and number of stops, positive correlation for spatial complexity, and statistically insignificant or inconclusive results for route length, stops per mile, and buses per hour. Finally, I propose that smartphone applications may provide transit planners with an incredibly rich vein of crowdsourced, real-time travel data, which could be used to augment public transit services.

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Thanks to my professors who sparked in me a suspicion that I could make ‘city kid’ a legitimate career.

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Introduction

1.1 Overview

New technologies will always reorganize society in unpredictable and very often completely unforeseen manners. Lasers were originally described as 'a solution looking for a problem,' but now underpin much of our digital technology; modern international trade was built on the back of shipping containers (Maiman 2000, Levinson 2008). The invention of the telegraph transformed society within a generation, to the extent that modern historians sometimes refer to as 'the Victorian Internet' (Standage 1999).

As technology evolves, there has been significant research on how to incorporate it into the urban landscape, often referred to as the 'smart city' or 'urban computation.' But despite what has been called “an underlying self-congratulatory tendency,” many developments in this field have failed to escape the confines of a computer engineering lab, and into the everyday, casual experience of the diverse, workaday city (Hollands 2008: 303). One exception, however, has been the 21st century’s explosion in mobile phones.

Mobile phones can be particularly powerful, because they essentially constitute an incredibly powerful, decentralized computer network. Significant research has been conducted on how best to utilize mobile technology in places like Kenya, where citizens regularly use their phones to conduct online banking, locate sources of clean water, and check local pharmaceuticals for counterfeiting (Jack and Suri 2010, Toyama and Dias 2008, Stanford Design School 2010). By some estimates, there are almost as many

Kenyans with mobile phones as those who have access to fresh drinking water (Aker and Mbiti, 2010, JMP 2010). And a decentralized communications infrastructure – in the form of mobile phones - has significant advantages for a continent where, even in relatively developed South Africa, a leading webfirm once demonstrated that they could more quickly deliver 4GB of data by carrier pigeon than by ADSL (BBC 2009).

Smartphones, by comparison, provide "a rich opportunity for planners to enhance their understanding of the city, which could lead to better planning and better planning outcomes" (Evans-Cowley 2010: 145). Evans-Cowley is here referring to planning on a professional level: the white-collar endeavor of orchestrating a city in such a way that its residents can go about their lives with a minimum of headaches either through the built environment or through a more comprehensive plan that incorporate more intangible social and economic development (Goodman and Freund 1968). And in this paper, unless otherwise stated, references to planners will largely refer to this 'capital-P' planning, as opposed to the everyday people who plan out their day. In fact, these individuals will generally be referred to as “users” or “commuters,” in relation to the application or transit modes that they utilize as a matter of course.

As early as 2000, Anthony Townsend saw two primary challenges in the face of mobile phones:

> First, mobile phones allow for the broad diffusion of time and space management, reinforcing the competitive advantages of the central city business districts by making them more efficient. Second, they make automobile-based urban sprawl more

> manageable and livable. Townsend argues that decentralization of control and coordination of urban activities threatens the foundations of city planning because the profession is based upon the notion that technicians operating from a centralized agency can make the best decisions on resource allocation and management and act upon these decisions on a citywide basis. He argues that planning tools intervene at a higher level, yet the dynamics of urban systems are determined at the individual level through individual behavior (Evans-Cowley 2010: 136).

These observations become even more true with the advent of real-time smartphone transit applications.

Broadly speaking, a smartphone transit app allows a mobile user to directly access information about their local transit system. Google Maps, while initially designed as a web-based application, now comes pre-installed on many smartphones, and allows users to request directions from Point A to Point B while utilizing different modes of transit: automobile, walking, and transit (if available). By 2011, Google Maps had begun to provide real-time info about public transit – a service they initially debuted in Boston, San Diego, San Francisco, Portland (Oregon), Madrid and Turin (Goldmark 2011).

Many cities and developers have also created transit applications that cater to particular transit agencies -such as TreKing in Chicago, Bart Rider in San Francisco, or OneBusAway in Seattle (City-Go-Round 2012). These transit apps (in addition to those apps decided explicitly for walking and driving purposes) provide three primary types of transit information: trip planning from one place to another, arrival times for selected bus and rail routes, and the location of routes and stops in a given area (Portland Afoot 2011).

Some transit agencies initially opposed outside attempts to make their services more accessible and user-friendly: in 2008 and 2009, transit services in Germany, Australia and the United Kingdom accused independent developers of 'copyright infringement' by making use of their timetables in the production of popular transit apps (in Europe, an organization can copyright public facts based on 'database rights') (Masnick 2008, Masnick 2009, Masnick 2009, Cellan-Jones 2009). But the versatility of smartphones, and their widespread adoption, has already significantly altered the experience of urban travel.

The underlying IT infrastructure of smartphones allows for data to be gathered from tens of thousands of participants at a time, while also avoiding many pitfalls of selection bias. Smartphones can effectively obtain data about the movements of the masses, much like an injection of radiocontrast agent into the human body can reveal aberrations or blockages. Using this data, this thesis will argue that city planners have the opportunity to utilize smartphone technology, instead of competing or running parallel to it:

> "For all that BART and the MBTA have done to share data... there is still a disconnect between transit apps and services that might be useful to riders. For example, MBTA and BART have teamed up with car sharing services to allocate parking for shared cars. Ideally, an app would meld the two services, allowing transit riders to have a car reserved the moment their train arrives. Another example is a new parking app in San Francisco that shows how many spaces are available at a given location. If it included transit schedules and other data, it could quickly and easily tell commuters whether they're better off driving or taking a bus." (Barry 2011)

But especially in relation to urban transportation, the whole principle of private phone ownership can still run counter to the very idea of 'public' transit. Why should commuters have to depend on private property in order to optimize their journey on a public system? And it's true: transit planners should be incredibly wary of deferring to easy, free-market solutions that conveniently allow them to avoid thorny public policy choices.

But it needn’t be either/or. Transit agencies and services need not demand universal acceptance of a technological norm in order to provide an essential service. Instead, these planners can also provide additional services based purely on the valuable data that these users have indirectly provided them. Transit planning does not require uniformity from its users – as a matter of fact, an effective transit plan must provide versatility and options in order to remain effective and competitive. But statistically, even the current rates of one-third market penetration provide planners with an incredibly deep and powerful set of data – and this from applications that were designed explicitly for users, and not planners. If planners were to coordinate with smartphone market developers, the information gathered could prove to be even richer.

Whatever their visions of the future, urban planners will need to analyze the claims of smart cities ‘in the wild,’ where lofty rhetoric and plans can be tested in the laboratory of citizens' everyday needs and experiences. While efforts to augment the cities of the future have been technically remarkable, very few of these technologies has seen widespread distribution and use. Widespread adoption of smartphones by the general populace, however, may allow researchers to finally take a serious look the reality of ‘the smart city.’

1.2 Research Questions

I am interested in how cities evolve, and how city planning can live up to its name

- not simply playing catch-up, but rather planning ahead to allow a city's future potential to take root and flourish. As such, my master's research aims to address how an increasingly powerful and eventually ubiquitous technology - not only mobile phones, but 'smartphones' - can become incorporated into urban transportation infrastructure.

1) *Does use of a smartphone transit app, in both time and space, parallel ridership numbers of the transit system as a whole?*

Since their introduction in 2006 as a luxurious gadget, smartphones have quickly become the new standard in pocket computing. In the first few years of their existence, smartphones remained a staple of the relatively well-off and gadget-friendly consumer; as such, a sample of their user base could not adequately represent the population of a whole city. But current estimates suggest that as many as forty percent of American and Canadians with mobile phones now utilize smartphones (comScore 2011, comScore 2012).

And in addition to its more infamous uses as a purveyor of angry cartoon birds and current celebrity gossip, smartphones have provided discerning consumers with a growing array of indisputably useful applications. As many as twenty percent of smart- phone users make daily use of applications related to maps and navigation (Ericsson ConsumerLab 2012). In particular, Put together, a single transit app can record thousands of queries from all across a city, as its users query their ideal route, consider alternatives, measure their prospective wait time, and more.

As smartphones become increasingly accessible, they may eventually become as standard as basic cell phones five years ago. If and when smartphones become evenly spread throughout the general populace, the data from these users effectively could serve as a representative sample of the population as a whole.

By extension, users of real-time transit apps may provide transit planners with a richer vein of travel information than they've ever had before; in fact, one objective of this thesis is to instill in transit planners and city government an appreciation for the kind of data to which they now have access.

2) *What transit system variables most encourage use of a smartphone transit app?*

Wide-scale use of transit applications provides a fascinating insight into the dynamics of commuter trip planning. A smartphone app can effectively measure commuters' casual frustrations and formulations of their travel plans. On a wide enough scale, the data can provide planners with insight as to which routes are on the minds of the populace, based purely on their search queries for particular routes and their arrival times.

As such, what spatial and complexity variables appear to be most important when commuters utilize their transit apps? Will a user most often turn to their smartphone to navigate more complex routes, or are they above all concerned about how long they can expect to wait for the next bus?

Based on these variables, how might considerate transit planners best incorporate the use of smartphone transit apps into the coordination of their system? For example: if an app measures that users examine maps of longer bus routes more often than shorter but more complex routes, then planners might take into account a user's variable ability to navigate these routes. A user's dependence on the app in relation to different routes may provide planners with insights as to the relative success or shortcoming of those very routes.

On as wide a scale as possible, what can we learn about how people utilize smartphone transit applications? Based on their usage, what might city agencies and planners do to increase the efficiency of public transit? Meanwhile, which groups benefit from ubiquitous technology more than others? And if, ideally, city residents are to shift from private automobiles to public transit, what role if any might smartphones play in that transition?

Literature Review

Smartphone transit applications fall into an unusual middle ground between top-down urban planning, and more exploratory research in urban computing. But in concert with social networking, widespread adoption of smartphones has paved the way for the collection of previously unimaginable datasets. And by virtue of having become not only powerful, but popular, smartphone applications may successfully thread the needle between the everyday pragmatism of urban design and the more speculative visions of the 'smart city.'

2.1 Urban Computing

Urban computing investigates the possibilities of incorporating "computing, sensing, and actuation technologies" into the urban experience (Kindberg, Chalers and Paulos 2007: 18). The purposes of this technology can range as widely as the technology itself, from monitoring important variables (i.e., traffic flow and air pollution) to making city services more transparent to the city's residents.

i. Smart Infrastructure

Barring certain outliers (Dubai, and a number of factory cities in China), the vast majority of any major city's built environment was constructed prior to the age of mobile computing. If any sensory equipment did exist, it was usually in the form of traffic detection, which began with simple pressure plates as early as the 1930s, and has since evolved to utilize video imaging and laser radar (Klein, Mills and Gibson 2006).

But more generally, technological revolution has progressed with impressive fealty to Moore's Law (Schaller 1997). Moore's Law, coined in 1970, suggested that the number of transistors inexpensively installed onto a microprocessor would double every eighteen months (since updated to every two years). Thus, in the past forty years, the number of transistors has progressed steadily from a couple thousand, to a couple billion.

In turn, the sheer computing power that surrounds our everyday lives is nothing short of astounding:

> "The total number of transistors in this global network is now approximately the same number of neurons in your brain. And the number of links among files in this network (think of all the links among all the web pages of the world) is about equal to the number of synapse links in your brain. Thus, this growing planetary electronic membrane is already comparable to the complexity of a human brain. It has three billion artificial eyes (phone and webcams) plugged in, it processes keyword searches at the humming rate of 14 kilohertz (a barely audible high-pitched whine), and it is so large a contraption that it now consumes 5 percent of the world's electricity" (Kelly 2010: 13)

The sheer scale of this 'global network' – both in the microscopic scale of its integral parts, and its macrocosmic spread across the globe – now allows for the distribution of complex computational devices throughout the built environment. And urban planners are beginning to make efforts to utilize this technological edge in both organizing the city, and making a resident's urban experience more efficient:

> "Urban planning is well into an undeclared crisis of thought leadership – despite it being one of the best avenues for dealing with global challenges like climate change and migration. Information science is poking its head out of the burrow and seeing the

enormous intellectual challenge of expanding what worked on the desktop of the elites, to a diverse and mobile urban population" (Townsend 2009: xxv).

The use of 'smart' parking meters has increased in the past decade, largely in Europe but increasingly in North America (Shaheen and Kemmerer 2008). San Francisco debuted a pilot program in 2007 in which parking meters could be paid by cell phone, and by 2010 the city was planning on incorporating sensors into parking spaces to determine occupancy, which commuters could view on their phones (Wilson 2007, Repas 2009, Ford 2010). Ultrasonic sensors have been field-tested to measure and relay information on open parking spaces: by attaching a $20 sensor to the side of a car and relaying its readings to a $100 GPS receiver, the researchers' algorithm could detect open parking spaces with up to 95% accuracy (Jonietz 2010). Researchers supposed that if the city's fleet of taxi cabs could be fitted with these sensors, then a constant stream of parking space information could be made available in the whole of downtown for only $200,000, or one-fifteenth of what a fixed sensor system might cost (Jonietz 2010).

One of the most extensive studies in community bicycles has been performed by the Intermodi Research Project at *Wissenschaftszentrum Berlin für Sozialforschung* (WZB) (i.e., the *Social Science Research Center Berlin*). The Call-A-Bike program launched in Munich on Easter Sunday 2000, and provided 2,000 bikes that could be rented via cell phone. One of the major strengths of Intermodi's research was its partnership with Call-a-Bike's parent company, and therefore their ability to make use of "subjective data as well as broad access to and **analysis of customer data** [emphasis in original];" Call-A-Bike's raw data allowed for incredibly deep research on bicycle-sharing, including analyses of ridership levels throughout the day, mode-share and trip purpose among customers, and demographic info (WZB 2008). Meanwhile, the "Copenhagen Wheel" has been designed to attach to the rear wheel of a bicycle in order to not only provide electric pedal assistance, but to gather valuable traffic data via the user's smartphone (Oatram, Ratti and Biderman 2010).

In more recent years, various systems have introduced SmartCards: credit card-sized, tamper-resistant card with embedded circuitry, which typically connects to a central database for purposes as diverse as health insurance, debit transactions and, indeed, transit fares (Chira-Chavala and Coifman 1996, Montreal Gazette 2007). In 2004, South Korea introduced smart cards that used 'T-money' to pay for buses, taxis and even books (Hartvig 2010) With each new development, researchers investigate how trip information, collected by the smart cards, can provide planners with valuable data; although smart cards typically don't contain personal information, planners can chart the movements of roughly-defined demographics through the distribution of student, elderly and adult transit passes. (Morency, Trépanier , and Agard 2007, Trépanier, Tranchant and Chapleau 2007, Chu and Chapleau 2008, Chapleau, Trépanier and Chu 2008).

Continual innovation in mobile computing need not limit itself to the small and portable. Wide-scale sensing networks have been proposed, for example, in the form of geotextiles, "a *computational fabric* that structurally strengthens and physically monitors the landscapes it is buried within" (Manaugh 2012). Many of these developments lend themselves to a greater vision for urban planning and design that has been called a 'robot-readable world': "What if, instead of designing computers and robots that relate to what we can see, we meet them half-way – covering our environment with markers, codes and RFIDs" (Jones 2011).

To no small extent, this is already happening: while society tends to have a very limited idea of robots (*Bladerunner, Short Circuit*, *Wall-E*), pocket-sized Androids seem to have been welcomed with open arms.

ii. Smartphones as Data

Wide-scale smartphone use provides an immense amount of data from an increasing number of users. If a sample of these users can be considered statistically representational of a greater urban whole, then transit agencies can make use of their anonymous, aggregate data to both improve and target their services.

As of September 2010, an estimated 58.7 million people owned smartphones in the United States alone - about 30% of the available market, and growing (comScore 2010, Privat 2010). And while talking and texting remains the most popular uses of mobile phones, third-party applications make up the fastest-growing use category (Yin 2010). As such, smartphones can serve as an ideal tool for research:

> "The device is willingly carried by a large fraction of people in developed countries, integrates a number of technologies for automatic observation, can be programmed to

interact with the user, and can communicate with remote researchers. This allows unobtrusive and cost-effective access to previously inaccessible sources of data on everyday social behavior, such as physical proximity of people, phone calls, and patterns of movement" (Raento, Oulasvirta and Eagle 2009: 426).

Meanwhile, widespread distribution of individual apps allows for potential of collecting uniform data across multiple regions: for instance, the AnyStop transit application is available (as of November 2010) in one hundred and twenty-five distinct agencies. Furthermore, smartphone applications can measure a range of data, not even including data entered by the user: smartphones can passively and continually measure factors such as noise pollution, air quality, and even seismology (Kim 2009, Maissonneuve 2009, Takeuchi and Kennelly 2009). Developers are currently working on turning smartphones into proximity sensors, capable of locating everything from groceries to lost toys (decaWave 2010). Some researchers have gone so far as to start explicitly designing software to gather a range of data (Hasu 2010).

Prior to the widespread distribution of smartphones, many researchers conducted relatively small-scale experiments with self-selected participants. But the potential of cellular phones as a data gathering tool was demonstrated in 2006, in a joint project with MIT's SENSEable City Laboratory and Telecom Italia, who conducted approximately forty percent of all mobile phone traffic in Italy. While limited in terms of data, the user base remained massive, and researchers collected four months of data over a forty-seven square kilometer area. Researchers were then able to chart the topography of mobile use in 3-D, in one instance displaying a virtual volcano of activity during a Madonna concert in Rome. Researchers also plotted out chronotypes of mobile use in six different areas in the city, and could clearly observe how cellular use ebbed and flowed over the course of the day and throughout the city (Reades 2007).

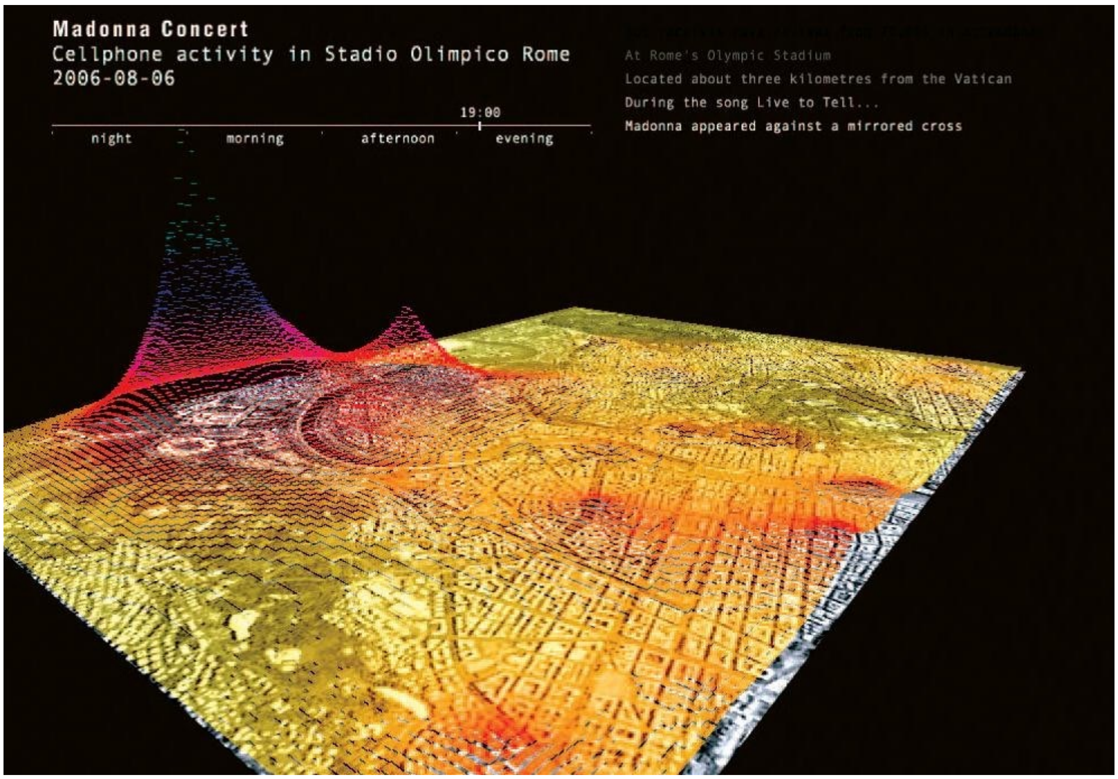


Figure 2.1: 3-D Map of Cell Phone Activity, Rome, August 2006 (Reades 2007)

In contrast, smartphones allow individuals to actively contribute to the collection of data, in what's been called 'participatory urbanism' (Paulos et al. 2009). In essence, its proponents remind us that this device – which many people carry with them in every waking moment – can do vastly more than most realize.

> We carry mobile phones with us nearly everywhere we go; yet they sense and tell us little of the world we live in. Look around you right now. How hot is it? Which direction am I facing? Which direction is the wind blowing and how fast? How healthy is the air I'm breathing? What is the pollen count right now? How long can I stay outside without getting sunburned? Is the noise level safe here? Were pesticides used on these fruits? Is this water safe to drink? Are my children's toys free of lead and other toxins? Is my new indoor carpeting emitting volatile organic compounds (VOCs)? Now look to your phone for answers about the environment around you. What is it telling you? For all of its computational power and sophistication it provides us with very little insight into the actual conditions of the atmospheres we traverse with it. In fact the only real-time environmental data it measures onboard and reports to you is a signal to noise value for a narrow slice of the electromagnetic spectrum (Paulos 2009: 415)

Researchers can utilize a smartphone platform to gather both objective data (such as temperature, location and other variables measured directly by the phone) and subject-ive data (entered by the user) (Ter Hofte 2007). Smartphone use could also serve a natural role in longitudinal studies, in which a user's ever-present phone can collect data over the course of years; a 2010 study estimated the average duration of mobile phone ownership at twenty and a half months. A one-time study of the use of smartphones by doctors and nurses in healthcare found that smartphone adoption was positively correlated to perceived usefulness (Park and Chen 2007).

Mobile devices have evolved so much that they can often replace custom-built measurement devices; urban planners, who once required subjects to carry single-purpose GPS devices, could today achieve superior functionality with a ready-made smartphone application. Many phones also encode their actions with a *geotag*, which allows third-parties to determine the precise location that the action occurred. Working purely with public information, a self-described 'map geek' successfully charted followed individual Twitter users as they traveled through cities, purely through the succession of their public tweets (Fischer 2012).

Smartphone data can easily become a double-edged sword, however. While widespread technology may allow for thousands of participants, diverse participation brings with it a lack of uniformity that may undermine the results; in one early study on smartphone applications designed for pedestrian navigation, researchers suggested that the users' "technical proficiency ranged from sketchy to profound" (Rehrl et al., 2005). Without the controlled conditions that science relies upon in order to replicate experiments, many of these data sets might not be considered scientifically valid. If participants have an active hand in gathering this data, it's entirely within reason to wonder if the results might be biased, and how distant researchers would go about monitoring for and eventually removing erroneous data.

Smartphone activity, at a minimum, comes with latitudes and longitudes, timestamps down to the second, and the ability to aggregate this information for little to no cost. Developers have been quick to collect this information to improve their product, understand their market, and generate more profit. But while the profit motive originally inspired this data collection, the data is as accurate as any scientist can hope for; if proper steps can be taken to analyze it in a methodologically sound manner, the potential is immense.

iii. Smartphone-Based Transit

In an average weekday, the City of Portland gathers as many as 500,000 entries through its bus dispatch system, which allows them to track passenger load and variation; smartphones, by comparison, have the potential to capture the time-stamped travel planning behavior of these passengers (Berkow et al. 2009).

It has been proposed that "Traffic information systems are one of the first instantiations of the potential of participatory sensing for large scale cyberphysical infrastructure systems" (Work and Bayen 2008: 1). But urban computing has been criticized for having wide rhetoric, but narrow application. Most development in mobile phones fall into two genres: either mobilizing desktop applications, such that users can e-mail, chat or perhaps link to their home computers; or providing the user with resources and information (Dourish, Anderson and Nafus 2007). Smartphone-based transit often falls neatly into that second camp.

At its most basic, ubiquitous communications technology increases a user’s ability to plan their journeys by increasing coordination between independent parties, consequentially altering travel behavior: in one study, the seventy-seven kilometers generated from altered travel plans did not quite match the eighty-eight kilometers saved from cancelations and other changes (Ling and Haddon 2006). This behavior gives additional power to independent agents, and therefore builds on the "models based on individual decision-making processes [that] have dominated transportation research" (Timmermans and Zhang 2009: 187).

But what originally began as a convenient consumer device can also serve as the digital backbone on which to build a city-wide information network. In the original designs for Intelligent Transportation Systems, no one seriously considered the potential of cell phones (Zhao 1997). Roadways and transit systems were expected to gain intelligence through dedicated sensors that had been designed for the purpose, and then installed directly into the roads or cars themselves. But the rise of smartphones has outpaced those earlier plans; in 2006, Atlanta resorted to an alternative solution to traffic monitoring that they called 'floating car data' (Schäfer, Thiessenhusen and Wagner 2002, Fouladvand and Darooneh 2005, Rass 2008):

> "Cellint has been delivering cellular-based traffic information to GDOT since 2006 on Georgia 400 and nearby arterials, after fiber communications to the current sensors was disabled due to massive construction work along the freeway. Mark Demidovich, GDOT's Assistant State Traffic Engineer said 'Deploying a replacement fiber backbone, from plan creation to completion, would have taken over two years. Cellint was able to have an alternative in place in four months, which demonstrates another

potential advantage of the cellular systems - speed of deployment.'" (Cellint 2007)

A similar study was conducted successfully in Bangalore in 2008, in which researchers demonstrated the smartphones' ability to detect everything from braking to honking to potholes (Mohan, Padmanabhan and Ramjee 2008). And this sort of innovation stands as a powerful example of what's known as 'leapfrogging': the ability for developing nations to skip less efficient technologies outright, and move directly to the 21st century (Worldchanging Team 2007).

To those users who do not currently use mobile internet, getting traffic information has actually been found to be the *most* compelling reason to adopt the technology (Essential Research 2010). And while smartphones and wireless technology get developed with their own visions in mind – most often, simply as a tool for socializing and entertainment - it's up to planners to anticipate relevant uses.

Many developers and planners initially used smartphone transit applications to aid commuters with physical or cognitive disabilities, as with Mobility Agents or Travel Assistant Device (Repenning and Ioannidou 2006, Barbeau et al. 2006). In Finland, home of telecommunications giant Nokia, the Finnish real-time transit system NOPPA (in English, "Dice") was originally developed to provide real-time transit information to the visually impaired, and similar efforts have been made to connect smartphones and Braille displays (Azenkot and Fortuna 2010). But over time, NOPPA expanded its user base, in direct response to "Finland's high interest in mobile technologies, relatively low population density, lack of automobile industry and winter weather" (Koskinen and

Koskinen 2006: 1).

Many cities and developers, operating both independently and in tandem, have developed a substantial range of options for the average commuter; TriMet, out of Portland, lists dozens of transit applications on their website, and the number of iPhone applications alone had crested into the six-digits by the end of 2009 (TriMet 2010, Apple 2009). Portland has been very proactive in providing open data for their transit system, going so far as to contact Google in 2005, and working to interface their transit data with Google Transit Trip Planner (Roth 2010). Transit agencies have become increasingly aware that opening their data, and allowing developers to build upon it, can directly and dramatically benefit their own services (Press 2010, Eaves 2011).

Planners have begun to make increasing use of technology. In San Francisco, the city government has introduced and promoted CycleTracks, an iPhone application that individual bicyclists can use to record their bicycle trips and submit them to transportation planners. By March 2010 – less than six months after its introduction - the San Francisco County Transportation Authority reported that they participating bicyclists had submitted almost 4,000 trips (Johnson 2010). Thanks in no small part to its gigantic tech industry, San Francisco has been in an ideal position to experiment with the possibilities of smartphones:

> Since March [2010], San Francisco residents have been able to let city hall know about potholes, trash and graffiti problems by using mobile apps or the Web, as well as through the more traditional (and expensive) call centers. Perhaps more important, the

> city encouraged developers to dive into its trove of data. The results: more than 50 privately produced mobile apps, which work on gadgets such as iPhones and Android cell phones, that track everything in San Francisco from restaurant health codes to the most popular biking routes. (Feldman 2010)

A smartphone application in New York City, known as "Weeels," suggests that it is the first application for "social transit." Weeels provides a means for smartphone users to coordinate the use of taxi cabs, such that strangers can share and split the fare for taxi cabs. The stated purpose of Weeels is to "[provide] urban citizens a middle-ground in their mass transit options between the bus and subway, which for most New Yorkers are affordable but not always 100% reliable, and conventional cabs, which may be unaffordable or unavailable in their neighborhoods" (Weeels 2010). And in 2011, a “deprivation study” in Boston and San Francisco found that eighteen people, deprived of their cars, were able to regain a sense of autonomy and independence from information that they derived from their smartphone applications (Latitude 2011).

When the Chicago Bus Tracker debuted in 2008, many Chicagoans heralded it as a one of the Chicago Transit Authority’s few successes after years of setbacks and political stagnation – and by the end of 2009, ‘Chicago Bus Tracker’ was the second most popular Google search term in the city (O’Neil 2009). After transit service cuts in Chicago (heralded by cries of ‘Doomsday’ in the local media), one local commentator proposed that the increasing ubiquity of smartphones had lessened the transit cuts’ impact:

> "In 2010, thanks to CTA Bus Tracker and the widespread use of smart phones, anyone with a home or mobile Internet connection now has the easy ability to find out when the next bus is getting to the nearest stop. Or, really, to find out when any bus on any route is getting to any stop in Chicago – not to mention where on its route any bus is right now. Cue communal sigh of relief. And exit one of the most important public points of pressure labor unions have been able to count on up to now to force concessions from transit agencies.
>
> Short of bus drivers going out on strike (which would be illegal and, judging by the experience of New York City's striking transit workers in 2007, would likely break the union financially), short-term service disruptions no longer have the power to take riders by surprise, confuse their journeys, or force them to fear finding alternate routes. Instead, a few seconds of surfing on the CTA website, or clicking on popular transit tracker apps like iPhone's (phenomenal) Buster or Android's TreKing, is all it takes for riders to plan their bus stops in real time" (Doyle 2010).

Doyle may be overstating his point for sake of politics. Many of these devices – iPhones, Androids, Blackberries, etc. - still exist outside the price range of a significant percentage of transit commuters. But the progress always drives down costs eventually - an original 8GB iPhone, which cost $599 when introduced in 2007, could be had only three years later for $95 at a Radio Shack, or even as low as $49 for a refurbished unit.

There will come a time, most likely within five years, when smartphones and their attendant applications will become as standard and accessible as text messaging today.

To date, most real-time traffic monitoring systems have depended upon the use of inductive loop detectors (the street-embedded coils which detect automobiles) and traffic cameras. Increasingly, research suggests that an alternative traffic monitoring system can function on the back of common cell phones: the Mobile Century study in Union City, California suggests that an accurate monitoring system can be gleaned from 2-3% network penetration (Herrera, Work, Herring et al. 2010). Researchers at the University of Minnesota have even worked to develop a smartphone-based application that would offer advice to teenage drivers, and "prevent vehicle operation in the presence of alcohol or unfastened seat bels [sic]." (Warzala 2010).

The increasing ubiquity of smartphone use has significant potential for future transit behavior - not only as commuters receive data from phones, but also provide it. Smartphone use could also provide a means for transit agencies to monitor and improve their services. In current generations of transit service, transit controllers monitor a transit network by means of, for example, automatic vehicle location (AVL) (Wilson et al. 1992, Hammerle, Haynes and McNeil 2005). By comparison, smartphone data provides a source of instant feedback from the perspective of the commuter, instead of the provider's own monitoring services.

Smartphones have also garnered attention for their potential in providing a framework for novel systems of traffic monitoring, although research has suggested that the effectiveness of such a decentralized network can vary widely (Lee and Geria 2009).

At least one study in Chicago proposed the development of "cooperative transit tracking," in which the GPS and accelerometers in smartphones would function as a decentralized tracking service for city transit, in cases where installing a top-down system may prove prohibitively expensive. By their estimates, even 5-20% smartphone use by transit riders could effectively reduce wait times by 2-6 minutes (Thiagarajan et al. 2010).

As of the end of 2011, these hypothetical rates of smartphone market penetration has been far exceeded by every major developed country, with the United States and Canada tied for 16th and 21st, respectively, for smartphones per capita (with the United States at 34%, and Canada at 30%). But from an urban planning perspective, the rates become even more remarkable when you consider the top two rankings are occupied by city-states: Singapore has achieved a smartphone per capita rate of 90%, followed by Hong Kong at 61% (Sterling 2011). Obviously, those nations have the benefit of affluence, but even relatively poorer countries have developed significant user bases: Romania and Brazil are tied with Japan, at 14%.

This widespread expansion of smartphone utilization and capability may generate behavior that, rather than simply modifying or expanding on current trends in behavior, instead produces entirely new and novel means of trip planning and activity. "Jigsaw," a smartphone app scheduled to be released sometime in 2011, "figures out what you are doing by monitoring your phone's microphone, GPS and accelerometer for patterns characteristic of routine activities - and it could be set to send the results to social networking sites," in essence functioning as a "continuous sensing engine" (Graham-Rowe 2010, Lu et al. 2010).

2.2 Travel Behavior

One of the difficulties in planning for transit users has been determining how transit users make decisions along their journey. Planners have expended considerable effort, often through laborious surveys or idiosyncratic travel journals, in an attempt to better understand the priorities of their transit commuters.

Public transit riders do not appear to express a distinct preference of bus versus rail travel, unless a distinct benefit (like diminished travel time) is provided by one mode or another (Ben-Akiva and Morikawa 2002). In fact, factors that seem to discourage bus travel could dissuade all sorts of behavior: feeling unsafe, lack of service, or preference for another mode (Stradling et al. 2007). Smartphone transit applications, however, have already been demonstrated to directly alleviate these factors (Ferris, Watkins and Borning 2010). Consequentially, continued and/or growing use of these applications could increase the viability of public transit not only logistically, not psychologically.

The pros and cons of taking the light rail in Phoenix differ widely from the same thought process when considering the same options in Seattle, let alone when exported to scenarios that draw upon vastly different traditions of land use (such as in much of Europe) or social conditions (such as mainland Asia). But in the context of AnyStop use in Chicago, some of the most complicating factors include:

i. Automobile Option

Decisions about potential travel behavior often operate in two stages: firstly, accessing the options available; and secondly, choosing the option that best fits the commuter's need (Zhang 2006). In much of North America - or anywhere where land use makes dense transit corridors infeasible, or where a lack of political will stunts any transit development - the automobile has effectively become the sole, viable transit mode. This dependency has a spill-over effect to other parts of the continent, where alternative transit options might be available but people continue driving out of habit, familiarity, or perceived benefit.

The challenge of transitioning commuter behavior from private automobile use to a more sustainable mode has been one of the most pressing questions in transportation research. Multiple attempts have been made to proactively shift users from one mode to the other, particularly with direct engineering or policy measures such as traffic calming, congestion pricing, reduced street parking, and gasoline taxes, ideally accompanied by additional investment into alternative transit modes. And indeed, several European cities such as Amsterdam and Copenhagen have had remarkable success over several decades of progressive transit planning. But in cities with minimal transit networks, otherwise interested commuters may discard public transit as a viable option, out of concern for time, cost of traveling, safety, or simply a sense of personal independence (Beirão and Cabral 2007). And even in cities with significant transit investment, psychological motives born out of a general 'car culture' can significantly impede the transition from one viable mode to another (Tertoolen, Kreveld and Verstraten 1998, Sheller and Urry

2002, Steg 2005).

One of the biggest questions about widespread smartphone use is whether the wealth of real-time information about public transit can prompt a shift of users from automobiles to transit (Multisystems 2003). In previous decades, obtaining transit information – such as expected arrival times - demanded significant time and resources from the traveler, in exchange for static information that could not adequately account for inevitably delays from weather, equipment malfunctions, or detours; there's something ridiculous in spending ten minutes scrutinizing a transit schedule, in order to save five minutes later on (albeit five minutes that might be spent waiting in the cold). Especially in transit systems where delays may last as long as the gap between one bus and the next, obtaining more analog information may have provided just as much of a vicarious sense of comfort and familiarity as any solid ability for commuters to plan their trips.

Immediate access to real-time information, however, may alter that assessment. Whereas mode choice itself may hinge heavily upon variables of land use and urban planning, availability of information about different modes may more profoundly alter the choice set formation. That is to say, public transit may be mentally re-categorized as a viable option, as compared to driving. And with access to real-time information on both traffic conditions and arrival times, these options can actually be weighed on their respective merits.

ii. Walk Shed

This directly challenges the prevailing notion of a rigid walkshed, through which planners have long maintained that residents will almost never walk more than a third of a mile to a transit stop. In fact, researchers have found that transit ridership can rapidly diminish as the distance between the origin and the transit stop reaches as little as 300 feet (Zhao 2003). Recent studies have gone so far as to suggest that "the average survey respondent walked a half mile, far farther than the quarter to a third of a mile assumed by many to be the maximum distance that Americans will walk." (Agrawal, Schlossberg, and Irvin 2007: Abstract). In Chicago, where eight city blocks fit correspond to one mile, this suggests that the vast majority of people will not walk as much as three or four blocks to a transit stop.

The methods used to calculate these walksheds, however, have often had severe limitations. The network ratio method, for instance, assumes that population is spread evenly throughout a study area (Zhao 1998). These methods have been deployed regardless of complicating factors like land use and population density, which has been demonstrated to have significant impacts on active transport and motorized commuting, respectively (Cervero 1995). Furthermore, the ridership of adjacent bus stops can overlap with one another, which can lead to cases of 'double-counting' (Kimpel, Dueker, and El-Geneidy 2007). In Detroit, a Monte Carlo simulation of random addresses suggested that transit riders walk an *average* of 0.8 miles, round-trip (Hoback, Anderson and Dutta 2008).

iii. Wait Times

Of all the uses of one's time, waiting can be one of the worst; in planning one's day, five or fifteen minutes spent waiting for the next bus or train can seem like a black hole of productivity. Waiting for transit from place to place extends far beyond one's daily commute: in 2010, an IBM study suggested that NYC office workers collectively spent over sixteen years simply waiting for the elevator (Bednarz 2010). But perception of travel times can vary, depending on the purpose of travel (Ory, Mokhtarian and Collantes 2007).

Research has demonstrated that wait times have a disproportionately negative effect on the commuter experience: a study of commuters on the Boston subway system revealed "an asymmetry in perceptions: although they were quick to sense a decline in service quality, they were far slower to recognize when the problem had been corrected" (Katz, Larson and Larson 1991: 13). Individuals have been found to value their ‘wait time’ at half to two-thirds of their wage rate (Hess et al. 2004). So when commuters consider travel options, it turns out that time spent *waiting* for transit can become far more influential than the time actually spent *on* transit, and many transit agencies have provided service accordingly:

> "In current practice, almost every travel demand model used in the United States (and elsewhere) considers waiting for a transit vehicle to be substantially more onerous than riding in a transit vehicle (it is typical for the negative coefficient of wait time in

a utility function to be 2 to 3 times larger in magnitude than the coefficient of in-vehicle travel time). As a result, proposed transit alternatives that have more frequent service may be favored by demand models over faster alternatives with less frequent service. Thus, the psychological impact of waiting for a transit vehicle is directly reflected in transportation policy decision making" (Ory, Mokhtarian and Collantes 2007: 495).

A transit-related study on smartphones can depend as much on psychology as planning: prior to widespread smartphone penetration, studies suggested that previously underutilized time spent on public transit could one day double as (paid) telecommuting, particularly for "knowledge workers" whose physical presence at work was not a constant requirement (Hayton and Malos 2005). On a more benign level, users may simply browse their favorite websites or social media, thereby making some decent use of their time (although perhaps at the cost of introspective, stimulation-less contemplation). If positively utilizing wait time can significantly decrease perception of duration, smartphones and other forms of digital technology may provide more than real-time information – they might also help replace otherwise idle time with - if not productivity - distraction, which can similarly reduce the perception of wait time.

iv. Habits

Efforts to modify travel behavior to a more sustainable model must deal not only with weighty, infrastructural concerns, but also that of human habit: "Habits may be a more efficient way of dealing with changes in the environment. Rather than finding out what is the best behavioral option, doing what has always been done in many cases turns out to be efficient in economic terms. In doing so, one does not have to invest in any information costs to find the best options" (Davidov 2007: 319). The idea is that individual trips involve more costs than just the time spent traveling from Point A to Point B, but also all the time consumed while collecting information on that trip and comparing alternative options.

As a result of minimizing energy expenditure, habits form. This natural human tendency towards efficiency (or, perhaps more descriptively, autopilot) can run counter to many behavioral models: "there is a growing body of literature that suggests that individuals do not deliberately reappraise all aspects of their travel decisions on an almost trip-by-trip basis as, in crude terms, the utility maximization theory-based mode choice step of the conventional four-step model assumes" (Behrens and Del Mistro 2010: 255-256).

The effect of information on transit choice is of central importance for smartphone transit apps. Smartphones can reduce the time spent collecting information, by porting appropriate information directly and in real-time to individual travelers. Using a phone's GPS to determine the transit routes closest to the user, for example, can radically reduce the labor spent manually examining maps and locating timetables. These actions can also be performed in convenient periods of 'down time' throughout the day.

But increased access to information has its limitations, when it comes to influencing travel choice. Moderate or temporary alterations in the transit network, such as road closures or weather conditions, may not disrupt travel habits to the point of encouraging commuters to seriously modify their behavior to a more efficient or sustainable mode. Indeed, one theory has posited that commuters may take lesser-known routes for the express purpose of obtaining more information with which to make future decisions:

> "A dilemma for any individual that has limited knowledge about current circumstances, for example because he or she has entered a new life cycle (e.g., getting married or children) or moved to another city or country, is the choice between exploration and exploiting current knowledge. Selecting actions that have not been tried before gives the opportunity of discovering new choices that yield higher rewards than the currently best action" (Arentze and Timmermans 2003: 38-39).

But true as this may be, human beings on the whole remain incredibly predictable. In a wide-scale study of human predictability, researchers monitored 50,000 anonymous cell phone users over the course of a three-month period, and tracked their movements between the ranges of different cell phone towers (Song et al. 2010). Human movement proved unnervingly consistent: the researcher's model could predict a user's whereabouts 93% of the time, and not a single user could be predicted with less than 80% accuracy.

2.3 A Case Study: OneBusAway

A significant amount of research must be conducted so that crowd-sourced, real-time transit information can be most effectively utilized by the public at large. One such study of a transit app in Seattle, known as OneBusAway, credited the app with significant improvement in the usability of the Seattle bus network.

i. The App

As a system, OneBusAway takes several forms in order to provide information to users. OneBusAway could originally be accessed via website, phone interactive-voice-response (IVR), SMS text-messaging, iPhone application, and an “Explore” tool that displayed areas of the city that can be easily accessed by public transit. The researchers also released their API (application programming interface), which allowed developers to code additional uses for OneBusAway, including functionality on different platforms.

On the phone interface, users can receive arrivals times at individual bus stops, search for transit options based on route and address, look at routes charted on a map, and receive alerts about approaching buses.

ii. The Research

OneBusAway was first evaluated by small samples of self-selected participants, recruited either from the computer science department at University of Washington-Seattle or from the OneBusAway Twitter feed.

A larger study of 488 OneBusAway users revealed that 91% of them reported a reduction in wait time. Similarly, 92% of these users reported an increase in transit satisfaction – 48% “much more satisfied” and 44% “somewhat more satisfied” - indicating an incredibly high correlation ($\chi 2=40.467$, $p <$ 10^-5) between the two factors (Ferris, Watkins and Borning 2010). The results are immense, for such a low-cost remedy.

In follow-up internet surveys, users were provided with space to provide free-form answers as to how OneBusAway changed their transit experience. A majority of these responses could be classified as describing a psychological change – 38% who spoke about the reduced uncertainty of waiting for a bus, and 35% who spoke about the increased flexibility and ease of planning their journey. One comment cited as “typical” included: “The biggest frustration with taking busses is the inconsistency with being able to adhere to schedules because of road traffic. Onebusaway solves all of that frustration” (Ferris, Watkins and Borning 2011: 8). By comparison, only 25% of users made comments that could be classified as being about “saving time.” The other 10% spoke about the convenience of tools provided by the OneBusAway application.

Access to their real-time transit app resulted in all types of stress reduction. While 79% of users reported no change in their perceptions of safety, the remainder (particularly amongst women) described themselves as feeling “somewhat safer” or “much safer.”

These feelings stemmed largely from both decreased wait time and increased certainty about a bus's arrival – particularly at night or at "unsavory" stops.

OneBusAway also contributed significantly to changes in travel behavior. There was an overall increase in the number of trips taken per week, particularly for trips not related to the users' commutes. More surprisingly to the authors was the finding that a full 78% of users reported an increase in walking activity, averaging an additional 6.9 blocks per week. These users most commonly walked to a stop on a different route altogether (reported by about 70% of users), although walking further down their initially selected route rated a close second (reported by 50%). One respondent explained that, "Before OneBusAway, I played what I like to call Metro Roulette: start walking to the next stop for exercise, and hope my bus didn't pass me by. Now, though I miss out on the adrenaline rush elicited by Metro Roulette, I can make an informed decision about whether or not to walk to the next stop..." (Ferris, Watkins and Borning 2011: 10).

The users' primary gripe was about the reliability of the data, which the application itself does not generate – rather, it simply relays information provided by the city's transit agency – although the researchers did suggest that the users themselves might help improve the city's tracking, by being able to crowdsource user-generated corrections. But users also had a number of helpful suggestions for improvement, "including requests for native apps tailored to specific mobile devices, location-aware search, real-time trip planning, better management of frequently accessed stop information, and easier search all recurrent suggestions" (Ferris, Watkins and Borning 2010: 7).

A follow-up study determined that use of OneBusAway decreased not just actual wait-time, but perceived wait-time; previous studies have shown that providing real-time arrival information can reduce perceived wait time fell by as much as 20% (Dziekan and Kottenhoff 2006). Via interviews with transit commuters at eight bus stops around the University of Washington, the researchers found that OneBusAway users report waiting an average of 7.5 minutes for a bus - compared to 9.9 for those who use traditional travel information – and furthermore, that OneBusAway users perception of their wait time more accurately represents their actual wait time (Watkins et al. 2011). And of the 156 respondents surveyed by researchers, the researchers also found that real-time information users did, as a matter of fact, wait two minutes less than their counterparts who utilized traditional means.

In addition to their findings on real and perceived wait-time, researchers also found that OneBusAway users reported similar levels of aggravation when using the bus, as compared to those who did not have access to real-time information. After this follow-up study, the researchers did voice a concern "real-time information users are a self-selecting group, which has a naturally higher level of aggravation with waiting for the bus and real-time information brings their aggravation down to the level of a typical rider" (Watkins et al. 2011: 847). The researchers have announced plans to conduct a longitudinal study in the future. The question of *equal distribution* of real-time transit apps has yet to be closely or definitively examined.

Seattle inaugurated their light rail system in 2009, after the initial debut of OneBusAway. To that end, OneBusAway researchers partnered with Transportation Choices Coalition (TCC) to conduct a study in which participants would be provided with "a subsidized transit pass, initial training in the use of public transit, email reminders, and a rewards program with local businesses" (Ferris 2011: 144). Half of those participants would also be trained in the use of OneBusAway, and the other half used as a control. Temporary free bus passes have been previously shown as to boost bus traffic, by simply introducing drivers to a public transit system with which they were not previously familiar (Fujii and Kitamura 2003).

While the group who used OneBusAway did report higher usage of transit, the difference did not qualify as statistically significant; rather, the most important factor for increased transit use was the provision of the subsidized transit card. Trip planning tools, however, did qualify as the most important factor for promoting modal shift from automobile to transit. Researchers concluded that OneBusAway provided an easier user experience to existing users of public transit – to the detriment of new users who possess less familiarity with the system – and that future versions of OneBusAway should carry trip planning features.

Of course, third-party apps are only as strong as their data feed. When a severe snowstorm hit Seattle in 22 November 2010, for instance, the altered routes and delays prompted Seattle Metro to cancel their data feed: "The technology hit its limitations at the very time people needed it most — when slick roads turned icier and numerous traffic accidents left much of the region in gridlock Monday night." For lack of real-time information, local third-party app OneBusAway instead displayed the equally erroneous scheduled arrival times (Long 2010). Increased reliance on real-time information can actually generate a disproportionate amount of grief when that real-time information turns out to be incorrect.

2.4 Limitations

As amazing as technology has become, there appears to be a large gap between its record and its rhetoric. Sci-fi novels of an earlier era expected human society to transform in a flurry of jetpacks and travels to other worlds; instead, the 21st century has been largely characterized by a renaissance of interconnectivity and transparency throughout our own single, familiar globe. But even in the middle of the current mobile computing gold rush, research has already pinpointed a number of concerns to keep in mind.

i. Universality

Smartphone ubiquity is not guaranteed. Granted, users of once cutting-edge technologies do eventually begin to better resemble the population as a whole: three years after its public debut in 2006, the makeup of U.S. Facebook users finally began to mirror the country's actual internet population (Axon 2009). But the steady march of technology can often find itself subject to hyperbole, and the idea that the latest gadget can essentially rework society is usually an idea propagated by a privileged few:

> "A majority of mobile Internet users are young, affluent, urban-dwelling professionals. They are on average between the ages of 16 and 34, living in a city and making more than $65,000 a year. Nearly three quarters of daily users are

> professionals…Overall, the study seems to contrast the general hype around mobile Internet and serve as a gentle reminder that, while we may surround ourselves with the technologically affluent, this isn't yet the norm for the whole of society. There is a definite demographic that uses the Internet on their mobile phones and, outside of that, it remains a costly, unusable and unavailable option in the public's eyes" (Melanson 2010).

Furthermore, the cost of a smartphone and its data plan may provide an extra hurdle for many public transit users. Users of public transit - particularly in the United States and Canada, where automobile use can constitute a substantial component of middle-class affluence - tend to be economically-marginalized. In the past, transit agencies have expended a disproportionate amount of capital in an attempt to lure middle- and upper-class commuters (as opposed to the lower-income commuters whose transit use can largely be taken for granted). The ridership of these two classes tends to forward distinct economic ends:

> "Due to financial constraints and auto unavailability, these disadvantaged riders could be counted on in spite of poor service and inequitably high fares. In contrast, the middle-income and upper-income segments of the market, primarily in the suburbs or outer portions of central cities, were seen as constituting a very demand-elastic submarket requiring high-quality service at heavily subsidized fares to woo them away from their automobiles. Discrimination in service distribution and fare structure might

> also result from efforts to enhance transit's effectiveness at promoting energy conservation, downtown revitalization, roadway congestion relief, and pollution abatement. The success of transit in contributing to the achievement of these environmental and economic goals depends primarily on the extent to which former auto drivers can be converted to transit riders. Because auto use is strongly correlated with income, transit programs aimed at reducing auto use almost inevitably involve preferential treatment for affluent riders. Given these incentives, one would expect to observe a pattern of unequal subsidization where those types of transit most relied on by the poor were the least subsidized and where those services used most frequently by the affluent were the most heavily subsidized…[and] this is indeed the case." (Pucher 1982: 316)

One study found that smartphone users could be correlated to an extraverted personality (although respondents were recruited off social networking sites, which may over-represent extraverts in the first place) (Lane and Manner 2011). A Finnish study found that self-perception can have a significant impact on smartphone use, as users who don't consider themselves tech-savvy hesitate to adopt a smartphone at all (Verkasalo et al. 2009) And despite widespread, even constant use, technological expertise also tends to become device-specific, rather than systemic: "Experienced users (casual users and experts) exhibited superior performance for representative tasks. This is mainly attributable to faster navigation and better knowledge of interface terminology, not to deeper conceptual representation of the problems" (Oulasvirta, Wahlström and Ericsson

2010: 155). Increased access to knowledge need not lead to wisdom.

But with regard to demographics, one of the relatively rare longitudinal studies on digital technology found that individuals of lower socioeconomic status actually demonstrate *more* reliance on their iPod Touch than their peers who possess higher status (Tossell 2011). And actually, while a higher level of income was one of the most reliable predictors for smartphone ownership, the demographic distribution often trended in a different direction: while 30% of non-Hispanic whites owned smartphones, that number was actually 44% for African-Americans, Hispanics, and Asian/Pacific Islanders (Smith 2011, Quick 2009, Sage 2011). This may stem from the additional finding that, in cases where the smartphone served as a primary means of internet access, the correlation between income and usage became negative (Moss et al. 2011). That is, individuals without regular internet access at home may make up for it with increased mobile internet use.

Considering that minority populations and poverty have both been on the rise, it behooves researchers to focus more attention on these classes. And in fact, different demographic groups have utilized technology in different ways, such as lower socioeconomic classes who display higher levels of sharing (Yardi and Bruckman 2012). And whereas white populations have statistically higher ownership of desktop computers and broadband internet access, African-Americans have actually become the *most* active and fastest-growing population of mobile internet users (Yardi and Bruckman 2012). As such, one should consider the very real possibility that smartphone transit use might actually *over-represent* poorer, transit-reliant populations.

More than any other demographic group, however, smartphones have been adopted by the younger generation, which risks the possibility of a new digital divide. At the same time, older populations may have the most to gain from user-centric transit information: not only do many studies suggest that the elderly actually become more mobile with age (Scott et al. 2009), but elderly citizens that lose their ability to operate an automobile may increasingly rely on efficient, wait-minimal public transit.

OneBusAway researchers did suggest, however, that there are ways to work around such a digital divide, including "implement[ing] a free-511 program similar to the free-911 program in which inactive cell phones can still make emergency calls. Such a program could distribute older cell phones and chargers to the transit-dependent population to enable access to real-time information at every stop in a system without the use of expensive real-time arrival signage" (Ferris et al. 2011). Of course, these programs have yet to grant universal access to individuals in need of emergency assistance; one could reasonably question the ability to achieve similar distribution just to save time while waiting for a bus.

ii. Open Data

In 2009, the City of Vancouver passed a resolution to "freely share with citizens, businesses and other jurisdictions the greatest amount of data possible" (CBC 2009). Instituting data transparency – 'open data' - comes with serious logistical challenges, as all the data gathered in the process of governmental duty has to be gathered, catalogued, uploaded, and then continually updated. But beyond the technical aspects, City Hall had to undergo a fundamental transformation: "The initiative doesn't just involve a handful of techies toiling in the bowels of city hall, but depends on every one of the city's 9,000 employees buying into the notion of constantly feeding the data they collect into this common database" (Jordan 2011) Two years later, the City of Vancouver won the title of "Most Innovative Organization in B.C." from BCBusiness.

One of the leading proponents for open source software, Tim O'Reilly, has often spoken of 'Gov 2.0,' or "government as platform," which proposes "a new compact between government and the public, in which government puts in place mechanisms for services that are delivered not by government, but by private citizens" (O'Reilly 2009). This philosophy evolved directly out of innovations from the tech community, best summed up by a mantra known as 'Linus' Law.': "Given enough eyeballs, all bugs are shallow." Essentially, open data proposes to utilize the pro-active curiosity and ambition – of both common citizens and free market denizens alike – to crowdsource away the inefficiencies and deficiencies of government.

These sorts of measures prompt another concern, as to both the strength of the local mobile network, and the accessibility of that city's transit data. A study on data accessibility pinpointed Boston/Cambridge as the metro region that provided the most easily accessible transit data, with Poughkeepsie, Portland, Washington D.C., and San Diego rounding out the top five. And while New York City and Los Angeles displayed significant openness, their overall score was reduced by a lack of coordination between their multiple transit agencies. And when compared to the strength of a city's mobile network, no cities placed in the top five for both categories; rather, first place for strongest mobile network went (unsurprisingly) to San Jose, followed by Philadelphia, Milwaukee, Salt Lake City, and Phoenix (Moss, Mandel and Qing 2011)

It also bears mentioning that outside observers have suggested that Gov 2.0 “is predicated on a positive notion of liberty that shares little with the contemporary expectations of government as a pro-active provider of services, and agent of last resort,” going so far as to describe ‘Gov 2.0’ as a “neo-liberal Trojan horse” (Chen 2011). The ability to utilize data requires significant cultural capital, and brings with it the risk of a ‘data divide’ that runs parallel to the better-known ‘digital divide’ (Gurstein 2010). As a stand-alone tactic of civil engagement, open data can essentially amount to an ‘empowerment of the empowered,” as evidenced by ‘Bhoomi,’ Bangladesh’s program to computerize and publish its twenty million land records:

> “[Bhoomi] allowed the well to do to take the information provided and use that as the basis for instructions to land surveyors and lawyers and others to challenge titles, exploit gaps in title, take advantage of mistakes in documentation, identify opportunities and targets for bribery, among others. They were able to directly translate their enhanced access to the information along with their already available access to capital and professional skills into unequal contests around land titles, court actions, offers of purchase and so on for self-benefit and to further marginalize those already marginalized.” (Gurstein 2010).

Despite its many laudable goals, Gov 2.0 does not appear capable of engineering corruption or unfairness out of existence. Although it might reorganize the playing field in new and perhaps fairer ways, the game itself can still have winners and losers – and some winners may simply have found new ways to cheat.

iii. Privacy

Ubiquitous computing can lead to serious concerns about privacy and cybersecurity: "Cisco has seen the emergence of so-called 'smishing' campaigns – phishing attacks aimed at previous smartphones term where the user can click on a link. More common, however, is the use of SMS messages, apparently from a trusted source, such as a bank, that encourage the user to call a number and reveal personal information – in other words, social engineering" (Network Security 2009). Smartphone users have also been found to be especially vulnerable to new scams, due to "to the 'always on' nature of smartphones, the fact that many of these platforms use push email technology and that users are always likely to be near their phone" (Computer Fraud and Security 2011). And just as desktop computers can struggle with computer viruses, smartphone viruses can pose an even greater risk, precisely due to the smartphone's direct access to the user's social networks, personal information, and even its sensing capacity (Li and Im 2011).

Users may have reason to worry about more than intrepid hackers. In early 2011, news reports surfaced that both Apple and Google regularly collected location data on their users, ostensibly to create maps of wi-fi spots; Google later defended their actions by reiterating that users could manually opt-out of their phone's location-awareness (although this would disable any use of maps) (Angwin and Devries 2011, Devries 2011). In the United States, law enforcement has increasingly turned to tracking suspect's phones, often without a warrant; these procedures may run counter to the Fourth Amendment's protection against "unreasonable searches and seizures" (Vanentino-Devries 2011). In 2012, the United States Supreme Court ruled that secretly installing a GPS device on a car to track subjects did, in fact, violate the Fourth Amendment. But they skirted around any more comprehensive ruling about modern technology's threats to personal privacy; while voting with the majority, Justice Sotomayor urged further consideration:

> In the pre-computer age, the greatest protections of privacy were neither constitutional nor statutory, but practical. Traditional surveillance for any extended period of time was difficult and costly and therefore rarely undertaken. The surveillance at issue in this case—constant monitoring of the location of a vehicle for four weeks—would have required a large team of agents, multiple vehicles, and perhaps aerial assistance…Devices like the one used in the present case, however, make long-term monitoring relatively easy and cheap. In circumstances involving dramatic technological change, the best solution to privacy concerns may be legislative (United States of the Supreme Court 2012).

On a more utilitarian level, users who carry their lives in their wallets are at risk of having those lives stolen; when even an average, non-specialist mugger steals a victim's phone, they are no longer just stealing a quick buck, but access to their victim's social networks, e-mail, and other sensitive information. Relatively few users take precautionary measures to protect this information from others, outside of password protection (provided that they haven't logged in permanently, or selected a password such as 'password'). One consumer study determined that only half of the participating smartphone users know how to turn off location tracking, and only a third know how to disable geotagging (PR Newswire 2012). In recruiting participants online, this survey may even have overrepresented respondents' technological literacy.

As late as March 2012, applications for both Google and Android phones had the capacity to access and upload a smartphone's private photos without explicit permission (Chen and Bilton 2012). A Google spokesperson attributed the design flaw to a holdover from earlier generations of smartphones, when photos were stored on removable SD ("Secure Digital") cards. This explanation provides little comfort:

> "…[W]e carry around location-sensitive, accelerometer-equipped A/V recording devices at all times (our phones). Adding network capability to these things means that design flaws, vulnerabilities and malicious code can all conspire to expose us to unprecedented privacy invasions. Unless you're in the habit of not undressing, going to the toilet, having arguments or intimate moments, and other private activities in the presence of your phone, you're at risk of all that leaking online.
>
> [But] neither the devices' designers nor their owners have gotten to grips with this yet.

> The default should be that our sensors don't broadcast their readings without human intervention. The idea that apps should come with take-it-or-leave-it permissions 'requests' for access to your camera, mic, and other sensors is broken. It's your device and your private life. You should be able to control -- at a fine-grained level -- the extent to which apps are allowed to read, store and transmit facts about your life." (Doctorow 2012)

Public embarrassments such as these have prompted increasing interest in how a user can either limit the amount of public information generated by their smartphone use, or reinstitute the privacy that many users have inadvertently and unknowingly relinquished (Cristofaro et al. 2011, Gilbert et al. 2011).

iv. Negative Impacts

Technological development has always generated pushback, from English textile workers taking direct action against their looms to modern disregard for daily e-mails and social media fads. Critics point to catastrophic instances in which technology has played a fatal role: in 2008, an engineer on a Los Angeles commuter train sent a text message only twenty-two seconds before running a red light and colliding head-on with a freight train on the same track, killing twenty-five people and injuring 125 others; on the third anniversary of the tragedy, local city officials declared "Don't Text and Drive Day" (Deng 2011).

In many instances, personalized technology has been likened to a 'social shield' that removes people from societal interaction, rather than integrates them (Bassoli et al. 2007) A parallel study found that sixteen pedestrians in the United States had been killed or injured while wearing headphones in 2004, compared to forty-seven in 2011 (Lichenstein et al. 2012) The National Traffic Safety Commission, in 2009, published findings that 6% of all auto accidents can be traced to personal use of cell phones (Dossey 2009).

Smartphones have also been subject to criticism because of their impact on human psychology:

> “The smartphone, said [Dr. David E.] Meyer, a cognitive psychologist [at University of Michigan], can be seen as a digital ‘Skinner box,’ a reference to the experiments of the behavioral psychologist B. F. Skinner in which rats were conditioned to press a lever repeatedly to get food pellets. With the smartphone, he said, the stimuli are information feeds. ‘It can be powerfully reinforcing behavior,’ he said. ‘But the key is to make sure this technology helps you carry out the tasks of daily life instead of interfering with them. It’s about balance and managing things’” (Lohr 2009).

In a society that increasingly enables multi-tasking, the human brain rarely does it very well – in fact, that a multi-tasking person can take more time and generate more errors than those individuals who simply focus on each task one at a time (Ophir, Nass and Wagner 2009). And yet, mobile phone technology strongly appeals to capitalist-friendly notions of efficiency and productivity, even if the data suggests that these achievements are largely an illusion (Nafus and Tracey 2002). Users may also process digital media so quickly that the brain doesn't have time to develop admiration or compassion – as opposed to responding to images of pain, which happens almost instantly (Immordino-Yang et al. 2009). The human brain spent millions of years learning to think in a manner that modern, digital society no longer demands.

There is also a question of the human cost. Eighty percent of the global supply of coltan - a heat-resistant mineral ore whose refined state can hold a high electrical charge, and which features in a wide variety of electronics - can be found in the Democratic Republic of the Congo, and its extraction has helped to fuel the war and devastation in the region (Rogerson 2003, Carmody 2009). Furthermore, Chinese factories that produce iPhones and iPads possess such harsh working conditions that some migrant workers have been driven to suicide as a form of protest (Chan and Pun 2010).

Methodology

Smartphone transit data can provide a second-by-second, city-wide picture of transit use by the smartphone-owning population. By analyzing this data, we can determine if users of smartphones ride public transit at the same times, and on the same routes, as the general commuter population.

A general web-survey might also provide a qualitative overview of why and how people utilize their smartphone applications. And for those routes that prompt more or less application use than statistically expected, we can attempt to determine factors that influence smartphone usage across the transit system.

3.1 Chicago Transit System

Chicago's transit system combines both rail and bus transit in order to serve a city population of approximately 2.6 million people. The rail transit operates under a hub-and-spoke model, circling around the downtown (known locally as "the Loop") before leaving the Loop to the further reaches of the city. The rail lines are labeled by color, and include the Red Line, Blue Line, Green Line, Brown Line Pink Line, Orange Line, Purple Line, and Yellow Line. Two of these lines – the Red and Blue – run non-stop. The rest of the lines typically run about 20-22 hours per day. The Purple Line runs as an express route to downtown during morning and evening rush periods, but otherwise reach from the northernmost neighborhood of Chicago to the nearest northern suburb of Evanston. The Yellow Line, also known as the "Skokie Swift," travels non-stop between Chicago's Far North Side and a northern suburb, Skokie.

The City of Chicago is further served by over 2,000 buses that travel one hundred and forty bus lines, which aim to serve the 227 square miles of land that rest within Chicago city limits (CTA 2012). By 2009, the CTA transported almost one and a half million riders a day, while the L alone averages over 150 million riders every year (Chicago Sun Times 2010). Upon reaching city limits, the suburbs are served by a separate bus system, known as Pace. AnyStop does not record any use of the suburban bus system.

3.2 Data Collection

For the purposes of this thesis, data was collected in two stages.

i. Quantitative Data

Much like OneBusAway (as explained in Section 2.3), real-time transit apps allows users to query arrival times for city buses to particular stops, access maps of local stops and routes, and receive directions on how to navigate from one place to the other via public transit. This thesis collected data from two apps:

Firstly, 'raw data' was collected from event logs for users of AnyStop, a real-time transit application available for Droid smartphones. Upon personal request, AnyStop's developers provided me with access to their account on Flurry, a website platform which collects and aggregates user data of various smartphone applications. On the aggregate level, Flurry recorded the amount of use that AnyStop received, the average length of a session, the geographic distribution of said sessions, and the users' navigation of the program itself. Flurry also recorded every session of AnyStop ever used, tracked by nine distinct variables.

From 10pm EST on Monday, 13 December 2010 to 12:30am EST on Tuesday, 28 December 2010, I manually saved the records of AnyStop use. My data files also show an absence of activity from 11:40:12PM EST on Sunday, 19 Dec 2010 to 1:38:59AM EST on Monday, 20 Dec 2010, most likely as a result either of AnyStop maintenance or errors in downloading the data. Downloads had to be conducted manually, file-by-file, and in deference to a full-time work schedule – so while a two-week holiday period may not constitute an ideal time for collecting transit data, it was the only foreseeable period where a solo researcher could consistently collect data for several hours a day without foregoing other responsibilities.

As a secondary source of data, I also received three months of data for TreKing, a real-time transit application local to Chicago. In this instance, the developer went into TreKing's use history and downloaded use data for the months of April, May and June 2011, and delivered summary files directly to the author. Unlike the AnyStop data, use data for TreKing did not include time-stamps, individual program actions, or model information. TreKing data consisted purely of total route ridership per month. As a result, the analysis of TreKing data could not provide insight into the distribution of app use throughout the day, or any information on how users navigated their app.

For the purposes of this thesis, AnyStop data served as the primary source of analysis. When analyzing log odds ratio and complexity variables, however, I did analyze TreKing data as additional data sets.

ii. Qualitative Data

In order to obtain a general picture of the users and psychology behind real-time transit applications, qualitative surveys were distributed in online forums. While such information does not directly bolster the analysis of quantitative variables, it may benefit the reader to hear from commuters in their own words.

From January to March 2010, an online survey was posted on Craigslist in twenty-seven cities: twenty-five cities in the United States, one in Canada (Edmonton), and one in Australia (Perth). Cities were chosen based on having averaged 1,000 or more ‘active users’ of AnyStop, in which ‘active users’ represents the number of people who have used AnyStop over the course of the past month. Although AnyStop debuted in San Francisco (whose residents, as of Feb 2012, make up approximately 7.3% of all active AnyStop use), the application has since expanded into dozens of cities across the world. These cities were surveyed:

Edison, New Jersey; Denver, Colorado; Dallas, Houston and Austin, Texas; Fort Lauderdale, Florida; Las Vegas, Nevada; Honolulu, Hawaii; St. Louis, Missouri; Philadelphia, Pennsylvania; Albany and New York, New York; San Francisco, Los Angeles, and San Diego, California; Chicago, Illinois; Seattle, Washington; Boston, Massachusetts; Atlanta, Georgia; Portland, Oregon; Washington D.C.; Cleveland, Ohio; Durham, North Carolina; Minneapolis, Minnesota; Milwaukee, Wisconsin; Edmonton, Canada; and Perth, Australia.

The survey attempted to gather information that couldn't otherwise be determined from the data collected by AnyStop. Comprised of twenty-five questions, survey queries fell into five general categories:

1) How frequently individual respondents use public transit and/or their transit apps,

2) The purposes of their trips on public transit and/or their transit apps,

3) How users travel behavior may have changed since they began to use their transit app (including whether there had been any modal shift from driving to public transit),

4) What factors might increase or decrease their use of the transit app, and

5) Respondent's basic demographic information.

The survey accepted respondents who used smartphone transit apps of any type, in addition to AnyStop. Respondents were required to be at least fourteen years old, and were enticed into participating with the promise of two $25 Amazon gift cards, to be distributed at random upon completion of the survey.

Because smartphone users have access to a vast ecosystem of transit and navigation apps, actual users of TreKing or AnyStop would not necessarily make up the majority of those who might complete the survey. As such, the survey accepted users of any transit app, many of which share strong similarities to the likes of TreKing, AnyStop, and OneBusAway. Results from the survey should not be considered definitive.

For the full survey, refer to **Appendix A**.

3.3 AnyStop Data

The original collection resulted in 4,278 individual .csv files, which collectively catalogued nearly 100,000 AnyStop sessions, and over a million individual events. Efforts were made to divide the bulk data into a handful of distinct cities - Chicago, Perth, Philadelphia, Portland, San Diego, San Francisco, and St. Louis - in the hopes of analyzing these cities individually, and going so far as to investigate factors – weather, for example - that might promote use of smartphone transit apps. Upon further consideration, however, it was decided to focus explicitly on Chicago, my hometown and a city whose public transit I know rather well.

AnyStop Chicago recorded 120,808 individual events, which comprised 9,150 individual sessions. Any sessions recorded on 13 December 2011 and 28 December 2011, because they provided information for only partial days, whereas the information for December 14-27 lasted from midnight to midnight. After trimming the data in this manner, I was left with 8,231 individual AnyStop sessions for Chicago, Illinois.

For any use of AnyStop, the program had the capacity to record nine distinct variables, of which only seven record any information at all, and one of which recorded four sub-variables:

i. Timestamp

Timestamp recorded the day and time at which an AnyStop sessions begins, in the format MM/DD/YR HR:MN:SC AM/PM PST; for example, 12/26/10 11:58:51 PM PST. All sessions were recorded in Pacific Standard Time, because AnyStop debuted and remains based in San Francisco, California.

ii. Session Index

Session Index indicates the sequence of actions taken by a user during their AnyStop Session. The original program action is labeled as 1, and each subsequent is labeled as 2, 3, 4 and so on, until the end of the session.

iii. Event

Event designates the action taken by the user. Possible actions include:

AllRoutes: AnyStop provides a list of all routes in the user's current city.

ByLocation: AnyStop provides a list of routes convenient to the user's current location.

ErrorItem: An error has occurred when processing a specific request.

FavRoutes: AnyStop displays a collection of the user's saved routes

FavStops: AnyStop provides links to the individual bus stops that the user most frequents.

GeneralError: A system error has occurred.

LocationMap: AnyStop displays a map around the user's current location.

NotFoundItem: AnyStop could not find the requested search query.

PredictionItem: AnyStop queries the arrival time for a bus or train on a particular transit route.

StopList: AnyStop displays a list of potential stops where the user can arrive or depart.

StopMap: AnyStop displays a map of potential stops where the user can arrive or depart.

iv. Description

This field, although present, remains blank throughout all AnyStop sessions.

v. Version

This field records the version of AnyStop being used by that particular user.

vi. Platform

This field lists the computing platform on which AnyStop is operating. Since AnyStop exists purely as an Android application, this field lists “Android” in every instance.

vii. Device

This field identifies the phone model of the current user.

viii. User ID

This field remains blank for all sessions of AnyStop. While AnyStop does record the individual actions of all users, it does not collect individual user histories.

ix. Params

This field identifies four distinct sub-variables:

RealTime: This variable is listed only “true” or “false.” If the program is being used in a city that exists in PST, then it is labeled as “true.” In all other cases, it is listed as “false.”

Route: The program identifies the route which is being queried by the user.

Direction: Although present, AnyStop does not record the direction the user is traveling.

Agency: AnyStop lists the transit agency providing the information; for example, “slippery-rock” for Slippery Rock University in Slippery Rock, Pennsylvania, or “vail” for Vail, Colorado.

3.4 Complexity Variables

Not all transit lines are made equal. For the purposes of this thesis, routes of Chicago’s public transit system were measured according to a series of complexity measures. In addition to charting the use of smartphone transit apps throughout the day and the city as a whole, complexity measures might give some insight as to why commuters use their apps for some routes more than others. These measures included:

i. Route Length

The CTA does not provide the length for Chicago-area bus routes. Lengths were calculated manually, via Google Maps, by requesting directions from the beginning to the end of a single route. The Google Maps Distance Calculator was then used to trace the route from one to the other. Efforts were made to trace bus routes as accurately as possible, and to achieve a route measurement to plus/minus 5% accuracy.

If the return trip took an identical route, the initial measurement was simply doubled. If the return trip took a slightly different route, the length of the return trip was also calculated separately.

ii. Number of Stops

Each bus and rail line in Chicago provides a list of stops on the CTA website. The number of stops included stops made in both directions, because the return route does not always make identical stops.

iii. Stops Per Mile

This metric combines the previous two variables into a measure that more accurately describes the accessibility of the route, based on the average distance along the whole route between individual stops.

iv. Buses Per Hour

This measure determines the average number of buses that a commuter can expect while standing at any given stops along that route. The average is determined in relation to the number of hours active per week.

v. Hours Active

The Chicago Transit Association regularly publishes a schedule brochure that outlines the routes and hours of all bus and rail routes. According to the brochure for December 2010, I calculated the number of hours that each route was active during weekdays, Saturdays and Sunday/Holidays. Because total run-time varies according to the direction of the route (e.g., twenty hours going north, but nineteen hours going south),

were measured in both directions. So for the purposes of the metric, a bus could be active for forty-eight hours a day – and over a two-week period, buses could be active for a maximum of 672 hours.

vi. Corners

As a measure of spatial complexity, I counted the number of turns that each bus or rail line made over the course of its route. Some routes had no such corners, as they simply went down one straight road for the entire length of their journey. I opted to count corners not geometrically, but systemically: for example, turning around via one-way streets did not count as four corners, but only one. Geometric turns along the same street, such as turning southeast while going south along Lake Shore Drive, did not qualify as corners. Similarly, turning around at the end of a route, without additional stops, did not count as a corner.

3.5 Standardization

CTA releases Monthly Ridership Reports, which outlines the number of commuters per bus and rail line. For rail lines, the CTA can measure ridership by individual station – whereas for buses, CTA can only measure ridership as a whole. Although CTA does not release ridership numbers by the day, they do release the number of riders per average weekday, Saturday, and Sunday/Holiday.

Using CTA's monthly ridership figures, I calculated how many riders rode the CTA over the course of December 14-27, both per route and for the system as a whole. I then calculated the percentage of CTA riders who rode each line – in that time, for example, 2.00% of all CTA riders rode the #36 Broadway, a bus that travels north-south between a neighborhood in the Far North Side (Roger’s Park) and downtown.

In an identical fashion, I calculated the percentage of AnyStop users who requested information for each line, in relation to the number of sessions that AnyStop registered as a whole. So while 2.00% of CTA ridership involved the #36 Broadway, 3.06% of all AnyStop use involved the same route.

These numbers will help determine, firstly, if the system distribution of AnyStop corresponds to the regular ridership across the whole city. If AnyStop use were considered representative of CTA use as a whole, then percentage of AnyStop use per line should correspond to percentage of CTA use for that same line. If AnyStop use demonstrates statistically significant departures from that baseline, then we can conceivably pinpoint those routes that have more or less ridership than expected.

i. Discarded Routes

As analysis progressed, ten bus routes (out of one hundred and forty-one) were discarded from AnyStop analysis. This left one hundred and thirty-one routes bus routes, not including the eight rail routes.

Two routes – the 154 Wrigley Field Express and the 168 UIC/Pilsen Express – were not running during the period of data collection. The Wrigley Field Express only runs during baseball season (which does not include December), and the UIC/Pilsen Express did not run at all in December and would be eliminated entirely in May 2011.

Six routes – the 54A North Cicero/Skokie Blvd., the 55N 55th/Narragansett, the106 East 103rd, the 128 Solider Field Express, the 130 Museum Campus, and the 169 69th-UPS Express - were excluded due to zero AnyStop ridership, which prevented the calculation of an log odds ratio (due to "Dividing By Zero" errors). Four of these routes – the 54A, 55N, 106, and 169 – had low ridership routes on the edges of the CTA system. The remaining two – the 128 and 130 – provided transit either to special events (football games at Soldier Field) or to major tourist attractions (Museum Campus).

Two routes – the 201 Central/Ridge and 201N Central/Sherman – were otherwise healthy data sets, except that AnyStop Chicago did not differentiate between the 201 and the 201N (the night bus). Each route has significantly different complexity measures, so the data for "201/201N" could not be connected to one or the other. Both sets of data were discarded in order not to skew the dataset as a whole.

When calculating TreKing data, these same routes were discarded, plus two additional routes for which TreKing had no data during one or more of the three sampled months. These routes included the 98X Avon Express, and the 122 Illinois Center/Ogilvie Express.

Results

4.1 Web-Survey Results

Over the course of January-March 2011, the survey received 242 responses, of which 110 completed the survey in full. Twenty-nine respondents began the survey, but did not use transit apps. Personal identifiers were not collected, and participants received a full explanation of the research before providing consent.

Twenty-nine of the initial respondents identified their transit app as "AnyStop." Of those twenty-nine, twenty-four completed the survey. Half of them were students (65% were aged 14-30 and 37.5% of them made under $20,000/year), two-thirds were female, and 68.9% of them said that they lived within five minutes of a transit stop. While respondents used the app the most often to travel to work (25% used AnyStop five or more times per week), the largest share of them used AnyStop for leisure (41.7% of respondents used AnyStop for this purpose 3-5 times a week). In addition, a number of these respondents replied that they used multiple transit apps, most commonly NextBus and TransitGuru. And yet, a majority of them (72%) reported that they'd only started using transit apps within the past five months.

Only seven people responded that they used the TreKing application. Of these, five were female, all were between the ages of eighteen and thirty-five, and a majority (4) made between $20-40,000/year.

Of the 110 responses, 27.5% replied that they were a student; besides this obvious outlier, personal professions appeared well distributed: 6.5% in Construction/Manufacturing, 7.2% in Education/Teaching, 8% in Technology/Programming, 13.8% in Science/Research, 9.4% in Office/Administrative/Retail, 2.2% in Civil/Government, and 25.4% in "Other." During travel, only six people (5.4%) reported an increase in wait-time, while 13.6% reported that they saved as much as ten or more minutes, and another 30.9% who reported they saved 5-10 minutes. 56.4% reported using their app at least daily, and a third of them (31.8%) reported using it to get to work five or more times a week. Of all trip purposes – work, school, shopping and leisure – only 8.2% of respondents said that they never used their transit app for leisure purposes, followed by only 14.5% for shopping; 23.6% replied that they never even used it for work.

Almost three-fifths of respondents also drove a private vehicle (63 of 110). Of those respondents, transit inaccessibility and time considerations ranked equally high for those who opted to drive (69.8% reported inaccessibility as the first or second most likely factor, compared to 73% who cited time). However, 42.8% of users also said that knowing real-time transit information was the first or second most likely factor why they might choose to take public transit instead of drive (compared to 65.1% who cited 'driving conditions,' and 54% who cited the reduced cost).

In a section for freeform responses about how their travel behavior has changed, most respondents cited increased ease, comfort and confidence with their travel plans. Most of their thoughts were couched in positive terms - "I feel more comfortable taking the bus because I know exactly when my bus is going to be there (even though my line is notoriously late). It allows me to spend less time waiting and more time 'doing'" – whereas only a single respondent focused on the general unpleasantness that they may have avoided: "I DONT HAVE TO CALL THE LOUSEY TRANSIT CUSTOMER SERVICE NUMBER AND WAITIN ONHOLD TO TALK TO A RUDE EMPLOYEE WITH USELESS INFO [sic]."

A handful of respondents credited the app with increasing their public transit, or simply their "spontaneity" when making trips. One respondent – a user of OneBusAway, in Seattle - credited the application with their continued use of public transit: "Bus service here has degraded under our economic conditions, but real-time transit apps allow me to keep riding the bus. Without these apps, I would not risk what might be a 15-minute wait for a late bus." This response bears out the hypothesis put forward during transit cuts in Chicago, that smartphone apps make even reduced service more accessible (Doyle 2010).

When asked how they might improve their apps, a few did request additional features, like "There is now [sic] way to tell the system how much walking is one willing to do... option to optimize for time vs walking distance," or "THEY SHOULD USE A

GPS SYSTEM TO GUIDE YOU TO ELEVATORS OR ESCELATORS(IM DISABLED) [sic].” More than anything, users criticized perceived inaccuracies in the program. Some lamented how the phone had a difficult time ascertaining their location (“Cell towers do not always properly locate me and so the app will misjudge where I am in relation to a stop, sometimes by a considerable distance”). But most users criticized inaccurate transit information, although only some of the respondents acknowledged that this information was provided by the local transit agency. And a few complained they could not use their application underground (which, again, cannot fault the app).

i. Limitations

Firstly, the recruitment of participants off an internet website introduces the potential for selection bias. In relation to the use of smartphone applications, users of an online message board may be able to navigate digital technology at an above-average level. Posting the advertisements in the section for “Volunteering,” meanwhile, may have self-selected for helpful participants, whereas offering a reward in the form of an Amazon gift certificate may entice additional but not completely altruistic or truthful participation.

This research does not, however, primarily focus on qualitative or behavioral data. This survey was designed to develop a general overview of how a populace, even self-selected, uses smartphone transit applications.

4.2 Decision-Making Tree

By gathering transit information via smartphone, researchers have the compelling capacity to watch decision models as they unfold. AnyStop records "User Paths," the step-by-step decision-making process of its users as they navigate the app. This user-path is handily represented as a decision-tree, tracking three actions deep into the start of AnyStop, over the course of millions of sessions (links in green can be further expanded, whereas links in grey effectively mark the end of AnyStop's user-path data).

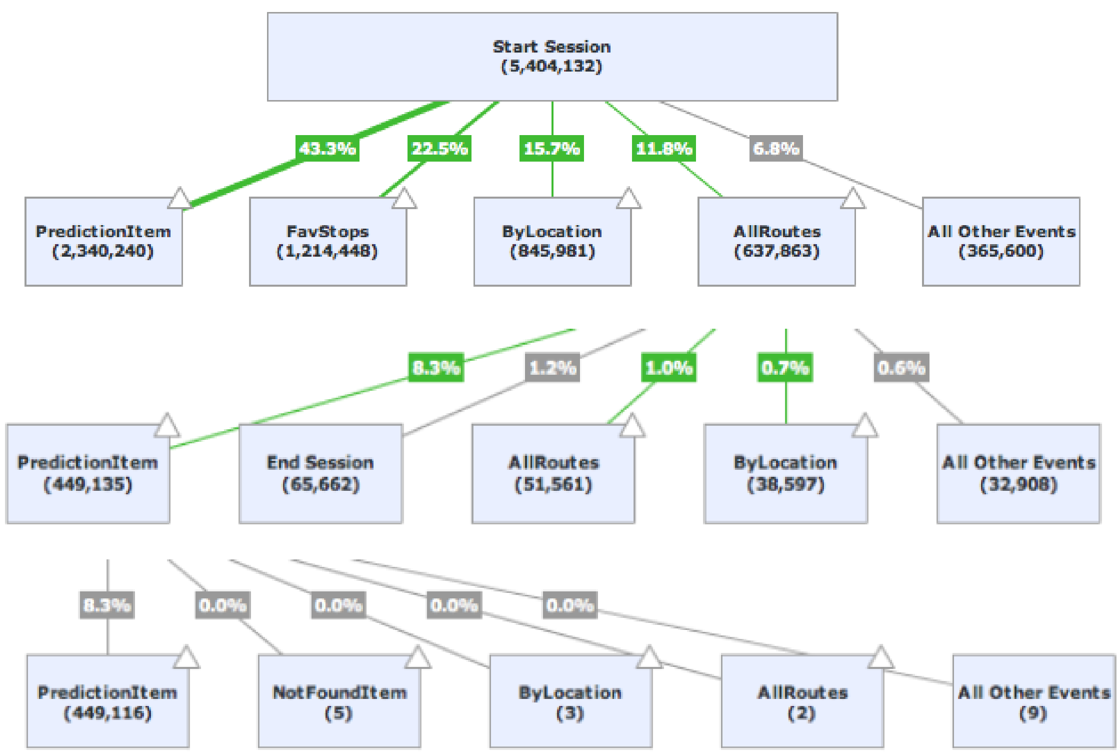


Figure 4.1: AnyStop User-Path, Start Session-->AllRoutes-->PredictionItem

Upon the activation of the program, the first act of a near majority of users – 43.3% - is to immediately request a ‘PredictionItem,’ in order to determine the arrival time of their particular route. The second-most common choice, making up slightly less than a quarter of all initial actions, is to request ‘FavStops,’ indicating a regular user’s desire to query their regular routes. The third-most common choice is ‘ByLocation,’ the action taken by about one-sixth of all users attempting to locate a route convenient to their current position, as determined by the smartphone’s GPS. The four-most common action is ‘AllRoutes,’ in which a user would peruse the entire selection of their city’s transit routes, in order to choose the appropriate route (and, by extension, one which has not already been saved in ‘FavRoutes’).

In the vast majority of instances where a user does not initially request a ‘PredictionItem,’ the vast majority of them do so within the first three actions. Over the course of millions of sessions, by volume, ‘PredictionItem’ makes up the lion’s share of all uses of the app. This dovetails quite well with prior research on the subject, which suggests that minimizing wait time is one of the primary goals of commuters who already possess both a functional transit system, and a familiarity with that system.

When conceptualizing how commuters utilize their transit apps, this decision tree offers a wide-scale snapshot of what might be on the mind of transit users. The prevalence of ‘PredictionItem’ suggests a primary, overriding interest in immediate concerns over wait time, and not necessarily future navigation.

‘PredictionItem’ can, by itself, not necessarily determine whether commuters are or are not already familiar with their route – although it does require the user to identify the route in question, the program cannot determine whether the user is recalling this route from memory or from reading it off a transit schedule or bus stop. On the other hand, the fifth of users who initially request 'FavRoutes' at the very beginning of the program are taking an action that strongly suggests prior familiarity, to the point of having saved that route; 96% of users who start their session with 'FavRoutes' then proceed straight to 'PredictionItem.'

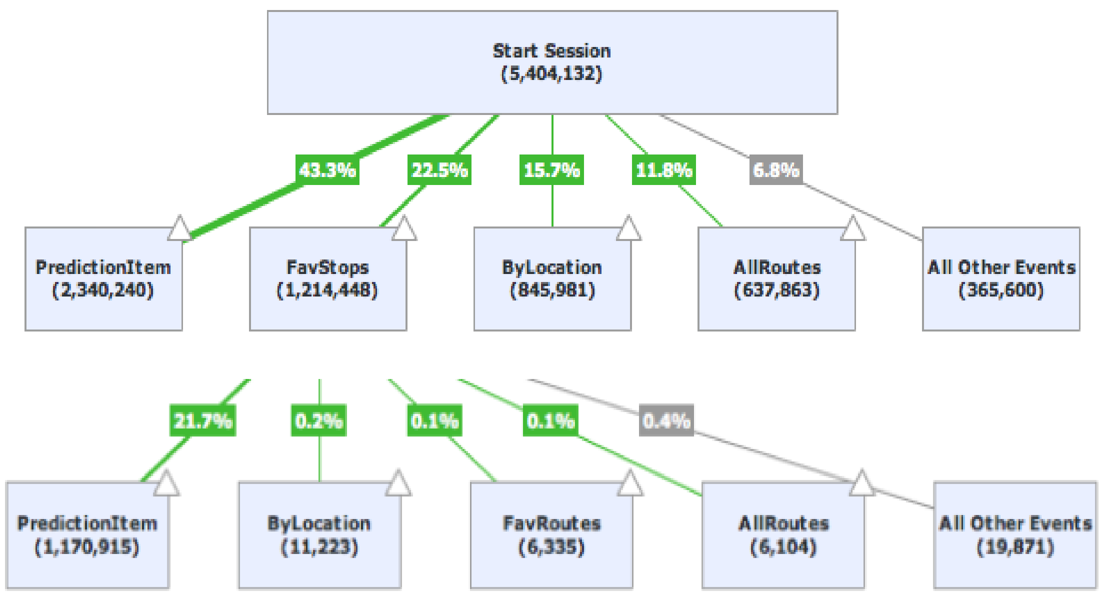


Figure 4.2: AnyStop User-Path, Start Session-->FavStops

The next most popular choice, 'ByLocation,' suggests quite the opposite, as users who use this function are requesting information about their environment; indeed, 56% of users who start their session with "ByLocation" then request a Location Map, while another 38% request a StopList.

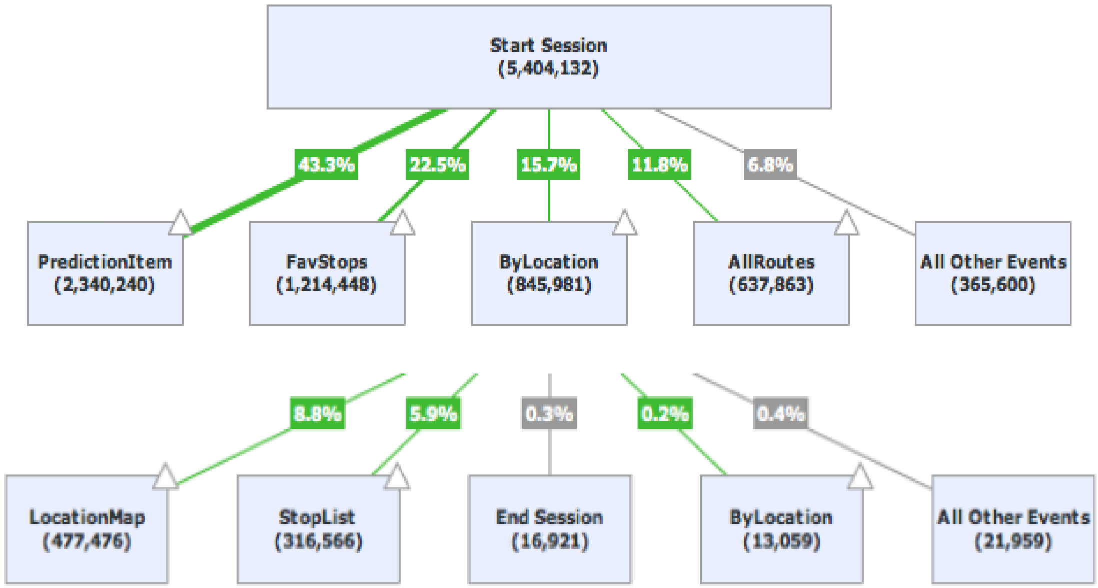


Figure 4.3: AnyStop User-Path, Start Session-->ByLocation

It still remains impossible to determine the relative degree of that user's knowledge; users may just as easily use the function when turned around in a familiar neighborhood as when lost in a completely foreign one.

Nevertheless, and of the options provided to users of AnyStop, the question of wait-time seems to demand a disproportionate amount of attention. It caters to a sense of instant gratification, as well as soothing the uncertainty that comes with relying on others to transport you from one place to another.

4.3 Daily Use Analysis

AnyStop data was first analyzed by use level throughout the course of the day. It was hypothesized that AnyStop use would peak in evening times, as users would travel from work to recreation, or from work or recreation to home. The null hypothesis proposed no discernible pattern throughout the day.

Using Microsoft Excel, I counted the number of AnyStop sessions that occurred in hour intervals (0:00:00am-0:59:59am, 1:00:00am-1:59:59am, et cetera). Those counts were then plotted on a line graph, so as to visually plot the use of AnyStop over the course of the day. These fourteen days consisted of ten weekdays, one Saturday, and three Sunday/Holiday schedules (including Christmas, on December 25). Of the fourteen days calculated, this resulted in data for six distinct plots: Weekdays, Saturday, Sundays, Weekends Without Christmas, Sundays Without Christmas, and Christmas Day.

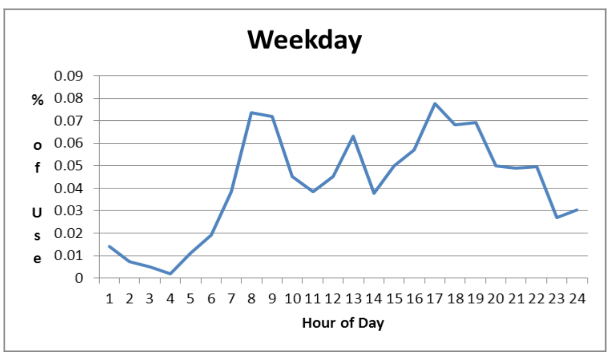
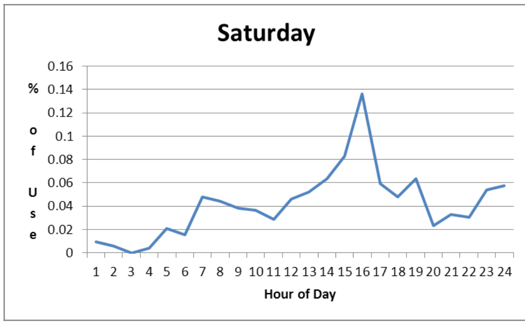


Figure 4.4: AnyStop Hourly Use, Weekday

Upon viewing the graph for use during Weekdays, AnyStop usage demonstrates a classic weekday transit pattern: a peak during morning and evening rush hours (Park, Kim and Lim 2008, Currie and Loader 2009)). It also includes a smaller but significant peak between 12pm and 1pm, the traditional lunch hour, which has also been found in previous studies of travel behavior (Hunt et al., 2005).



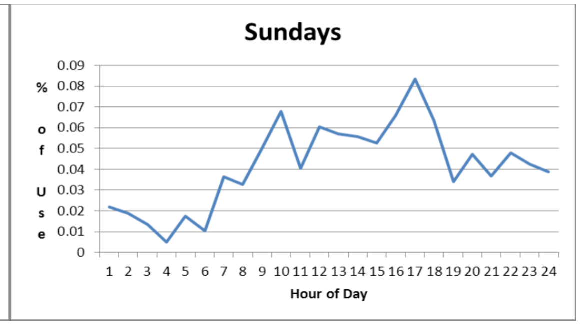


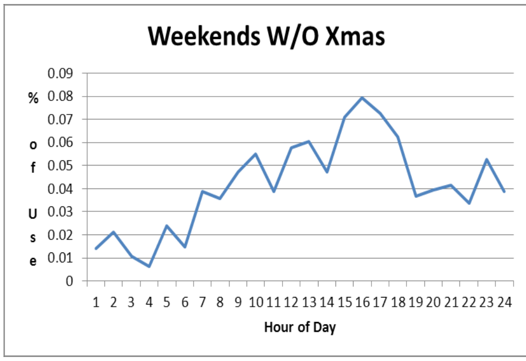
Figure 4.5: AnyStop Hourly Use, Sundays (Left)

Figure 4.6: AnyStop Hourly Use, Saturday (Right)

Saturday shows a significant peak in the mid-afternoon from 3-4pm, which made up 13.6% of all AnyStop use that day. More broadly, Saturday displays a relatively evenly elevated period of transit use that lasts throughout the day, from 6am to 7pm. Sundays, by contrast, demonstrated more varied use throughout the day. Previous studies of weekday travel behavior in Calgary and San Francisco have found plateaus in transit use around 12-5pm on Saturday, and 11-5pm on Sunday (Hunt et al., 2005). AnyStop usage suggests a similar trend, albeit while fluctuating more erratically, and subsiding an hour or two later (around 6-7pm).

However, that the study period only gathered data for one 'normal' Saturday (December 18th), because Christmas Day fell on Saturday of the next week, thereby prompting the CTA to run on a Sunday/Holiday schedule. To that end, a measure of

“Weekends” may not be considered wholly representative.



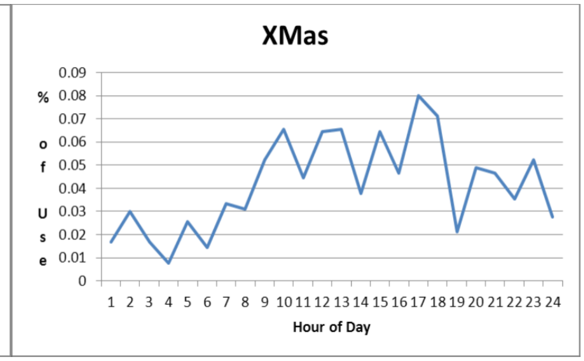


Figure 4.7: AnyStop Hourly Use, Weekends w/o Christmas (Left)

Figure 4.8: AnyStop Hourly Use, Christmas Day (Right)

Nevertheless, activity during Christmas Day does display similar ebbs and flows throughout the course of the day, as are found in an otherwise Christmas-less weekend. Weekends displays a daytime peak between 3-5pm, and a gentle ebbing of traffic from 5-9pm (plus an additional end-of-day peak that likely corresponds to Saturday nightlife). In comparison, Christmas Day experienced a more dramatic drop-off around dinner, and sustained activity thereafter which could represent post-dinner departure traffic.

Although Christmas Day could have disrupted overall travel behavior, it does nevertheless display similar peaks as Sundays and Weekend. Sundays and Christmas Day display significantly more activity during the morning hours, which may correspond to either brunch or church services.

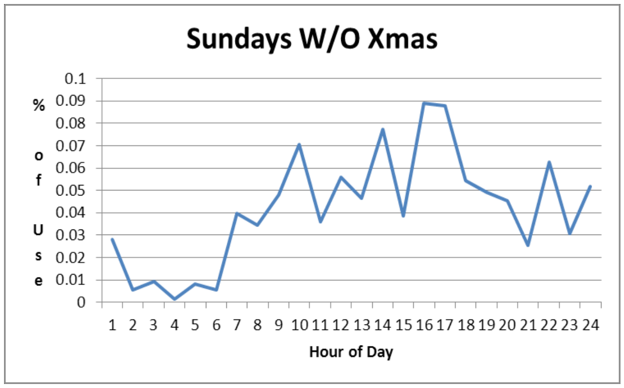


Figure 4.9: AnyStop Hourly Use, Sundays w/o Christmas

These findings effectively refute both the hypothesis and null hypothesis. Not only does smartphone transit use display a distinct pattern, but these patterns occur generally in line with use of the transit system as a whole. It remains to be determined whether the accumulation of additional data, over a longer period of time, would bring the use of smartphone transit apps even more in line with the trend of the overall city.

There may be indications, however, that smartphone transit use may peak slightly after the peak in the general population. This observation may dovetail with the next set of findings, which attempts to correlate AnyStop use with certain complexity variables in the local transit lines.

4.4 Log Odds Ratio

An odds ratio was calculated in order to compare ridership between lines on AnyStop and the CTA system as a whole. An odds ratio, as per its name, calculates the relative chances that similar results would occur in a comparable data set: in this instance, relative ridership users of a smartphone transit app versus the ridership on the transit system itself. Commonly used in public health studies, it serves well in this type of research, in which ridership numbers collected by the CTA can serve as the "control" population, and numbers gathered from AnyStop and TreKing data can serve as the test group (Bland and Altman 2000). By taking the natural logarithm of this ratio, one can arrive to the confidence interval: any result between 1 and -1 falls within the bounds of expected probability. In this particular instance, anything above 1 or below -1 would suggest a relatively positive or negative departure from statistically expected ridership.

Of 131 bus routes and eight rail lines, the average log odds ratio comes to approximately .109, with a standard deviation of 1.081 across the entire sample. As a whole, the data set trends closely to the prediction. Across the 139 lines, only twenty-five showed ridership above 1, and only sixteen showed less than statistically expected use (-1); approximately 29.5% of all routes do not display similar AnyStop use as they did ridership levels. That leaves 70.5% of all routes whose ridership levels closely align with that of the overall distribution of hundreds of thousands of passengers using public transit across the city.

Those routes with higher ridership than expected include: #1 Indiana/Hyde Park, #2 Hyde Park Express, #5 South Shore Night Bus, #10 Museum of Science and Industry, #11 Lincoln/Sedgwick, #19 United Center Express, #33 Mag Mile Express, #55A 55th/Austin, #56A North Milwaukee, #64 Foster-Canfield, #65 Grand, #84 Peterson, #120 Ogilvie/Wacker Express, #121 Union/Wacker Express, #122 Illinois Center/Ogilvie, #124

Navy Pier, #129 West Loop/South Loop, #132 Goose Island Express, #134 Stockton/LaSalle Express, #136 Sheridan/LaSalle Express, #143 Stockton/Michigan Express, #144 Wilson/Michigan Express, #148 Clarendon/Michigan Express, #165 West 65$^{\text{th}}$, and the #206 Evanston Circular.

Those routes with lower ridership than expected include: #9 Ashland, #17 Westchester, #18 16$^{\text{th}}$/18$^{\text{th}}$, #47 47$^{\text{th}}$, #52A South Kedzie, #57 Laramie, #63 63$^{\text{rd}}$, #67 67$^{\text{th}}$-69$^{\text{th}}$-71$^{\text{st}}$, #71 71$^{\text{st}}$/South Shore, #79 79$^{\text{th}}$, #86 Narragansett/Ridgeland, #87 87$^{\text{th}}$, #95E 93$^{\text{rd}}$-95$^{\text{th}}$, #95W West 95$^{\text{th}}$, #103 West 103$^{\text{rd}}$, and #119 Michigan/119$^{\text{th}}$.

A comprehensive analysis of the geographic distribution – comparing higher or lower AnyStop usage to demographic information, census tract data, et cetera - falls outside the scope of this thesis. But at a glance, the majority of those lines with higher than predicted AnyStop use include lines to major tourist attractions or sites of special event sites (Navy Pier, Museum of Science and Industry, and United Center), a high number of express routes (typically to, from, or around downtown), and a few scattered across the north side of the city (#11, #56A, #64, #65, #84, and #206). By comparison, the lines with lower-than-predicted ridership reside almost exclusively on the South Side – particularly the Far South Side, a section of the city that has suffered a disproportionate share transit-deprivation. Recent calls to expand transit in Chicago have centered on the extension of the Red Line from 95$^{\text{th}}$ to 130$^{\text{th}}$ St., and for a stalled bid to convert Metra's South Chicago Branch into a full-time transit line (Wronski 2009, CTA 2011).

Reduced levels of smartphone usage may stem from more than just relative transit inequity. In neighborhoods suffering from a shortage of local job opportunities, commuters may have less reason to precisely budget their time while riding local (and largely east-west) bus routes. If Chicagoans had greater reason to commute to these neighborhoods – thereby generating higher needs for real-time transit information during morning and evening rush hours - smartphone usage may begin to better represent the higher levels of overall ridership.

From April-June, TreKing displayed similar tendencies. Routes with above-expected use included: #10 Museum of Science and Industry, #17 Westchester, #19 United Center Express, #36 Broadway, #49A South Western, #144 Marine/Michigan Express, #170 U. of Chicago/Midway, and #205 Chicago/Golf.

Routes with less-than-expected ridership included: #4 Cottage Grove, #34 South Michigan, #47 47th, #52A South Kedzie, #57 Laramie, #63 63rd, #67 67th-69th-71st, #79 79th, #106 East 103rd, #111 Pullman/111th/115th.

Over the course of three months, use of the TreKing application across all city bus lines demonstrates even less divergence from the overall ridership levels of Chicago: eight routes show higher-than-expected ridership, and ten routes show the opposite. Of the one-hundred and twenty-nine bus routes surveyed, ridership levels fall within expected parameters for 86% of all routes.

For routes that do display statistically remarkable ridership numbers, the geographic spread appears very similar to what we found in AnyStop: overrepresentation to special destinations like museums and sports facilities (MSI and United Center), an express route, one north side route, and a university/airport route. TreKing also demonstrates larger ridership for two routes that reach and service Chicago-adjacent suburbs (#17 Westchester into Forest Park, and #205 Chicago/Golf into Evanston), and one route on the far south-west side that reaches suburbs in that region (#49A South Western into Blue Island). Lower-than-predicted ridership, meanwhile, occurs almost exclusively on the far south side, plus two routes on the far west or southwest side (#52A South Kedzie and #57 Laramie).

Interestingly, the TreKing data demonstrates remarkably different results for ridership on Chicago's rail lines. Whereas AnyStop demonstrated no significantly above- or below-expected use on any rail line, TreKing use proved far more varied. TreKing users made significantly less use of the Red Line, which travels north-south for twenty-four hours a day, and the Brown Line, which heads back and forth between the Loop and the Northwest Side until 2am. Meanwhile, TreKing users display significantly higher use of the Pink and Purple Lines, which service the near-west side and near-northern suburbs, respectively. One possibility is that TreKing has developed a substantial user base around the vicinity of University of Illinois-Chicago, whose campus (and adjacent medical hospitals) are served largely by the Pink Line.

For all Ridership Numbers and Log Odds Ratios, refer to **Appendix B**.

4.5 Pearson's r for Log Odds Ratio and Complexity Variables (Bus)

The size of the data set allows for Pearson's product-movement correlation coefficient. The odd ratio stands as Variable X, and the relative complexity variable (as designated earlier) stands as Variable Y.

For all scatter plots, refer to **Appendix C**.

i. Log Odds Ratio and Route Length

Route Length (ranging from 2.4 to 35.62 miles) was found to be of minor negative correlation (r = -.20), in that longer routes led to less use of the AnyStop application. The longest routes appear to have been fairly evenly distributed, although none of them crest over a correlation of approximately 1.5, and routes with a higher correlation do not occur until their full route length measures less than twenty-five miles.

To sample the five longest routes, the two negative x-values represent Routes #9 and #49, both of which are direct north-south lines with a substantial number of stops. The three routes with positive-x values are all express lines: Route #2 Hyde Park Express, Route #14 Jeffery Express, and #169 69^{th}-UPS Express.

This correlation with express lines will be further examined in *Log Odds Ratio and Hours Active.*

By comparison, however, the same metric when compared to TreKing data does not show steady, significant correlation over the course of three months: r = -0.05 in April, -0.02 in May, and -0.21 in June.

ii. Log Odds Ratio and Number of Stops

Number of Stops (ranging from 3 to 329) was also found to be negatively correlated with AnyStop use (r = -.40), and moreso than route length. By comparison, TreKing also demonstrate negative correlation over the period of April-June, albeit to a lesser extent: r = -0.19 in April, -0.12 in May, and -0.30 in June.

Express routes, as suggested in the previous section, may promote a higher level of app use; by virtue of their being express, these express routes also tend to have fewer stops. An increased number of stops can decrease the overall speed of the line, which may dissuade riders from riding this line, and may prompt them to consider alternative options. This variable may illustrate this.

iii. Log Odds Ratio and Stops Per Mile

Buses in Chicago range from 0.14 to 16.04 Stops Per Mile, which produces an r-value of -0.34. This comes despite significant clustering in a y-value of 5-10 Stops/Mile, which appears to serve as the common range for bus lines across the city. In addition, especially high and low values of Stops Per Mile appear to all promote increased AnyStop use; the negative correlation stems from the bulk of the routes, which are more evenly distributed across increased and decreased AnyStop use.

By comparison, no reliable correlation could be found among TreKing use. The r-value in April came to -0.08, but retreated to insignificant values of 0.02 in May and -0.05 in June.

iv. Log Odds Ratio and Buses Per Hour

Of all the measures calculated, “Buses Per Hour” (ranging from 0.51 to 9.19) was determined to be the least influential ($r = 0.05$), and the only variable to confirm the null hypothesis; i.e., the frequency of the bus has no significant bearing on the use of the AnyStop application. This refutes the hypothesis that diminished bus frequency would result in increased application use, in order to diminish a user’s wait-time.

This finding is particularly surprising in light of how much urban planning has focused on optimizing route frequency as a means of reducing wait time and system cost and increasing customer satisfaction.

However, TreKing data suggests a stronger correlation: $r = -0.24$ in April, -0.21 in May, and -0.19 in June.

One possibility is that the AnyStop sample period (December 14-27) may have skewed the available data. Because this period occurred over a significant holiday period, commuters may have had less pressing time concerns (and overall, less work days) that prompted them to strictly budget their time.

v. Log Odds Ratio and Hours Active

“Hours Active” serves as a primary, negative factor when determining app use. The strongest negative correlation comes from AnyStop, which recorded an r-value of -0.60.

While not as strong, these values remained significant in the TreKing data, with April-June r-values of -0.30, -0.19, and -0.33, respectively.

While sixteen bus routes run all day and night, routes operated for as little as 25.42 hours over two weeks. As a bus reduces its number of active hours, app use rises significantly. Bus routes with the least active hours often serve only morning and evening rush hours, such that their service begins and ends around peak use. Routes that run twenty-four hours a day actually trend towards significantly less app use than the system as a whole, by virtue of the user knowing that they'll come eventually, even if not immediately.

vi. Log Odds Ratio and Corners

Bus routes in Chicago possess anywhere from zero to twenty-two corners, but rarely crest above fifteen.

Pearson's r for the corners variable was found to be reasonably positive for AnyStop, with an r-value of 0.30. TreKing figures, however, varied considerably more: r = 0.12 in April, 0.6 in May, and .10 in June. So while there may appear to be consistent correlation between application use and geographic complexity of individual bus lines, its influence may range from distinctly influential to barely significant.

4.6 Pearson's r for Log Odds Ratio and Complexity Variables (Rail)

Research has already demonstrated that commuters utilize bus and rail transit in distinct ways. One should keep in mind, however, the smaller number of rail lines in Chicago (8), as compared to bus lines (141) – an as as a result, any analysis of app use will need to clear a higher hurdle to qualify as statistically significant.

When calculating Pearson's r for the AnyStop data, no complexity variables were found to be significant, as determined by a critical value of 0.707, for six degrees of freedom and with 95% certainty: Trains Per Hour (r = -0.20), Number of Stops (r = 0.28), Route Length (r = 0.18), Corners (r = 0.56), Hours Active (r = 0.14), and Stops Per Mile (r = 0.54). This finding might be particular valid because the complexity measures for Chicago's rail lines (excluding the express suburban Yellow Line) do not significantly differ from one another: the seven remaining lines vary from 4.78-7.45 trains per hour, 24 to 64 Stops, 22.4 to 69.2 Miles in Length, 2 to 5 Corners, 567.25 to 672 Hours Active, and 0.96 to 2.02 Stops Per Mile.

When calculating Pearson's r for TreKing data, the month of April recorded no activity on the Yellow Line (the least used line, which makes only two stops and typically comprises three-quarters of a percent of overall rail transit), and so that month had only five degrees of freedom, and a critical value of 0.754.

The same calculations consistently found positive correlation between TreKing use and two complexity variables: Corners (r = 0.87 in April, 0.83 in May, and 0.92 in June) and Stops Per Mile (r = 0.77 in April, 0.81 in May, and 0.89 in June). These numbers actually compare nicely to the AnyStop data, for which Corners and Stops Per Mile were also the most influential complexity variables (r = 0.56 and 0.54, respectively), albeit not influential enough to be deemed statistically significant in that particular data set.

TreKing did also indicate negative correlation for Route Length in April ($r = -0.81$), but this correlation did not continue into May ($r = -0.42$) and June ($r = -0.14$). Otherwise, no other variables demonstrated significance: Buses Per Hour ($r = 0.11$ in April, 0.21 in May, and 0.40 in June), Number of Stops ($r = -0.48$ in April, 0.05 in May, and 0.30 in June), or Hours Active ($r = 0.49$ in April, -0.06 in May, and 0.22 in June).

Conclusions and Discussions

5.1 Findings

The depth of data provides a few solid findings, in relation to where and why commuters might make user of real-time transit applications. These findings do not definitively represent travel behavior itself, as we have no data to directly correlate the trip plan itself, and the actions actually taken by the user; that is, we cannot assume that a user requesting a bus or train's arrival time actually embarked on that route.

In addition, the available data sets – however massive they may seem for a single researcher – could become more definitive if they increased their sample size and period. Courtesy of collecting research over a holiday weekend, AnyStop data – for weekend periods especially – cannot be considered as technically "pure." But the data provides enough insight that future researchers – perhaps even with access to a staff greater than one, or a budget greater than zero – could pursue similar questions over a larger scale.

i. Distribution

It appears that distribution of smartphone transit application in Chicago roughly corresponds to general ridership numbers, both by time of day and by line. And based on the data sets provided to us, a longer sample period (three months of TreKing data from April-June 2011) displays greater overall representation then the deeper but shorter data provided by AnyStop (during two weeks in December 2010). If one were to analyze similar numbers over a six-month or year-long period, such representation may increase further.

Some general geographic locations, however, appear to demonstrate over- or under-representation in the sample of app users. The Far South Side, in particular, seems to contain a cluster of underrepresented routes, and half a dozen individual routes appeared underrepresented in both the AnyStop and TreKing samples (47 47^{th}, #52A South Kedzie, #57 Laramie, #63 63^{rd}, #67 67^{th}-69^{th}-71^{st}, and #79 79^{th}).

Similarly, North Side and express routes both seemed more likely to receive more than their fair share of smartphone use, although only three such routes appeared in both sets of data (#10 Museum of Science and Industry, #19 United Center Express, and the #144 Wilson/Michigan Express). In fact, the relatively large number (25) of overrepresented buses in the AnyStop data included eleven express routes, which makes up nearly half of the overrepresented routes.

This discrepancy becomes far more prominent, however, when you consider the ridership of these particular lines. While the number of lines overrepresented by AnyStop does outnumber the number of underrepresented ones, the same cannot be said for these routes' ridership: overrepesented routes display significantly lower ridership than underrepresented ones. The smaller sample sizes would also make these routes more likely to present as overrepresented, and therefore less significant.

Tallied together, those twenty-five bus routes with higher-than-average AnyStop use makes up only 3.94% of ridership on all CTA buses. The underrepresented lines, in contrast, represent 18.78% of all bus ridership in Chicago. Each overrepresented line carries an average of 0.15% of the city's ridership (or a median of 0.09%), compared to the underrepresented average of 1.17% (and a median of 0.89%). By whatever measure, the underrepresentation actually outweighs overpresentation by a factor of five to ten.

TreKing displays similar trends, albeit to a lesser extent on a system-wide basis: overrepresented routes accounted for 2.30% of all bus traffic in Chicago (with an average of 0.32%, and a median of 0.08%), and underrepresented ones accounted for 12.74% (an average of 1.27%, and a median of 0.92%). TreKing's user base for rail transit, meanwhile, appears incredibly skewed: when requesting rail information, 56-60% of TreKing users requested information for the Pink Line, which makes up 4% of CTA's rail ridership. Furthermore, TreKing's paucity of traffic on the Red Line – the city's primary line, which makes up more than a third of rail transit ridership across the city – cannot be easily explained in the scope of this thesis.

That said, these figures may only slightly change the overall picture. While use of AnyStop and TreKing adequately represented 70.5% and 86% of all bus routes, respectively, ridership figures suggest that AnyStop equitably represented 77.28% of all bus passengers, compared to TreKing's 84.96%.

ii. Accessibility

More frequent stops appear to have most discouraged users from using AnyStop. In Chicago, this makes particular sense when considering the popularity of express routes that do not make any stops at all for miles on end, particularly along Lake Shore Drive in and out of downtown. But this also speaks to a recognized tradeoff in public transit design, in which additional stops increase access, but decrease speed (Murray and Wu 2003). AnyStop transit users may prioritize, or self-sort into using, faster bus lines.

But conceivably, access to real-time transit information may have begun to function as *surrogate access*. In previous eras - when no real-time arrival information had been available - transit agencies could only provide static timetables that would still leave commuters at the whim of delays or uncertainty. And having immediate access to transit information may decrease a user's reliance on tightly-packed transit stops, as users can now plan to arrive at particular stops at particular times without risking increased wait time.

In addition, planners have long accounted for a predicted walk-shed, in which they essentially expected transit users to reduce their transit use when required to walk more than half a mile. If the OneBusAway study is any indication, this walk-shed may turn out to be a product not of human laziness or disinterest, but rather a reasonable response to the lack of real-time, actionable information.

Commuters will gladly walk to a more distant stop if they have the information to guide them: a study on commuter tendency suggested that transit maps, waiting time and operating hours were the most important factors when considering one's commute, whereas the walking time to the station was almost universally considered one of the lowest (Abdel-Aty, Kitamura, and Jovanis 1996). While using OneBusAway, users demonstrated a marked increase in the amount of trips, and 78% actually walked to a different route or further down the same route – at an average of 6.9 additional blocks every week. Some riders, upon seeing a long wait time, opted to walk all the way to their destination (Ferris, Watkins and Borning 2010).

When provided with clear options – walk for eight minutes, or wait for ten - commuters may willingly exert themselves, rather than submit themselves to the stress of waiting. Psychologically, this may also attest to an increased sense of control, as users utilize a transit network's timetable without feeling subservient to it.

iii. Frequency

Upon first glance, the relative unimportance of route frequency in relation to smartphone use might suggest a quandary. When wait-time has been found to be one of the most influential variables in commuter behavior, why would more or less wait time not influence how a commuter accesses real-time travel information?

But more or less smartphone use may not benefit the user, regardless of the route's relative frequency. A single session typically provides the user with arrival times for all the buses in the next twenty or thirty minutes; additional or refreshed sessions would not provide any additional information to the user. Individual sessions may grow longer in direct relation to wait time, but the number of sessions need not increase unless the user exit the program entirely, and then launch it again for the very same trip.

Although AnyStop does record the average length of a session, the length of individual sessions cannot be accurately determined with the available data. While the program can auto-refresh into a new Session Index, these auto-refreshes cannot be differentiated from user actions; that is, two equally long sessions, as measured by Session Index, may have lasted for different periods of time. If one could accurately measure individual session lengths, however, one could correlate these sessions to a route's average wait-time.

The length of each route's service, however, proved to be the most influential factor of all those that were measured. If commuters intend to travel near the beginning or end of their route's running hours, it would certainly behoove them to determine whether their preferred route remains running at all. As per the AnyStop data, users don't query route lines based on how often their buses run, but whether they run at all.

In fact, further research could be conducted to determine AnyStop use on individual bus lines throughout the day. Such an analysis could more definitively determine if usage experienced statistically significant peaks around the beginning and end of these routes' hours, suggesting that users might be confirming whether they had started or stopped running. Alternatively, no such relationship might be found, making it more likely that the routes' popularity had more to do with many of these routes running express.

Furthermore, additional conclusions might be reached if the measure were calculated more precisely. Calculating the average number of buses per hour across across a whole week may obscure correlation, by essentially diluting high-traffic periods or glossing over differences between weekdays and weekends.

iv. Spatial Complexity

A basic measure of route complexity did suggest that users made greater use of their smartphone transit application as the routes grew more spatially complex. Users may utilize their app to better navigate the twists and turns of a particular route, such that they don't wind up missing their destination or getting lost entirely. This variable alone held true not only for buses, but for rail as well. Rail lines that ran consistently in one direction or the other – such as the Red and Purple Lines (which run straight north and south) and the Blue Line (which runs directly west or northwest) – received the least TreKing use.

However, the metric used to gauge complexity – corners – may not adequately describe the complexity of these routes. For a more definitive determination, additional research might require more comprehensive parameters – including not just corners of a network, but also edges, degrees, clustering, and distance between stops, routes, or transfers (Lu 2007). And for an additional correlation, future research could also search for correlations between queries for individual routes, and queries for maps of those routes. Future researchers might even be able to determine which points of a route are most often scrutinized.

A user's perception of complexity, meanwhile, may actually correspond to the structure of the application and how it relays spatial information, rather than the relative complexity of the route itself. Prior research has found that commuters have the most difficulty comprehending spatial information when presented with an alphabetical list of buses, less difficulty when the bus list is presented sequentially, even less when presented with a road map, and the least difficulty when presented with a schematic map (Bantram 1980). Depending on the application's unique user interface, users may find themselves making more use of the application's navigation tools as a response to the program's usability, and not the routes themselves (Thorndyke and Hayes-Roth 1982).

5.2 Future Work

i. Anonymity

The analyzed data used anonymous data, and did not track individual users from session to session. Even if two AnyStop sessions were to register daily activity that requested the same line and used the same model phone, it is impossible to definitively determine whether these sessions stem from the same user.

This also prohibits the possibility of longitudinal studies. Research cannot determine how a user's behavior or application use changes over time, or even whether an individual session comes from a long-term user, or whether this session is the user's first and last use of the application. One-time users may request info on certain bus lines without intending to use this information, thereby skewing the greater whole.

Furthermore, these users were not contacted in order to better explain their actions.

ii. Demographics

Even if AnyStop use appears to have become evenly distributed across all bus and rail lines, there is no data on whether the applications have become as distributed across the populations who use those lines. Even if half of the city used a particular line, and half of AnyStop also used that particular line, it cannot be considered representative if smartphone users of real-time transit apps differ significantly from public transit users who either don't own smartphones, or don't utilize smartphone transit apps; i.e., if every AnyStop user on the #81 bus turned out to be young, white, middle-upper-class, car-owning IT workers.

These groups may differ in both in background and behavior. By virtue of downloading a real-time transit application in the first place, AnyStop users may be more reliant on public transit, more proactive when budgeting their time, more prone to getting lost, or more unfamiliar with the city's public transit system. By owning smartphones and knowing that real-time transit applications exist in the first place, they may have more access to disposable income, or may be more comfortable with modern technology.

iii. Precise Location

This data does not provide the location of the user when requesting information.

While this location might be roughly inferred by the user's queries for particular bus and rail lines, one cannot determine whether the user was waiting at a stop and inquiring about their wait time, pulling up the wait times in advance well before leaving work, sitting in their apartment around the corner and waiting to leave three minutes before a bus's scheduled arrival, or even checking arrival time for a friend across town who does not happen to have the same access to real-time transit information. Or one single individual – such as the author - can cite having used their application for all these purposes, sometimes in one session.

iv. Scope

The author originally intended to analyze and compare the use of smartphone transit apps across multiple cities, including Chicago. But the sheer amount of data – and the time spent simply trying to organize it, let alone analyze - prompted the author to focus specifically on Chicago. Future research could be conducted on the author's dataset, which will be available on USB. One could not only perform the same analysis as this thesis has done for AnyStop use in Chicago, but determine how these cities might differ.

Future research could also analyze data over a longer period of time than two weeks. The use of smartphone transit apps might show statistical variation over the course of the seasons, or in relation to a city's particular climate and its daily road conditions (Guo, Wilson and Rahbee 2007).

5.3 Final Thoughts

By studying urban transportation, I was able to successfully chart the geographic distribution of smartphone usage in one of America's largest cities. But as much as public transportation affects the lives of millions of people on a daily basis, the lessons of this research could be applied far beyond that.

Rather than simply providing top-down transit information to the consumer, the consumers' use of local transit applications might provide data that can flow back up the chain: for example, what neighborhoods most elicit use of a map function, or for which bus routes travelers might compare arrival times. With real-time information comes real-time feedback, and transit agencies could use that to their great benefit.

Many of these applications provide access to access to existing information about public transit, but do not necessarily encourage commuters to engage in the larger-scale planning that creates that transit in the first place. Transit agencies and developers could conceivably create a direct bridge between transit application users and the transit agencies themselves: for example, allowing users to send in notice of potholes or malfunctioning equipment. While transit agencies have bolstered their transparency to the benefit to commuters and developers, and may be able to receive valuable data in return, these same agencies could also benefit by opening up direct lines of dialogue.

Mobile phones have become the norm rather than the exception, and transit agencies and planners should consider how to make the most of these changes in new and innovative ways. By counting the number of cell phone signals in individual train cars, for example, one could estimate just how packed each of those cars had become, and provide that information to commuters at the next station; passengers could then distribute themselves along the platform accordingly. Or the act of riding public transit could be tied to a city-run rewards program, thereby incentivizing the use of transit.

Smartphones will not become any less relevant. For more and more users, their phones now serve as an almost visceral cornerstone of their social lives, and a near-indispensable means of obtaining information. These users can serve as *embodied data*, whose existence can provide researchers with unparalleled insight into how cities operate on a macroscopic scale. This novel ability has the potential to enable planners to discern deep, complicated, and heretofore-unseen patterns within cities and amongst their inhabitants. And it is incumbent upon us, as citizens, to plan accordingly.

Appendix A: Web Survey

We are researchers at Concordia University who are trying to better understand how people use smartphone apps that provide real-time public transit information. This survey will take about 25-30 minutes. All responses will be confidential.

At the end of the survey, you will be invited to enter a drawing for a $25 Amazon gift certificate. Entrance is optional.

If at any time during the survey you want to terminate your participation, you are free to do so. Your responses will not be recorded. Also, if there is any particular question you don't want to answer, just skip it and go on to the next.

You must be 14 years or older to participate in this survey.

Question 1

Approximately how often do you take the following forms of transit each week, on average? (If your trip involves a transfer, please count that as just one trip. However, count going to and returning from a destination as two trips.)

I don't regularly ride the train	I don't regularly ride the bus	I don't regularly drive/I don't own a car
1-4 times/week	1-4 times/week	1-4 times/week
5-8 times/week	5-8 times/week	5-8 times/week
9-12 times/week	9-12 times/week	9-12 times/week
13-16 times/week	13-16 times/week	13-16 times/week
16+ times/week	16+ times/week	16+ times/week

Question 2

For what purposes do you take these forms of transit? (Please check all that apply.)

I don't regularly ride the train	I don't regularly ride the bus	I don't regularly drive/I don't own a car
Work	Work	Work
School	School	School
Personal business	Personal business	Personal business
Shopping	Shopping	Shopping
Leisure	Leisure	Leisure
Other:	Other:	Other:

Question 3

Approximately how far of a walk, in minutes, is the nearest public transit stop from your home, workplace and/or school?

Live: ____________________ Work: ________________ School: ________________

Question 4

If you own a smartphone - which transit apps, if any, do you use?

RouteShout

NextBus

AnyStop

Other: _________

None of the above

Question 5

If you clicked 'none of the above': would you consider using a real-time transit app? Why or why not?

____

____

(If respondent selected "None of the above" for Question 4, jump to demographic information)

We would now like to ask some questions about real-time transit apps and how you use them.

Question 6

What model of mobile phone do you own? Please be as precise as you can.

____

Question 7

How often do you use your smartphone transit app?

Multiple times a day

Once or twice a day

Once a week or more (but less than once a day)

Less than once a week

Once a month or less

Question 8

How long have you been an regular user of AnyStop?

0-1 Months

1-3 Months

3-5 Months

5-8 Months

8 Months+

Question 9

What public transit routes do you take on a regular basis, at what times, and for what purpose (work, school, etc.)?

Route:	Time:	Days:	Purpose:
Route:	Time:	Days:	Purpose:
Route:	Time:	Days:	Purpose:
Route:	Time:	Days:	Purpose:
Route:	Time:	Days:	Purpose:

Question 10

For what trips are you most likely to use your transit apps? Rank 1-5, where '1' is 'most often' and 5 is 'least often.'

____ Trips that you make on a regular basis

____ Trips that you make only infrequently

____ Trips that you are undecided about taking

____ Trips that you have never taken before

____ Other

Question 11

How often do you use the following features of your transit apps? Rank the same as above.

____ Planning out your journeys

____ Determining immediate wait-time

____ Locating nearby transit stops

____ Comparing travel options (i.e., driving vs. public transit)

____ Other

Question 12

Has the number of trips you take per week changed as a result of using real-time transit apps?

Rail (If Not Available, Click 'No Change')	Bus	Car
3 or more additional trips	3 or more additional trips	3 or more additional trips
2 additional trips	2 additional trips	2 additional trips
1 additional trip	1 additional trip	1 additional trip
No change	No change	No change/Do not own
1 fewer trip	1 fewer trip	1 fewer trip
2 fewer trips	2 fewer trips	2 fewer trips
3 or even fewer trips	3 or even fewer trips	3 or even fewer trips

Question 13

Is there a change in your wait-time on public transit, on average, as a result of using your smartphone?

10+ minutes less wait-time

5-10 minutes less wait-time

1-5 minutes less wait-time

No change

1-5 minutes more wait-time

5-10 minutes more wait-time

10+ minutes more wait-time

Question 14

On average, how many times do you use this app for trips involving...

Work	School?	Shopping?	Leisure?	Other?
5+ trips/week	5+ trips/week	5+ trips/week	5+ trips/week	5+ trips/week
3-5 trips/week	3-5 trips/week	3-5 trips/week	3-5 trips/week	3-5 trips/week
1-2 trips/week	1-2 trips/week	1-2 trips/week	1-2 trips/week	1-2 trips/week
0-1 trips/week	0-1 trips/week	0-1 trips/week	0-1 trips/week	0-1 trips/week
Never	Never	Never	Never	Never

Question 15

Imagine that you used your real-time transit app, and decide not to travel on that route or line (i.e., because of wait-time). In the past, what alternative means of transport have you taken? Rank 1-5, where '1' is 'most likely' and 5 is least.

__Walk to my destination

__Walk to an alternative line or route

__Opt not to make the trip

__Drive to destination (taxi or private auto)

__Other

Question 16

In addition to taking public transit, do you also drive a private vehicle?

Yes/No

Question 17

What factors have prompted you to drive instead of riding public transit? Rank 1-5, where '1' is 'most likely' and 5 is least.

__Destination is inaccessible by public transit

__Driving takes less time than public transit

__Desire for private space or personal control

__Require storage capacity (i.e., groceries)

__Other

Question 18

What factors has convinced you to take public transit when you would ordinarily drive? Rank the same as above.

__Driving conditions: weather, traffic, etc.

__Knowing real-time public transit information

__Reduced overall cost in fuel and parking fees

__Desire to read or work while in transit

___Other

Question 19

What factors have prompted you to drive instead of riding public transit? Rank 1-5, where '1' is 'most likely' and 5 is least.

__Destination is inaccessible by public transit

__Driving takes less time than public transit

__Desire for private space or personal control

__Require storage capacity (i.e., groceries)

___Other

Question 20

Please describe, in one or two sentences, how your use of real-time transit apps has changed your travel behavior.

____

____

Question 21

Are there any problems you've had with using real-time transit apps, or do you have suggestions for improving them?

____

____

Demographic Questions

Question 22

What is your age?

14-18

19-24

25-30

31-35

36-40

41-45

46-50

51 or older

Question 23

Gender?

Female

Male

Question 24

In what industry do you work?

Construction/Manufacturing

Education/Teaching

Technology/Programming

Science/Research

Office/Administrative/Retail

Civil/Government

Student

Other:

Question 25

Annual household income?

Under $20,000

$20,000 - $40,000

$40,000 - $60,000

$60,000 - $80,000

$80,000 - $100,000

Over $100,000

Thanks for helping out! In appreciation for your participation, would you like to enter a drawing for one of two $25 Amazon gift certificates? If so, please enter your e-mail below. There will no link between your survey data and your email address.

Yes/ No

If the researchers have any addition questions for you, would you consent to being contacted by them? As before, all your responses will be kept completely confidential. If you are contacted, you will be entered into a second raffle, for an additional $25 Amazon gift certificate. If you select 'no,' you will not be contacted. Thank you again for your time.

Yes/No

Appendix B:

Ridership Percentages

Event Label	AnyStop-Dec	**CTADec 14-27**	TreKingApril	**CTAApril**	TreKingMay	**CTAMay**	TreKingJune	**CTAJune**
001 - Indiana/Hyde Park	1.39249	**0.23548**	0.424722	**0.24067**	0.378384	**0.23899**	0.29098	**0.238381**
002 - Hyde Park Express	0.85816	**0.20572**	0.541886	**0.23575**	0.368681	**0.23585**	0.29098	**0.234635**
003 - King Drive	2.47733	**2.20189**	1.508494	**2.25146**	1.106044	**2.29921**	1.216824	**2.308518**
004 - Cottage Grove	1.48964	**2.47295**	1.244874	**2.43342**	0.747065	**2.41398**	0.696588	**2.432561**
005 - South Shore Night Bus	0.43718	**0.06167**	0.161101	**0.06337**	0.194043	**0.06167**	0.158716	**0.069452**
006 - Jackson Park Express	1.3601	**1.15248**	1.698887	**1.24643**	1.232172	**1.23731**	1.446081	**1.238549**
007 - Harrison	0.61528	**0.52499**	0.248975	**0.61425**	0.203745	**0.52914**	0.299797	**0.531278**
008 - Halsted	1.63536	**2.09243**	3.617458	**2.47461**	3.463665	**2.25973**	3.624019	**2.213712**
008A - South Halsted	0.16192	**0.39948**	0.424722	**0.41717**	0.456001	**0.46049**	0.264527	**0.427835**
009 - Ashland	0.74482	**3.18447**	2.768014	**3.22148**	2.561366	**3.28597**	2.42483	**3.214702**
010 - Museum of S & I	0.80959	**0.09241**	0.26362	**0.11927**	0.261958	**0.03648**	0.299797	**0.148641**
011 - Lincoln/Sedg-wick	2.41256	**0.52064**	1.537786	**0.55287**	1.406811	**0.53465**	1.305	**0.543025**
012 - Roosevelt	0.76101	**1.58198**	1.010545	**1.5835**	0.708257	**1.54323**	0.890574	**1.535134**
014 - Jeffery Ex-press	1.89443	**1.2178**	0.541886	**1.21094**	0.95081	**1.19429**	0.864121	**1.206609**
015 - Jeffery Local	0.84197	**0.85927**	0.878735	**0.85208**	0.776172	**0.92807**	0.820034	**0.858782**
017 - Westchester	0.01619	**1.30766**	0.073228	**0.04211**	0.213447	**0.04482**	0.467331	**0.039591**
018 - 16th/18th	0.03238	**0.34323**	0.717633	**0.36889**	0.620937	**0.36135**	0.917027	**0.354978**
019 - United Center Express	0.40479	**0.05326**	0.087873	**0.02153**	0.048511	**0.00974**	0.03527	**0.003524**
020 - Madison	1.92681	**2.19753**	1.230228	**2.06437**	0.824682	**2.07754**	0.925844	**2.069952**
021 - Cermak	1.24676	**0.97174**	0.527241	**0.98939**	0.417192	**0.98957**	0.449696	**1.049526**
022 - Clark	2.96308	**2.43815**	5.741066	**2.44566**	6.578054	**2.43687**	6.428005	**2.458549**
024 - Wentworth	0.29145	**0.27945**	0.117165	**0.27795**	0.097021	**0.30096**	0.220439	**0.288843**
026 - South Shore Express	0.29145	**0.24367**	0.380785	**0.24467**	0.203745	**0.24566**	0.158716	**0.250732**
028 - Stony Is-land	0.29145	**0.53958**	0.483304	**0.5632**	0.184341	**0.5583**	0.282162	**0.547402**
028X - Stony Is-land Express	0.71244	**0.34391**	0.205038	**0.34293**	0.291064	**0.35789**	0.238074	**0.346279**
029 - State	1.70013	**1.46212**	1.596368	**1.51354**	1.600854	**1.54795**	1.208006	**1.567343**
030 - South Chicago	0.17811	**0.32711**	0.278266	**0.33251**	0.329873	**0.36276**	0.273345	**0.336791**
033 - Mag Mile Express	0.55052	**0.05481**	0.073228	**0.05805**	0.048511	**0.05495**	0.070541	**0.058147**
034 - South Michigan	0.24288	**0.62978**	0.161101	**0.63741**	0.203745	**0.6615**	0.238074	**0.631225**
035 - 35th	0.21049	**0.49862**	0.512595	**0.5265**	0.475405	**0.52795**	0.220439	**0.525679**
036 - Broadway	3.06023	**1.9972**	5.33099	**1.94363**	5.297371	**1.86923**	4.673309	**1.879307**
039 - Pershing	0.22668	**0.18452**	0.322203	**0.17478**	0.242554	**0.17772**	0.211622	**0.180096**
043 - 43rd	0.27526	**0.20238**	0.175747	**0.21044**	0.155234	**0.21938**	0.061723	**0.226561**

044 - Wallace-Racine	0.40479	**0.46296**	0.336848	**0.4624**	0.281362	**0.49304**	0.211622	**0.454929**
047 - 47th	0.27526	**1.17272**	0.483304	**1.1959**	0.329873	**1.22199**	0.352703	**1.206578**
048 - South Damen	0.04858	**0.09157**	0.058582	**0.09486**	0.077617	**0.10551**	0.096993	**0.093295**
049 - Western	1.23057	**2.87032**	2.870533	**2.96544**	2.93975	**3.02718**	3.280134	**2.978396**
049A - South Western	0.06477	**0.04938**	0.205038	**0.0488**	0.164936	**0.05259**	0.273345	**0.052567**
049B - North Western	1.11723	**0.55066**	0.454013	**0.57343**	0.533618	**0.59778**	0.546689	**0.591377**
050 - Damen	1.3763	**0.96878**	2.504394	**0.99583**	2.891239	**0.98488**	2.319019	**0.991986**
051 - 51st	0.46956	**0.21599**	0.102519	**0.20842**	0.067915	**0.22365**	0.079358	**0.213489**
052 - Kedzie/California	1.27915	**1.3372**	1.02519	**1.37465**	0.960512	**1.42181**	0.793581	**1.400481**
052A - South Kedzie	0.12953	**0.44555**	0.146456	**0.45715**	0.126128	**0.46166**	0.079358	**0.468417**
053 - Pulaski	1.08484	**2.22042**	1.25952	**2.24046**	0.795576	**2.29281**	0.855304	**2.243738**
053A - South Pulaski	0.37241	**0.71919**	0.981254	**0.79166**	0.95081	**0.82912**	0.414426	**0.802514**
054 - Cicero	1.05246	**1.37966**	0.527241	**1.33259**	0.882895	**1.32371**	0.996385	**1.340682**
054A - North Cicero/Skokie Blvd.	0	**0.08349**	0.175747	**0.08755**	0.13583	**0.08209**	0.167534	**0.0922**
054B - South Cicero	0.71244	**0.44433**	0.292912	**0.43688**	0.291064	**0.43286**	0.299797	**0.443267**
055 - Garfield	0.56671	**1.36685**	0.995899	**1.4274**	0.785874	**1.47583**	1.366723	**1.458151**
055A - 55th/Austin	0.06477	**0.02021**	0.043937	**0.02095**	0.019404	**0.02132**	0.026453	**0.020366**
055N - 55th/Narragansett	0	**0.0535**	0.087873	**0.05006**	0.038809	**0.05398**	0.079358	**0.053651**
056 - Milwaukee	1.21438	**1.1657**	1.435267	**1.127**	1.387407	**1.12535**	1.428445	**1.123927**
056A - North Milwaukee	0.22668	**0.07314**	0.190393	**0.06392**	0.038809	**0.06319**	0.123446	**0.065455**
057 - Laramie	0.09715	**0.27952**	0.014646	**0.28712**	0.038809	**0.30642**	0.176351	**0.284497**
059 - 59th/61st	0.16192	**0.3377**	0.351494	**0.35176**	0.27166	**0.35901**	0.193986	**0.344476**
060 - Blue Island/26th	1.21438	**1.19823**	0.673697	**1.28546**	0.785874	**1.15283**	0.493784	**1.193467**
062 - Archer	0.53433	**1.22657**	0.820152	**1.22589**	0.620937	**1.243**	0.423243	**1.237527**
062H - Archer/Harlem	0.08096	**0.12023**	0.13181	**0.12679**	0.048511	**0.1229**	0.052905	**0.124866**
063 - 63rd	0.29145	**2.11528**	0.410076	**2.11911**	0.417192	**2.15948**	0.423243	**2.120183**
063W - West 63rd	0.27526	**0.15445**	0.248975	**0.15877**	0.155234	**0.16355**	0.149899	**0.170574**
064 - Foster-Canfield	0.08096	**0.01587**	0.029291	**0.01646**	0.058213	**0.01502**	0.017635	**0.017934**
065 - Grand	2.5421	**0.8168**	1.274165	**0.84182**	1.338896	**0.85084**	1.878141	**0.879709**
066 - Chicago	2.88212	**2.67296**	2.226128	**2.63747**	2.17328	**2.61524**	2.689357	**2.670474**
067 - 67th-69th-71st	0.43718	**1.50561**	0.322203	**1.47711**	0.242554	**1.50527**	0.282162	**1.478648**
068 - Northwest Highway	0.17811	**0.11895**	0.248975	**0.12512**	0.155234	**0.13904**	0.39679	**0.121466**
069 - Cumberland/East River	0.09715	**0.03864**	0.058582	**0.03823**	0.067915	**0.03514**	0.03527	**0.037908**
070 - Division	1.68394	**1.04058**	1.171646	**1.02199**	1.125449	**1.04747**	1.305	**1.015492**
071 - 71st/South Shore	0.34003	**1.13674**	0.702988	**1.07407**	0.485107	**1.06642**	0.837669	**1.080163**
072 - North	1.48964	**1.76169**	2.065026	**1.73166**	2.17328	**1.71132**	2.42483	**1.817714**
073 - Armitage	0.76101	**0.56354**	0.732279	**0.59706**	0.892597	**0.62391**	1.119831	**0.608377**
074 - Fullerton	1.19819	**1.31259**	2.372583	**1.40387**	2.590472	**1.40188**	1.983952	**1.389145**
075 - 74th-75th	1.29534	**0.88893**	0.205038	**0.83106**	0.329873	**0.85826**	0.608412	**0.829651**

076 - Diversey	1.18199	**1.19781**	1.903925	**1.21387**	2.765111	**1.21166**	1.728243	**1.243805**
077 - Belmont	1.9592	**2.37189**	2.899824	**2.43291**	3.871156	**2.4369**	3.571114	**2.421814**
078 - Montrose	1.19819	**0.84957**	0.951963	**0.92434**	1.076938	**0.8876**	1.490168	**0.927676**
079 - 79th	0.69624	**3.48519**	1.010545	**3.31804**	1.251577	**3.3042**	0.97875	**3.267331**
080 - Irving Park	0.84197	**1.58445**	1.464558	**1.58319**	1.824003	**1.57361**	1.560709	**1.57**
081 - Lawrence	1.61917	**1.56213**	1.845343	**1.54444**	1.542641	**1.52848**	1.728243	**1.559466**
081W - West Lawrence	0.3886	**0.15546**	0.102519	**0.16777**	0.164936	**0.17054**	0.202804	**0.170936**
082 - Kimball-Homan	1.3763	**1.90576**	0.951963	**1.95462**	0.921704	**1.98919**	1.075743	**1.946638**
084 - Peterson	1.3601	**0.42944**	0.278266	**0.42459**	0.320171	**0.4334**	0.299797	**0.436653**
085 - Central	0.92293	**1.19895**	0.512595	**1.16384**	0.611235	**1.20103**	0.987567	**1.201079**
085A - North Central	0.12953	**0.0832**	0.058582	**0.0838**	0.077617	**0.08387**	0.132263	**0.087312**
086 - Narragansett/Ridgeland	0.01619	**0.18275**	0.13181	**0.20243**	0.067915	**0.21005**	0.193986	**0.189891**
087 - 87th	0.46956	**1.67153**	0.483304	**1.65207**	0.727661	**1.69699**	0.749493	**1.635377**
088 - Higgins	0.1943	**0.12542**	0.219684	**0.13483**	0.329873	**0.13297**	0.238074	**0.128536**
090 - Harlem	0.51813	**0.57125**	0.424722	**0.56577**	0.485107	**0.55131**	0.458513	**0.548282**
090N - North Harlem	0.03238	**0.04045**	0.043937	**0.03788**	0.038809	**0.03995**	0.052905	**0.040148**
091 - Austin	0.85816	**0.79218**	0.644405	**0.78502**	0.533618	**0.79921**	0.432061	**0.774912**
092 - Foster	1.29534	**0.73853**	1.405975	**0.78505**	1.144853	**0.806**	1.119831	**0.788815**
093 - California/Dodge	0.21049	**0.30087**	0.600469	**0.31322**	0.727661	**0.31919**	0.925844	**0.314431**
094 - South California	0.37241	**0.95843**	0.424722	**0.9657**	0.465703	**1.04016**	0.608412	**1.023365**
095E - 93rd-95th	0.09715	**0.47308**	0.248975	**0.52019**	0.27166	**0.50025**	0.29098	**0.499415**
095W - West 95th	0.17811	**0.50459**	0.322203	**0.48956**	0.329873	**0.5053**	0.32625	**0.489586**
096 - Lunt	0.12953	**0.08635**	0.146456	**0.07851**	0.194043	**0.0765**	0.079358	**0.081337**
097 - Skokie	0.56671	**0.4101**	0.556532	**0.42618**	0.417192	**0.40901**	0.599594	**0.435758**
098X - Avon Express	0.03238	**0.01444**	0	**0.01234**	0	**0.00817**	0.026453	**0.009368**
100 - Jeffery Manor Express	0.08096	**0.07038**	0.073228	**0.0774**	0.038809	**0.0848**	0.052905	**0.070266**
103 - West 103rd	0.08096	**0.31533**	0.146456	**0.33594**	0.281362	**0.34338**	0.176351	**0.322497**
106 - East 103rd	0	**0.15567**	0.029291	**0.18445**	0.097021	**0.20196**	0.03527	**0.173326**
108 - Halsted/95th	0.06477	**0.1725**	0.146456	**0.16583**	0.281362	**0.1795**	0.246892	**0.164591**
111 - Pullman/111th/115th	0.56671	**0.61083**	0.161101	**0.59344**	0.252256	**0.63307**	0.176351	**0.594624**
112 - Vincennes/111th	0.12953	**0.26437**	0.219684	**0.26633**	0.13583	**0.29006**	0.096993	**0.27645**
119 - Michigan/119th	0.04858	**0.65906**	0.424722	**0.63956**	0.368681	**0.63466**	0.308615	**0.64512**
120 - Ogilvie/Wacker Express	0.59909	**0.08349**	0.014646	**0.07001**	0.009702	**0.06237**	0.105811	**0.06549**
121 - Union/Wacker Express	0.50194	**0.10754**	0.102519	**0.09213**	0.067915	**0.08785**	0.202804	**0.096093**
122 - Illinois Center/Ogilvie Express	0.14573	**0.05352**	0.043937	**0.04486**	0	**0.04191**	0.061723	**0.042757**
123 - Illinois Center/Union Express	0.11334	**0.0486**	0.014646	**0.04373**	0.009702	**0.04358**	0.03527	**0.046527**

124 - Navy Pier	1.3601	**0.11845**	0.161101	**0.11162**	0.232851	**0.11929**	0.273345	**0.163431**
125 - Water Tower Express	0.37241	**0.17684**	0.175747	**0.17269**	0.291064	**0.15617**	0.246892	**0.171892**
126 - Jackson	0.72863	**0.68409**	0.746924	**0.71344**	0.485107	**0.71078**	0.546689	**0.679273**
128 – Soldier Field Express	0	**0.05471**	0	**0**	0	**0**	0	**0**
129 - West Loop/South Loop	0.85816	**0.09965**	0.058582	**0.09715**	0.038809	**0.0948**	0.044088	**0.088707**
130 - Museum Campus	0	**0**	0.087873	**0**	0.038809	**0.01161**	0.185169	**0.115886**
132 - Goose Island Express	0.29145	**0.02592**	0.13181	**0.02978**	0.038809	**0.03101**	0.044088	**0.030211**
134 - Stockton/LaSalle Express	1.10104	**0.23125**	0.161101	**0.2519**	0.174639	**0.24631**	0.158716	**0.262452**
135 - Clarendon/LaSalle Express	0.55052	**0.30508**	0.307557	**0.32692**	0.339575	**0.30284**	0.29098	**0.334278**
136 - Sheridan/LaSalle Express	1.26295	**0.17161**	0.175747	**0.18845**	0.349277	**0.18337**	0.238074	**0.195432**
143 - Stockton/Michigan Express	0.93912	**0.11405**	0.161101	**0.11589**	0.145532	**0.11288**	0.282162	**0.124355**
144 - Marine/Michigan Express	0.82578	**0.09739**	0.278266	**0.09043**	0.145532	**0.08404**	0.343885	**0.091608**
145 - Wilson/Michigan Express	1.58679	**0.72691**	1.25952	**0.70594**	1.319492	**0.69148**	1.357905	**0.710183**
146 - Inner Drive/Michigan Express	1.53821	**1.11631**	2.28471	**1.08936**	2.182982	**1.06046**	1.931047	**1.13275**
147 - Outer Drive Express	2.38018	**1.63255**	2.533685	**1.6389**	2.192685	**1.56283**	1.869324	**1.618243**
148 - Clarendon/Michigan Express	0.64767	**0.19271**	0.26362	**0.20048**	0.417192	**0.19544**	0.299797	**0.20442**
151 - Sheridan	2.7364	**2.43155**	3.837141	**2.37158**	4.327156	**2.31616**	4.214796	**2.550484**
152 - Addison	1.02008	**0.95092**	1.552431	**1.04275**	1.90162	**1.09297**	1.719425	**1.034029**
154 – Wrigley Field Express	0	**0**	0	**0.02556**	0	**0.03101**	0	**0.018314**
155 - Devon	0.35622	**0.83399**	0.541886	**0.86055**	0.620937	**0.84801**	0.476148	**0.83475**
156 - LaSalle	0.66386	**0.73179**	0.922671	**0.67409**	1.028427	**0.65918**	0.740675	**0.735829**
157 - Streeterville/Taylor	0.51813	**0.43943**	0.908026	**0.51058**	0.630639	**0.37545**	0.696588	**0.399365**
165 - West 65th	0.01619	**0.00542**	0.014646	**0.00589**	0.009702	**0.00585**	0.008818	**0.006044**
168 – UIC/Pilsen Express (Eliminated May 11)	0	**0**	0	**0**	0	**0**	0	**0**
169 - 69th-UPS Express	0	**0.03517**	0.014646	**0.03021**	0.019404	**0.02844**	0.008818	**0.031955**
170 - U. of Chicago/Midway	0.06477	**0.02661**	0.043937	**0.02448**	0.029106	**0.02598**	0.158716	**0.022902**
171 - U. of Chicago/Hyde Park	0.09715	**0.1204**	0.146456	**0.16356**	0.126128	**0.14942**	0.070541	**0.081383**
172 - U. of Chicago/Kenwood	0.09715	**0.15571**	0.292912	**0.23835**	0.145532	**0.21275**	0.176351	**0.122284**
192 - U. of Chicago Hospitals Express	0.08096	**0.06545**	0.073228	**0.07347**	0.009702	**0.07027**	0.026453	**0.072034**
201 - Central/Ridge	0.79339	**0.19439**	0.278266	**0.21819**	0.27166	**0.20706**	0.299797	**0.201204**
205 - Chicago/Golf	0.11334	**0.09019**	0.336848	**0.09177**	0.40749	**0.09145**	0.555507	**0.090986**
206 - Evanston Circulator	0.17811	**0.06151**	0.117165	**0.06119**	0.058213	**0.07351**	0.123446	**0.046865**

Blue Line	25.4501	**22.6073**	13.5476	**22.2533**	12.2485	**22.2683**	13.5	**22.2775**
Brown Line	14.4526	**13.6127**	0.57405	**14.1698**	0.17498	**14.3551**	0.5625	**14.88585**
Green Line	10.9976	**9.20624**	12.3995	**8.63863**	11.986	**8.75319**	7.9375	**8.838535**
Orange Line	8.51582	**7.33439**	12.2847	**7.0758**	11.5486	**7.39323**	13.9375	**7.446188**
Pink Line	6.08273	**4.11017**	57.0608	**4.02229**	56.4304	**4.04251**	59.6875	**4.075675**
Purple Line	6.08273	**4.93063**	1.60735	**5.31038**	2.62467	**5.29769**	1.6875	**5.443519**
Red Line	28.0292	**37.489**	0	**37.7854**	1.5748	**37.1555**	0.1875	**36.34427**
Yellow Line	0.38929	**0.70959**	2.52583	**0.74437**	3.41207	**0.73444**	2.5	**0.688457**

Log Odds Ratios

Event Label	Dec (Any) OR	**DecNatLog**	Apr(Trk)OR	**AprNatLog**	May(Trk)OR	**MayNatLog**	June(Trk)OR	**June Nat Log**
001 - Indiana/Hyde Park	5.982660468	**1.78886536**	1.767985326	**0.56984066**	1.585458109	**0.46087339**	1.221293347	**0.199910418**
002 - Hyde Park Express	4.199021274	**1.43485147**	2.305620663	**0.83534991**	1.565297649	**0.448076**	1.240838158	**0.215787085**
003 - King Drive	1.128272806	**0.12068797**	0.66495362	**-0.408038**	0.475249664	**-0.743915**	0.521276544	**-0.65147458**
004 - Cottage Grove	0.596360966	**-0.51690915**	0.505416795	**-0.6823719**	0.304277564	**-1.18981495**	0.281353767	**-1.26814244**
005 - South Shore Night Bus	7.116195854	**1.96237329**	2.544620162	**0.93398139**	3.150873175	**1.14767961**	2.287307269	**0.827375261**
006 - Jackson Park Express	1.18264213	**0.16775103**	1.369278534	**0.31428398**	0.995794209	**-0.00421466**	1.17001887	**0.157019877**
007 - Harrison	1.173066966	**0.15962166**	0.403848282	**-0.906716**	0.383796007	**-0.9576441**	0.562984231	**-0.57450366**
008 - Halsted	0.777928366	**-0.25112083**	1.479163242	**0.39147655**	1.551895739	**0.43947724**	1.661033919	**0.507440252**
008A - South Halsted	0.404358799	**-0.90545268**	1.018176043	**0.01801283**	0.990209189	**-0.00983906**	0.617279554	**-0.48243327**
009 - Ashland	0.22814226	**-1.4777859**	0.855228397	**-0.1563867**	0.773689623	**-0.25658449**	0.748187932	**-0.29010109**
010 - Museum of S & I	8.824161924	**2.17749363**	2.213471911	**0.79456228**	7.197009802	**1.97366563**	2.019979149	**0.703087189**
011 - Lincoln/Sedg- wick	4.723687279	**1.5525897**	2.809281294	**1.03292868**	2.654559739	**0.97627882**	2.421757388	**0.88449347**
012 - Roosevelt	0.477070688	**-0.74009061**	0.634476625	**-0.4549548**	0.455084492	**-0.78727218**	0.576355002	**-0.55103149**
014 - Jeffery Ex- press	1.566347688	**0.4487466**	0.444482366	**-0.8108449**	0.794171249	**-0.23045616**	0.713682746	**-0.33731675**
015 - Jeffery Loc- al	0.97969646	**-0.02051249**	1.031562541	**0.03107468**	0.835044594	**-0.18027015**	0.954506649	**-0.04656067**
017 - Westchester	0.012222308	**-4.40449248**	1.739372071	**0.55352417**	4.770249876	**1.56239869**	11.85469601	**2.472724077**
018 - 16th/18th	0.094055064	**-2.36387488**	1.952220935	**0.66896767**	1.722856625	**0.54398374**	2.597987921	**0.954737269**
019 - United Center Express	7.627482423	**2.03175783**	4.084021649	**1.4070822**	4.980428543	**1.60551594**	10.01176484	**2.303760885**
020 - Madison	0.874388556	**-0.13423043**	0.5909025	**-0.5261042**	0.39193638	**-0.93665575**	0.442112976	**-0.81618983**
021 - Cermak	1.28659682	**0.25200061**	0.530421644	**-0.634083**	0.419168244	**-0.8694829**	0.425893401	**-0.8535662**
022 - Clark	1.221873985	**0.20038573**	2.429525201	**0.88769585**	2.819044978	**1.03639817**	2.725465132	**1.002639104**
024 - Wentworth	1.043080168	**0.04217804**	0.42085615	**-0.8654642**	0.321713252	**-1.13409465**	0.762656504	**-0.27094754**
026 - South Shore Express	1.196680155	**0.17955119**	1.558446167	**0.44368928**	0.82904	**-0.18748687**	0.632427797	**-0.45818922**
028 - Stony Is- land	0.538795074	**-0.61841998**	0.857448982	**-0.1537936**	0.328944631	**-1.11186584**	0.514085704	**-0.66536529**
028X - Stony Is- land Express	2.079249674	**0.73200709**	0.597075789	**-0.5157112**	0.812733888	**-0.20735154**	0.686775754	**-0.37574745**
029 - State	1.165603112	**0.15323865**	1.055614371	**0.05412294**	1.034732974	**0.0341434**	0.767931755	**-0.26405441**
030 - South Chicago	0.543685944	**-0.60938351**	0.836404462	**-0.178643**	0.909041872	**-0.09536412**	0.811098276	**-0.20936605**

033 - Mag Mile Express	10.09507326	**2.31204751**	1.261571366	**0.23235806**	0.882726127	**-0.12474029**	1.213291577	**0.193336978**
034 - South Michigan	0.384158003	**-0.95670134**	0.251538843	**-1.3801579**	0.306593971	**-1.18223098**	0.375675899	**-0.97902848**
035 - 35th	0.420931856	**-0.86528432**	0.973452651	**-0.0269061**	0.899998401	**-0.10536229**	0.418058854	**-0.87213306**
036 - Broadway	1.549068292	**0.43765365**	2.840938635	**1.0441345**	2.936566728	**1.07724112**	2.559604575	**0.939852784**
039 - Pershing	1.228999296	**0.20620026**	1.846171005	**0.61311377**	1.365710473	**0.31167479**	1.175419812	**0.161625371**
043 - 43rd	1.361071308	**0.30827212**	0.834847748	**-0.1805059**	0.70716382	**-0.34649293**	0.271984792	**-1.30200913**
044 - Wal-lace-Racine	0.87385516	**-0.13484064**	0.727553503	**-0.3180677**	0.569461382	**-0.56306431**	0.46404069	**-0.76778304**
047 - 47th	0.232605721	**-1.45841045**	0.401240495	**-0.9131943**	0.267531392	**-1.31851837**	0.289811585	**-1.23852427**
048 - South Da- men	0.530230426	**-0.6344436**	0.617315237	**-0.4823755**	0.735419652	**-0.30731399**	1.03967845	**0.038911482**
049 - Western	0.42160431	**-0.86368806**	0.967050917	**-0.0335041**	0.970242605	**-0.03020913**	1.104744667	**0.099614238**
049A - South Western	1.311701682	**0.27132529**	4.208086039	**1.43700792**	3.140083819	**1.14424949**	5.211437585	**1.650855746**
049B - North Western	2.040499563	**0.71319466**	0.790806169	**-0.2347024**	0.892087824	**-0.11419069**	0.924018616	**-0.07902306**
050 - Damen	1.426518151	**0.35523662**	2.55379665	**0.93758113**	2.993240969	**1.09635674**	2.369513535	**0.862684675**
051 - 51st	2.17955074	**0.77911877**	0.491359537	**-0.7105792**	0.303197897	**-1.19336956**	0.37122078	**-0.9909583**
052 - Kedzie/California	0.95602442	**-0.04497182**	0.743150782	**-0.2968563**	0.672408601	**-0.39688909**	0.563182252	**-0.57415199**
052A - South Kedzie	0.289808766	**-1.238534**	0.319371185	**-1.1414013**	0.272284551	**-1.30090761**	0.168757937	**-1.77928992**
053 - Pulaski	0.482967792	**-0.72780531**	0.55658454	**-0.5859362**	0.341750974	**-1.07367295**	0.375857604	**-0.97854492**
053A - South Pu- laski	0.516015513	**-0.66161845**	1.241863442	**0.21661303**	1.148178753	**0.13817699**	0.51439664	**-0.66476064**
054 - Cicero	0.760317803	**-0.27401877**	0.392447981	**-0.9353513**	0.664020205	**-0.4094427**	0.740607951	**-0.30028388**
054A - North Cicero/Skokie Blvd.			2.009144329	**0.69770892**	1.655604906	**0.50416644**	1.818439787	**0.597978874**
054B - South Cicero	1.607736201	**0.4748271**	0.669499167	**-0.4012254**	0.671463524	**-0.39829558**	0.675362218	**-0.39250611**
055 - Garfield	0.411274696	**-0.88849393**	0.694661348	**-0.3643308**	0.52879409	**-0.63715617**	0.936429507	**-0.06568103**
055A - 55th/Aus-tin	3.206606697	**1.16521327**	2.097461014	**0.74072757**	0.909961921	**-0.09435253**	1.298944529	**0.261552034**
055N - 55th/Nar-ragansett			1.756029257	**0.56305516**	0.718770103	**-0.33021372**	1.479534364	**0.391727419**
056 - Milwaukee	1.042268506	**0.04139959**	1.27751178	**0.24491426**	1.236140553	**0.21199407**	1.274867834	**0.242842513**
056A - North Milwaukee	3.104115932	**1.13272895**	2.982410089	**1.09273173**	0.614004359	**-0.48775325**	1.887061036	**0.635020611**
057 - Laramie	0.34693126	**-1.05862862**	0.050869933	**-2.9784832**	0.126312602	**-2.06899548**	0.619198932	**-0.47932868**
059 - 59th/61st	0.478622676	**-0.73684273**	0.99924887	**-0.0007514**	0.756031844	**-0.27967178**	0.562285687	**-0.57574522**
060 - Blue Island/26th	1.013640466	**0.01354827**	0.520861678	**-0.6522708**	0.679168326	**-0.38688628**	0.410829584	**-0.88957679**
062 - Archer	0.432594265	**-0.83795502**	0.666287874	**-0.4060335**	0.496419739	**-0.70033346**	0.339210418	**-1.08113466**
062H - Archer/Harlem	0.673119601	**-0.39583225**	1.039628023	**0.03886298**	0.394415369	**-0.93035069**	0.423392247	**-0.85945623**
063 - 63rd	0.135263102	**-2.00053349**	0.190192828	**-1.6597168**	0.189811287	**-1.66172492**	0.196223813	**-1.62849937**
063W - West 63rd	1.784347366	**0.57905273**	1.569549528	**0.45078865**	0.949068273	**-0.05227454**	0.878607287	**-0.12941725**
064 - Foster-Can-field	5.104731507	**1.63016786**	1.779361574	**0.57625463**	3.87735995	**1.3551545**	0.983332021	**-0.01680845**
065 - Grand	3.167346112	**1.15289405**	1.520217012	**0.4188531**	1.581403497	**0.45831274**	2.156681534	**0.768570713**
066 - Chicago	1.080572324	**0.07749083**	0.840487352	**-0.1737734**	0.827253126	**-0.18964455**	1.007266527	**0.007240253**
067 - 67th-69th-71st	0.28724799	**-1.24740936**	0.215603338	**-1.534315**	0.159096883	**-1.83824194**	0.188534719	**-1.66847311**
068 - Northwest Highway	1.498168409	**0.4042433**	1.9923534	**0.68931655**	1.116642227	**0.11032617**	3.275708588	**1.186534208**
069 - Cumber-land/East River	2.515738148	**0.92256626**	1.532501028	**0.42690106**	1.933247361	**0.65920116**	0.930392732	**-0.07214849**
070 - Division	1.628860128	**0.48788046**	1.148172194	**0.13817128**	1.075294156	**0.07259426**	1.288860559	**0.253758541**
071 - 71st/South Shore	0.296731375	**-1.21492801**	0.652063551	**-0.4276133**	0.452236981	**-0.79354894**	0.773605629	**-0.25669306**

072 - North	0.843237433	**-0.17050671**	1.196571252	**0.17946018**	1.275941674	**0.24368447**	1.342300078	**0.294384619**
073 - Armitage	1.353104578	**0.30240164**	1.228143736	**0.20550387**	1.434517853	**0.3608288**	1.850206339	**0.615297168**
074 - Fullerton	0.911781825	**-0.09235454**	1.706795883	**0.53461786**	1.87039866	**0.6261516**	1.436848981	**0.362452508**
075 - 74th-75th	1.463189549	**0.38061868**	0.245170496	**-1.4058014**	0.382314283	**-0.96151228**	0.731702453	**-0.31238133**
076 - Diversey	0.986639971	**-0.01345008**	1.579513875	**0.45711713**	2.31854332	**0.84093911**	1.396329935	**0.33384732**
077 - Belmont	0.822529313	**-0.19537116**	1.197649795	**0.18036113**	1.612259159	**0.4776364**	1.492136233	**0.400208807**
078 - Montrose	1.415322894	**0.3473577**	1.030174494	**0.0297282**	1.21564245	**0.1952727**	1.615518022	**0.479655662**
079 - 79th	0.194161159	**-1.63906675**	0.297461693	**-1.2124698**	0.370909616	**-0.99179687**	0.292632973	**-1.22883611**
080 - Irving Park	0.527415708	**-0.63976622**	0.923954771	**-0.0790922**	1.16208021	**0.15021168**	0.990970388	**-0.00907063**
081 - Lawrence	1.037112691	**0.03644059**	1.198490481	**0.18106283**	1.009412105	**0.00936809**	1.110130536	**0.104477609**
081W - West Lawrence	2.505608861	**0.91853176**	0.610674705	**-0.4931909**	0.967078347	**-0.03347577**	1.186811125	**0.171269983**
082 - Kimball-Homan	0.71829917	**-0.33086913**	0.48210296	**-0.7295976**	0.4583633	**-0.78009318**	0.547750742	**-0.60193495**
084 - Peterson	3.197024234	**1.16222045**	0.654418727	**-0.4240079**	0.737909887	**-0.30393357**	0.685637503	**-0.37740621**
085 - Central	0.767634023	**-0.26444219**	0.437550772	**-0.8265625**	0.505907768	**-0.6814009**	0.820460295	**-0.19788976**
085A - North Central	1.557555309	**0.44311748**	0.698882167	**-0.3582731**	0.925436974	**-0.07748925**	1.51551908	**0.415758008**
086 - Narragansett/Ridgeland	0.088452918	**-2.42528487**	0.650688664	**-0.429724**	0.322875472	**-1.13048857**	1.021609139	**0.021378971**
087 - 87th	0.277523894	**-1.28184824**	0.28910833	**-1.2409538**	0.424608306	**-0.85658817**	0.454209159	**-0.78919748**
088 - Higgins	1.550255105	**0.4384195**	1.630683113	**0.48899901**	2.485799539	**0.91059435**	1.854232655	**0.617470948**
090 - Harlem	0.906542361	**-0.09811752**	0.749638994	**-0.2881635**	0.879324908	**-0.12860082**	0.835518696	**-0.17970255**
090N - North Harlem	0.80044878	**-0.22258273**	1.160073367	**0.14848325**	0.971486113	**-0.0289283**	1.317927181	**0.276060185**
091 - Austin	1.084009289	**0.08066647**	0.819713306	**-0.1988006**	0.665899606	**-0.40661636**	0.555641042	**-0.5876328**
092 - Foster	1.7638353	**0.56749059**	1.802225424	**0.58902225**	1.425277861	**0.35436678**	1.424389113	**0.353743029**
093 - California/Dodge	0.698986206	**-0.35812427**	1.922599615	**0.65367824**	2.289059206	**0.82814091**	2.962678349	**1.086093707**
094 - South California	0.386276249	**-0.95120249**	0.437416579	**-0.8268693**	0.445138757	**-0.80936923**	0.59203889	**-0.52418295**
095E - 93rd-95th	0.204584611	**-1.58677364**	0.477320902	**-0.7395663**	0.541799569	**-0.61285914**	0.581422979	**-0.54227677**
095W - West 95th	0.351821424	**-1.04463155**	0.657036317	**-0.420016**	0.651678768	**-0.42820353**	0.665287124	**-0.40753657**
096 - Lunt	1.500788891	**0.4059909**	1.86679182	**0.62422135**	2.539505792	**0.93196949**	0.975650806	**-0.02465054**
097 - Skokie	1.384050554	**0.32501438**	1.307584341	**0.26818142**	1.020076516	**0.01987764**	1.378248183	**0.32081326**
098X - Avon Express	2.242932942	**0.80778436**					2.824211606	**1.038229248**
100 - Jeffery Manor Express	1.150439381	**0.14014394**	0.946091562	**-0.0554159**	0.457424656	**-0.78214309**	0.752799334	**-0.28395658**
103 - West 103rd	0.256142628	**-1.36202085**	0.435127558	**-0.8321161**	0.818884984	**-0.19981164**	0.546030216	**-0.60508096**
106 - East 103rd			0.158553898	**-1.8416607**	0.479898062	**-0.73418157**	0.203209839	**-1.59351614**
108 - Halsted/95th	0.375058905	**-0.98067219**	0.883021981	**-0.1244052**	1.569073107	**0.45048507**	1.501269847	**0.406311314**
111 - Pullman/111th/115th	0.927356593	**-0.07541711**	0.270294109	**-1.3082446**	0.3969423	**-0.92396435**	0.295333453	**-1.21965021**
112 - Vincennes/111th	0.489317171	**-0.71474439**	0.824455144	**-0.1930325**	0.467564018	**-0.760219**	0.350222393	**-1.04918692**
119 - Michigan/119th	0.073253289	**-2.61383214**	0.662647893	**-0.4115115**	0.579364166	**-0.54582404**	0.476768727	**-0.74072376**
120 - Ogilvie/Wacker Express	7.212921208	**1.97587403**	0.209079288	**-1.5650417**	0.155473406	**-1.86128058**	1.616330493	**0.480158452**
121 - Union/Wacker Express	4.68598631	**1.54457642**	1.112928775	**0.10699508**	0.772907876	**-0.25759541**	2.112753681	**0.747992159**
122 - Illinois Center/Ogilvie Express	2.725144089	**1.0025213**	0.979341083	**-0.0208753**			1.443849328	**0.367312691**
123 - Illinois Center/Union Express	2.33387992	**0.84753208**	0.334840632	**-1.0941006**	0.222529396	**-1.50269607**	0.757974653	**-0.27710533**

124 - Navy Pier	11.62684397	**2.45331656**	1.444031186	**0.36743864**	1.954236252	**0.66999945**	1.674381043	**0.51544357**
125 - Water Tower Express	2.110100155	**0.74673541**	1.017709307	**0.01755432**	1.866329463	**0.62397365**	1.437399269	**0.362835418**
126 - Jackson	1.065583652	**0.06352268**	1.047287395	**0.04620339**	0.680947724	**-0.38426974**	0.803741939	**-0.21847703**
128 – Soldier Field Express								
129 - West Loop/South Loop	8.677221721	**2.1607014**	0.602753421	**-0.5062471**	0.409124892	**-0.89373481**	0.496783147	**-0.69960167**
130 - Museum Campus					3.344638119	**1.2073585**	1.598962641	**0.46935507**
132 - Goose Is- land	11.27243461	**2.42236033**	4.430615386	**1.48853849**	1.251541882	**0.2243763**	1.459532741	**0.378116344**
134 - Stockton/LaSalle Express	4.803188987	**1.56928007**	0.638951094	**-0.4479274**	0.708523235	**-0.34457243**	0.604115249	**-0.50399029**
135 - Clarendon/LaS- alle Express	1.808984088	**0.59276541**	0.940594959	**-0.0612427**	1.121732007	**0.11487393**	0.870093977	**-0.13915405**
136 - Sheridan/LaSalle Express	7.440733047	**2.00696937**	0.932494549	**-0.069892**	1.907984276	**0.64604733**	1.218715494	**0.19779743**
143 - Stockton/Michiga n Express	8.303149071	**2.11663485**	1.390737787	**0.32983439**	1.289711983	**0.25441892**	2.27259538	**0.820922518**
144 - Marine/Michigan Express	8.541560717	**2.14494374**	3.082787675	**1.12583428**	1.732766599	**0.54971932**	3.763378258	**1.325317027**
145 - Wilson/Michigan Express	2.202001437	**0.78936669**	1.794182702	**0.5845496**	1.920362005	**0.65251371**	1.924604606	**0.654720547**
146 - Inner Drive/Michigan Express	1.383847729	**0.32486783**	2.122960856	**0.75281174**	2.082149304	**0.73340068**	1.718618995	**0.541521059**
147 - Outer Drive Express	1.469115879	**0.38466078**	1.560157958	**0.44478707**	1.412061071	**0.34505039**	1.158111984	**0.146791079**
148 - Clarendon/Michi gan Express	3.376318508	**1.21678592**	1.315754401	**0.27441019**	2.13935856	**0.76050605**	1.467977664	**0.383885715**
151 - Sheridan	1.12890149	**0.12124503**	1.642627931	**0.49629736**	1.907516194	**0.64580197**	1.681261237	**0.519544248**
152 - Addison	1.073477815	**0.07090367**	1.496499676	**0.40312883**	1.754203999	**0.56201519**	1.674436737	**0.515476832**
154 – Wrigley Field Express								
155 - Devon	0.425074155	**-0.85549164**	0.627676495	**-0.4657304**	0.730556379	**-0.31394887**	0.568353211	**-0.5650122**
156 - LaSalle	0.906556295	**-0.09810215**	1.372203952	**0.31641817**	1.565978333	**0.44851076**	1.006635495	**0.006613577**
157 - Streeterville/Tayl or	1.180047118	**0.16555437**	1.785567325	**0.57973619**	1.684014681	**0.52118063**	1.74945862	**0.55930638**
165 - West 65th	2.986964411	**1.09425762**	2.488745047	**0.91177859**	1.657842225	**0.50551689**	1.458935998	**0.377707401**
168 – UIC/Pilsen Express (Elimin- ated May 11)								
169 - 69th- UPS Express			0.484668851	**-0.7242894**	0.682240841	**-0.38237254**	0.275873079	**-1.28781438**
170 - U. of Chicago/Midway	2.434489849	**0.88973723**	1.795352542	**0.5852014**	1.120469612	**0.11374789**	6.939658733	**1.937252599**
171 - U. of Chicago/Hyde Park	0.806682519	**-0.2148251**	0.895254249	**-0.1106475**	0.843926032	**-0.16969043**	0.86667809	**-0.14308766**
172 - U. of Chicago/Ken- wood	0.62354521	**-0.47233401**	1.229574679	**0.20666832**	0.683605886	**-0.38037372**	1.442926373	**0.366673255**
192 - U. of Chicago Hospit- als Express	1.237129871	**0.21279408**	0.996687553	**-0.0033179**	0.137989997	**-1.98057408**	0.367057682	**-1.00223627**
201 - Central/Ridge	4.10608056	**1.41246894**	1.276126119	**0.24382902**	1.312836406	**0.27218999**	1.491489555	**0.399775322**
205 - Chicago/Golf	1.256966069	**0.22870094**	3.679517911	**1.30278174**	4.469947705	**1.49737671**	6.133926384	**1.813835064**
206 - Evanston Circulator	2.899085763	**1.06439543**	1.915866132	**0.65016981**	0.791732669	**-0.23353148**	2.636094251	**0.969298371**
Blue Line	1.168674889	**0.15587053**	0.547487843	**-0.602415**	0.487234169	**-0.71901043**	0.544500108	**-0.60788714**
Brown Line	1.072121725	**0.06963961**	0.03497254	**-3.3531921**	0.010457771	**-4.5604099**	0.032344501	**-3.43131125**
Green Line	1.21862042	**0.19771942**	1.496983966	**0.40345239**	1.419625846	**0.35039335**	0.889266606	**-0.11735819**
Orange Line	1.176075031	**0.16218265**	1.839262316	**0.60936458**	1.635427017	**0.49190394**	2.012941884	**0.699597276**
Pink Line	1.51100536	**0.41277523**	31.70892573	**3.45659821**	30.74384065	**3.42568967**	34.84759922	**3.550984246**

Purple Line	1.248795496	**0.22217948**	0.291289032	**-1.2334393**	0.481836597	**-0.73015023**	0.298158091	**-1.21013143**
Red Line	0.649391986	**-0.43171876**	#DIV/0!	**#DIV/0!**	0.027062267	**-3.6096149**	0.003290167	**-5.71681707**
Yellow Line	0.54685616	**-0.60356947**	3.455241018	**1.23989221**	4.77459717	**1.56330961**	3.698778312	**1.308002579**

Appendix C: Scatter Plots

Log Odds Ratio and Route Length

Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	0.110315406870229	15.8917557251908
Biased Variance	1.22418072786962	49.7340755433832
Biased Standard Deviation	1.10642700973431	7.05223904468526
Covariance	-1.57451750401216	
Correlation	-0.200248723258391	
Determination	0.0400995511666157	
T-Test	-2.32140819676348	
p-value (2 sided)	0.0218327835873995	
p-value (1 sided)	0.0109163917936998	
Degrees of Freedom	129	
Number of Observations	131	

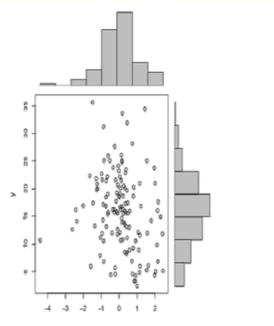


Figure C.1: AnyStop, December (Left)

Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	-0.04098161	15.9626356589147
Biased Variance	0.520777281792407	48.9424891773331
Biased Standard Deviation	0.721649001795476	6.99589087803212
Covariance	-0.27532652623125	
Correlation	-0.0541127085679258	
Determination	0.00292818522855727	
T-Test	-0.610714052658872	
p-value (2 sided)	0.542480323616192	
p-value (1 sided)	0.271240161808096	
Degrees of Freedom	127	
Number of Observations	129	

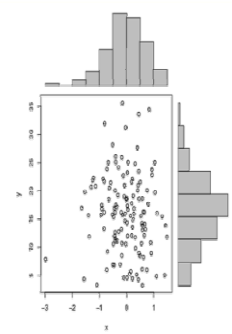


Figure C.2: TreKing, April (Right),

Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	-0.112567469612403	15.9626356589147
Biased Variance	0.611427203917042	48.9424891773331
Biased Standard Deviation	0.781938107472095	6.99589087803212
Covariance	-0.136628355222905	
Correlation	-0.0247825330470372	
Determination	0.000614173944227492	
T-Test	-0.279370767942617	
p-value (2 sided)	0.780414755989837	
p-value (1 sided)	0.390207377994919	
Degrees of Freedom	127	
Number of Observations	129	

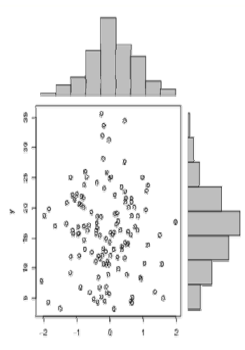


Figure C.3: TreKing, May (Left)

Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	-0.0199620425038760	15.9626356589147
Biased Variance	0.584577194146061	48.9424891773331
Biased Standard Deviation	0.764576480246457	6.99589087803212
Covariance	-1.11220318860772	
Correlation	-0.206319574868865	
Determination	0.0425677669740694	
T-Test	-2.37622889453806	
p-value (2 sided)	0.0189848093023268	
p-value (1 sided)	0.00949240465116338	
Degrees of Freedom	127	
Number of Observations	129	

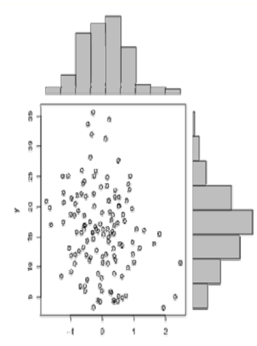
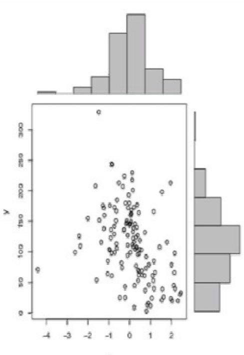


Figure C.4: TreKing, June (Right)

Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	0.110315406870229	112.885496183206
Biased Variance	1.22418072786962	3666.2845987996
Biased Standard Deviation	1.10642700973431	60.5498521781813
Covariance	-26.820396588515	
Correlation	-0.397284293526485	
Determination	0.157834809882838	
T-Test	-4.91697055647018	
p-value (2 sided)	2.62201033525805e-06	
p-value (1 sided)	1.31100516762903e-06	
Degrees of Freedom	129	
Number of Observations	131	



Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	-0.04098161	114.519379844961
Biased Variance	0.520777281792407	3547.9550507782
Biased Standard Deviation	0.721649001795476	59.5647131343566
Covariance	-8.36492848382813	
Correlation	-0.193093396521663	
Determination	0.0372850597802722	
T-Test	-2.21779002875721	
p-value (2 sided)	0.0283470627399605	
p-value (1 sided)	0.0141735313699803	
Degrees of Freedom	127	
Number of Observations	129	

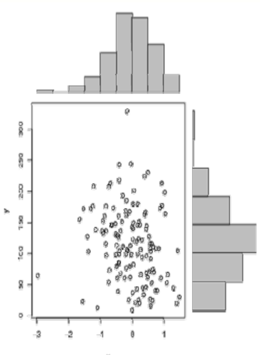
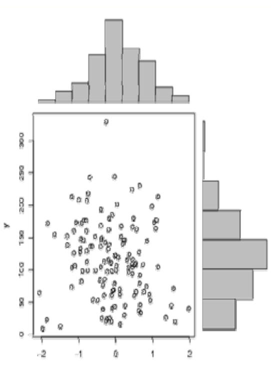


Figure C.5: AnyStop, December (Left)

Figure C.6: TreKing, April (Right)

Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	-0.112567469612403	114.519379844961
Biased Variance	0.611427203917042	3547.9550507782
Biased Standard Deviation	0.781938107472095	59.5647131343566
Covariance	-5.93583422199976	
Correlation	-0.126456334561793	
Determination	0.0159912045508041	
T-Test	-1.43662347795704	
p-value (2 sided)	0.15328391120488	
p-value (1 sided)	0.0766419556024401	
Degrees of Freedom	127	
Number of Observations	129	



Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	-0.019962042503876	114.519379844961
Biased Variance	0.584577194146061	3547.9550507782
Biased Standard Deviation	0.764576480246457	59.5647131343566
Covariance	-13.9244628022831	
Correlation	-0.303381238501654	
Determination	0.0920401758747977	
T-Test	-3.58803990419685	
p-value (2 sided)	0.000474141799814839	
p-value (1 sided)	0.000237070899990742	
Degrees of Freedom	127	
Number of Observations	129	

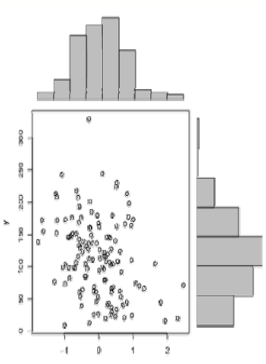
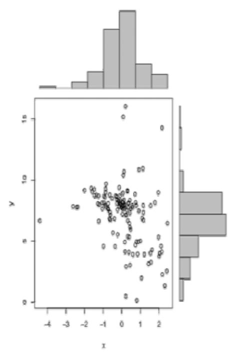


Figure C.7: TreKing, May (Left)

Figure C.8: TreKing, June (Right)

Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	0.110315406870229	7.17075588835115
Biased Variance	1.22418072786962	5.97780264642526
Biased Standard Deviation	1.10642700973431	2.44495452849849
Covariance	-0.9305578092803	
Correlation	-0.341367254420801	
Determination	0.116531602390796	
T-Test	-4.1249738982952	
p-value (2 sided)	6.60112277962346e-05	
p-value (1 sided)	3.30056138981173e-05	
Degrees of Freedom	129	
Number of Observations	131	



Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	-0.04098161	7.01960349324031
Biased Variance	0.520777281792407	6.51399153469343
Biased Standard Deviation	0.721649001795476	2.55225224746564
Covariance	-0.150050219119324	
Correlation	-0.0808364593633609	
Determination	0.0065345331624043	
T-Test	-0.913971715445135	
p-value (2 sided)	0.362463641028857	
p-value (1 sided)	0.181231820514429	
Degrees of Freedom	127	
Number of Observations	129	

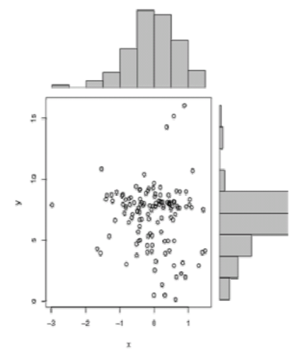
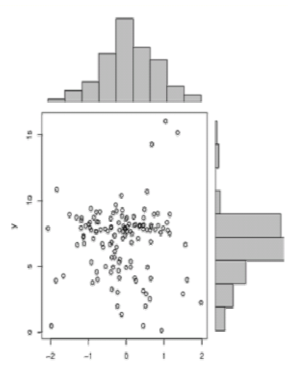


Figure C.9: AnyStop, December (Left)

Figure C.10: TreKing, April (Right)

Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	-0.112567469612403	7.01960349324031
Biased Variance	0.611427203917042	6.51399153469343
Biased Standard Deviation	0.781938107472095	2.55225224746564
Covariance	0.0317147189901384	
Correlation	0.0157683101384475	
Determination	0.000248639604622266	
T-Test	0.17772192630511	
p-value (2 sided)	0.859224518441176	
p-value (1 sided)	0.429612259220588	
Degrees of Freedom	127	
Number of Observations	129	



Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	-0.019962042503876	7.01960349324031
Biased Variance	0.584577194146061	6.51399153469343
Biased Standard Deviation	0.764576480246457	2.55225224746564
Covariance	-0.10584050764888	
Correlation	-0.0538180111637934	
Determination	0.00289637832562619	
T-Test	-0.607378420814821	
p-value (2 sided)	0.544684260843003	
p-value (1 sided)	0.272342130421502	
Degrees of Freedom	127	
Number of Observations	129	

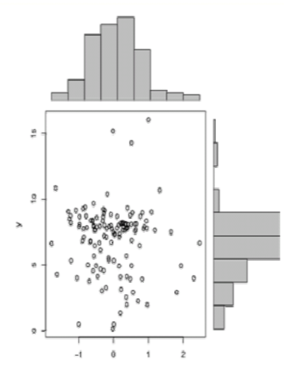
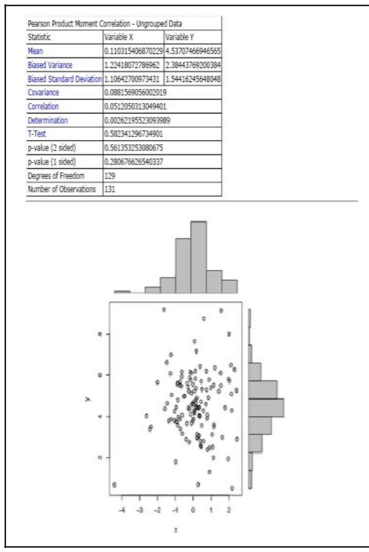
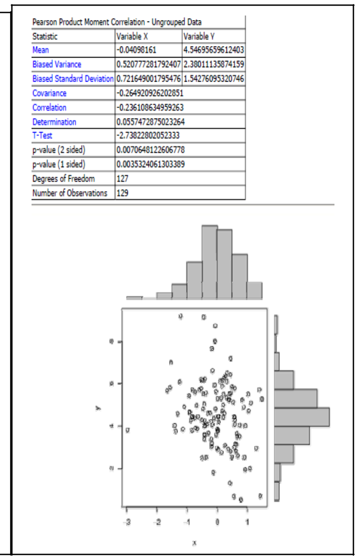


Figure C.11: TreKing, May (Left)

Figure C.12: TreKing, June (Right)



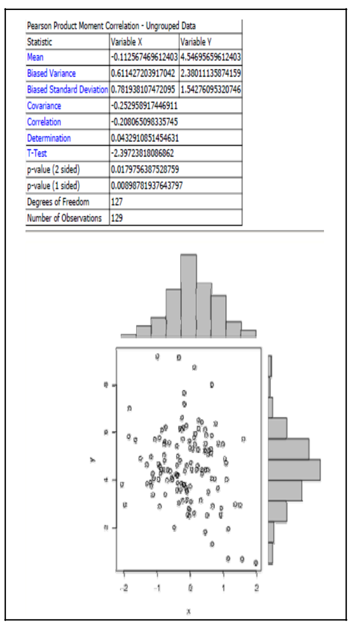
Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	0.110315406870229	4.53707466946565
Biased Variance	1.22418072786962	2.38443769200384
Biased Standard Deviation	1.10642700973431	1.54416245648048
Covariance	0.0881569056002019	
Correlation	0.0512050313049401	
Determination	0.00262195523093989	
T-Test	0.582341296734901	
p-value (2 sided)	0.561353253080675	
p-value (1 sided)	0.280676626540337	
Degrees of Freedom	129	
Number of Observations	131	



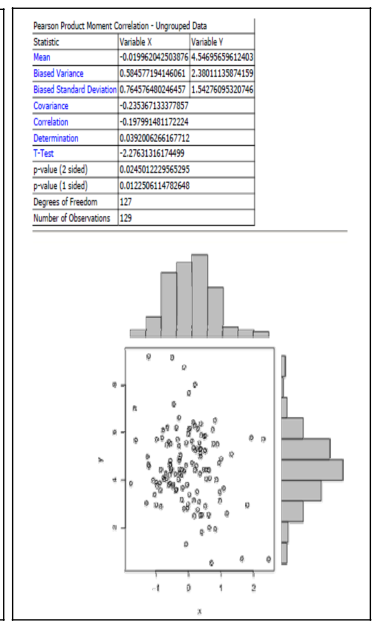
Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	-0.04098161	4.54695659612403
Biased Variance	0.520777281792407	2.38011135874159
Biased Standard Deviation	0.721649001795476	1.54276095320746
Covariance	-0.264920926202851	
Correlation	-0.236108634959263	
Determination	0.0557472875023264	
T-Test	-2.73822802052333	
p-value (2 sided)	0.00706481226067778	
p-value (1 sided)	0.0035324061303389	
Degrees of Freedom	127	
Number of Observations	129	

Figure C.13: AnyStop, December (Left)

Figure C.14: TreKing, April (Right)



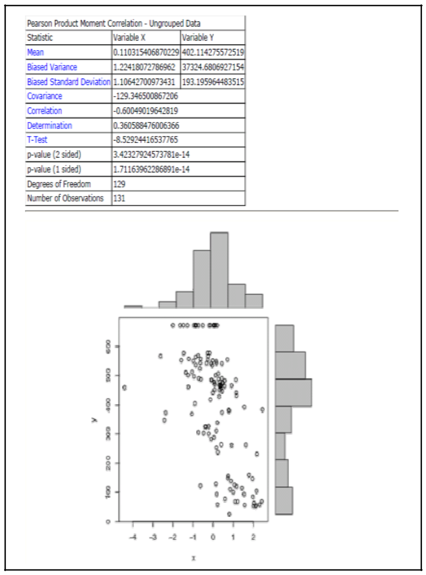
Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	-0.112567469612403	4.54695659612403
Biased Variance	0.611427203917042	2.38011135874159
Biased Standard Deviation	0.781938107472095	1.54276095320746
Covariance	-0.252958917446911	
Correlation	-0.208065098335745	
Determination	0.0432910851454631	
T-Test	-2.39723818086862	
p-value (2 sided)	0.0179756387528759	
p-value (1 sided)	0.00898781937643797	
Degrees of Freedom	127	
Number of Observations	129	



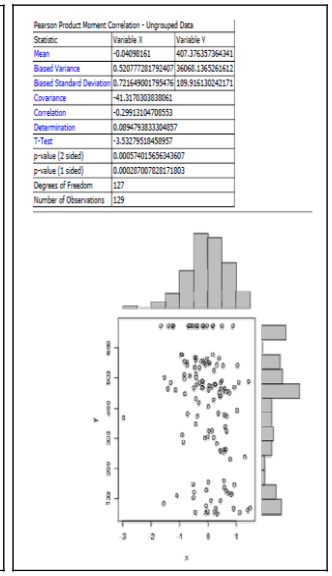
Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	-0.0199620425038876	4.54695659612403
Biased Variance	0.584577194146061	2.38011135874159
Biased Standard Deviation	0.764576480246457	1.54276095320746
Covariance	-0.235367133377857	
Correlation	-0.197991481172224	
Determination	0.0392006266167712	
T-Test	-2.27631316174499	
p-value (2 sided)	0.0245012229565295	
p-value (1 sided)	0.0122506114782648	
Degrees of Freedom	127	
Number of Observations	129	

Figure C.15: TreKing, May (Left)

Figure C.16: TreKing, June (Right)



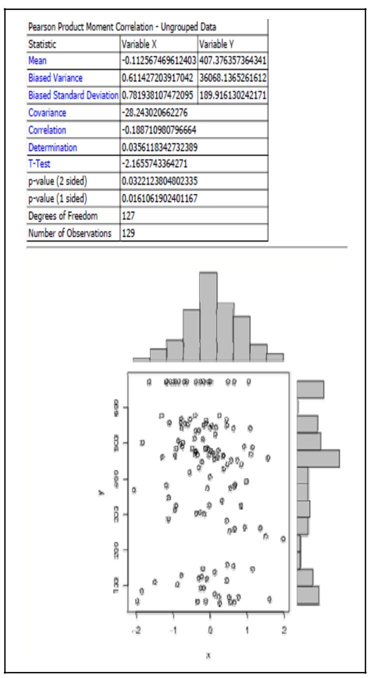
Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	0.110315406870229	402.114275572519
Biased Variance	1.22418072786962	37324.6806927154
Biased Standard Deviation	1.10642700973431	193.195964483515
Covariance	-129.346500867206	
Correlation	-0.60049019642819	
Determination	0.360588476006366	
T-Test	-8.52924416537765	
p-value (2 sided)	3.42327924573781e-14	
p-value (1 sided)	1.71163962286891e-14	
Degrees of Freedom	129	
Number of Observations	131	



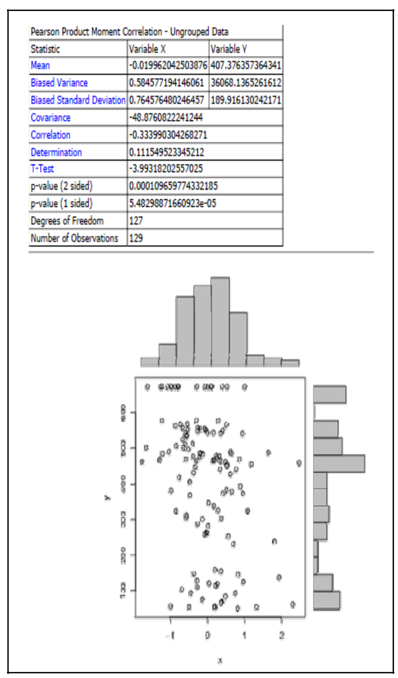
Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	-0.04098161	407.376357364341
Biased Variance	0.520777281792407	36068.1365261612
Biased Standard Deviation	0.721649001795476	189.916130242171
Covariance	-41.3170303838061	
Correlation	-0.29913104708553	
Determination	0.0894793833304857	
T-Test	-3.53279518458957	
p-value (2 sided)	0.000574015656343607	
p-value (1 sided)	0.000287007828171803	
Degrees of Freedom	127	
Number of Observations	129	

Figure C.17: AnyStop, December (Left)

Figure C.18: TreKing, April (Right)



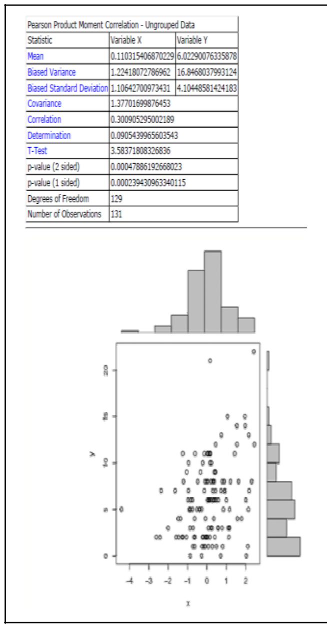
Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	-0.112567469612403	407.376357364341
Biased Variance	0.611427203917042	36068.1365261612
Biased Standard Deviation	0.781938107472095	189.916130242171
Covariance	-28.243020662276	
Correlation	-0.188710980796664	
Determination	0.0356118342732389	
T-Test	-2.1655743364271	
p-value (2 sided)	0.0322123804802335	
p-value (1 sided)	0.0161061902401167	
Degrees of Freedom	127	
Number of Observations	129	



Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	-0.019962042503876	407.376357364341
Biased Variance	0.584577194146061	36068.1365261612
Biased Standard Deviation	0.764576480246457	189.916130242171
Covariance	-48.8760822241244	
Correlation	-0.333990304268271	
Determination	0.111549523345212	
T-Test	-3.99318202557025	
p-value (2 sided)	0.000109659774332185	
p-value (1 sided)	5.48298871660923e-05	
Degrees of Freedom	127	
Number of Observations	129	

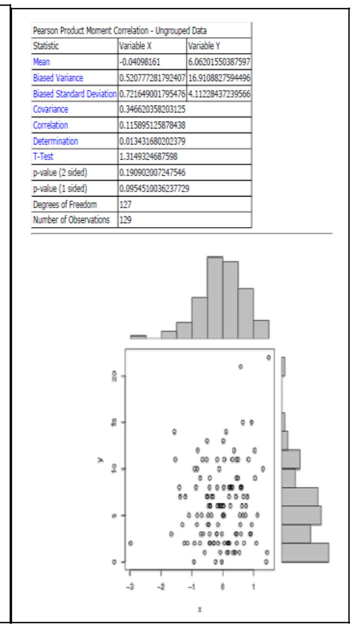
Figure C.19: TreKing, May (Left)

Figure C.20: TreKing, June (Right)



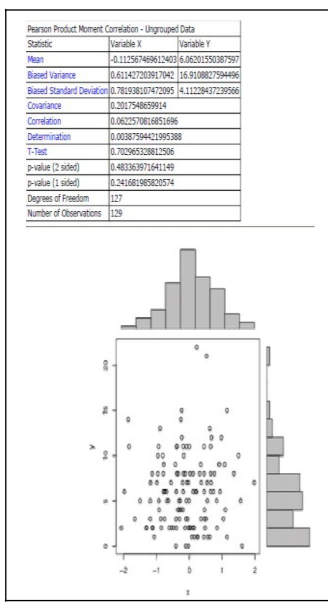
Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	0.110315406870229	6.02290076335878
Biased Variance	1.22418072786962	16.8468037993124
Biased Standard Deviation	1.10642700973431	4.10448581424183
Covariance	1.37701699876453	
Correlation	0.300905295002189	
Determination	0.0905439965603543	
T-Test	3.58371808326836	
p-value (2 sided)	0.00047886192668023	
p-value (1 sided)	0.000239430963340115	
Degrees of Freedom	129	
Number of Observations	131	

Figure C.21: AnyStop, December (Left)



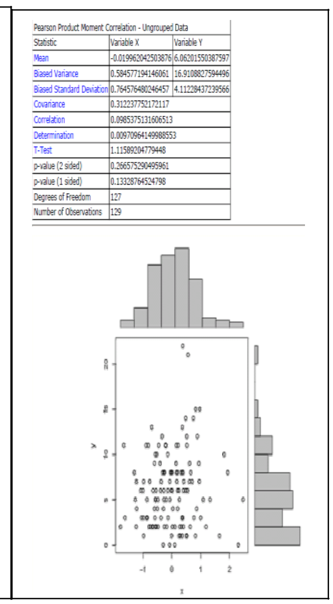
Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	-0.04098161	6.06201550387597
Biased Variance	0.520777281792407	16.9108827594496
Biased Standard Deviation	0.721649001795476	4.11228437239566
Covariance	0.346620358203125	
Correlation	0.115895125878438	
Determination	0.013431680202379	
T-Test	1.3149324687598	
p-value (2 sided)	0.190902007247546	
p-value (1 sided)	0.0954510036237729	
Degrees of Freedom	127	
Number of Observations	129	

Figure C.22: TreKing, April (Right)



Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	-0.112567469612403	6.06201550387597
Biased Variance	0.611427203917042	16.9108827594496
Biased Standard Deviation	0.781938107472095	4.11228437239566
Covariance	0.2017548659914	
Correlation	0.0622570816851696	
Determination	0.00387594421995388	
T-Test	0.702965328812506	
p-value (2 sided)	0.483363971641149	
p-value (1 sided)	0.241681985820574	
Degrees of Freedom	127	
Number of Observations	129	

Figure C.23: TreKing, May (Left)



Pearson Product Moment Correlation - Ungrouped Data		
Statistic	Variable X	Variable Y
Mean	-0.0199620425038761	6.06201550387597
Biased Variance	0.584577194146061	16.9108827594496
Biased Standard Deviation	0.764576480246457	4.11228437239566
Covariance	0.312237752172117	
Correlation	0.0985375131606513	
Determination	0.00970964149988553	
T-Test	1.11589204779448	
p-value (2 sided)	0.266575290495961	
p-value (1 sided)	0.13328764524798	
Degrees of Freedom	127	
Number of Observations	129	

Figure C.24: TreKing, June (Right)

Works Cited

Agrawal, Asha Weinstein, March Schlossberg, and Katja Irvin. “How Far, by Which Route and Why? A Spatial Analysis of Pedestrian Preference.” *Journal of Urban Design*, Vol. 13, No. 1, Pages 81-98: Feb 2008.

Aker, Jenny C. and Mbiti, Isaac M. “Mobile Phones and Economic Development in Africa.” *Journal of Economic Perspectives*, Vol. 24, No. 3, Pages 207-232: Summer 2010.

Anderson, Michael. “The best transit apps in Portland? Prepare to be surprised.” *Portland Afoot*. 7 Feb 2011. <http://portlandafoot.org/2011/02/the-best-transit-apps-in-portland-prepare-to-be-surprised/> Accessed 28 Nov 2012.

Angwin, Julia and Valentino-Devries, Jennifer. “Apple, Google Collect User Data.” *Wall Street Journal*, 22 Apr 2011. <http://online.wsj.com/article/SB10001424052748703983704576277101723453610.html> Accessed 20 Jan 2012.

Apple Inc. “Apple Announces Over 100,000 Apps Now Available on the App Store.” 4 Nov 2009. <http://www.apple.com/pr/library/2009/11/04appstore.html> Accessed 25 Apr 2010.

Arentze, Theo and Harry Timmermans. "Modeling learning and adaption processes in activity-travel choice." *Transportation*, Vol. 30, No. 1, Pages 37-62: 2003.

Arentze, Theo and Harry Timmermans. "Social networks, social interactions, and activity-travel behavior: a framework for microsimulation." *Environment and Planning B: Planning and Design*, Vol. 35, Pages 1012-1027: 2008.

Axon, Samuel. "Facebook's U.S. racial demographics mirror those of the country as a whole." *Obsessable*. 17 Dec 2009. <http://www.obsessable.com/news/2009/12/17/facebooks-u-s-racial-demographics-mirror-those-of-the-country-as-a-whole/> Accessed 28 Apr 2010.

Azenkot, Shiri and Fortuna, Emily. "Improving public transit usability for blind and deaf-blind people by connecting a braille display to a smartphone." *ASSETS '10 Proceedings of the 12th international ACM SIGACCESS Conference on Computers and Accessibility*: 2010.

Bantram, D.J. "Comprehending spatial information: The relative efficiency of different methods of presenting information about bus routes." *Journal of Applied Psychology*, Vol. 65, No. 1, Pages 103-110: Feb 1980.

Barry, Keith. “How Smartphones Can Improve Public Transit.” 8 April 2011. <http://www.wired.com/autopia/2011/04/how-smartphones-can-improve-public-transit/> Accessed 23 Nov 2012.

Bassoli, Arianna, Johanna Brewer, Karen Martin, Paul Dourish, and Scott Mainwaring. “Underground Aesthetics: Rethinking Urban Computing.” *Pervasive Computing*, Vol. 6, No. 3: Jul 2007.

BBC. “SA pigeon ‘faster than broadband.’” 10 Sep 2009. <http://news.bbc.co.uk/2/hi/8248056.stm> Accessed 7 Feb 2012.

Bednarz, Ann. "Time spent waiting for elevators? 16 years for NYC office workers." *Network World*. 30 April 2010. <http://www.networkworld.com/news/2010/043010-ibm-smarter-building-study.html> Accessed 31 Mar 2011.

Behrens, Roger and Del Mistro, Romano. "Shocking habits: Methodological issues in analyzing changing personal travel behavior over time." *International Journal of Sustainable Transportation*, Vol. 4, No. 5, Pages 253-271: Sep 2010.

Beirão, Gabriela and Cabral, J.A. Sarsfield. “Understanding attitudes towards public transport and private car: A qualitative study.” *Transport Policy*, Vol. 14, No. 6, Pages 478–489: Nov 2007.

Ben-Akiva, Moshe and Morikawa, Takayuki. “Passenger perceptions and the ideal urban bus journey experience.” *Transport Policy*, Vol. 14, No. 4, Pages 283-292: Jul 2007.

Benjamin, Solomon, R Bhuvaneswari, and Manjunatha P. Rajan. “Bhoomi: ‘E-Governance’, Or, An Anti-Politics Machine Necessary to Globalize Bangalore?” CASUM-m Working Paper, Jan 2007.

Berkow, Matthew, Ahmed M. El-Geneidy, Robert L. Bertini, and David Crout. “Beyond Generating Transit Performance Measures: Visualizations and Statistical Analysis with Historical Data.” *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2111, Pages 158-168: 2009.

Bland, J. Martin and Douglas G. Altman. “The odds ratio.” BMJ, Vol. 320, No. 7247, Page 1468: 27 May 2000.

Carmody, Padraig. "A New Socio-Economy in Africa? Thintegration and the Mobile Phone Revolution." *The Institute for International Integration Studies Discussion Paper Series*: Feb 2009.

CBC. “City of Vancouver embraces open data, standards and source.” 22 May 2009. <http://www.cbc.ca/news/technology/story/2009/05/22/tech-vancouver-open-

source-standards-software-city.html> Accessed 19 Jan 2012.

Cellan-Jones, Rory. “Who owns the train times - or the news?” BBC, 24 Mar 2009. <http://www.bbc.co.uk/blogs/technology/2009/03/who_owns_train_times_or_th.html> Accessed 18 Jan 2012.

Cellint Atlanta. “Cellint and GDOT accomplished a breakthrough milestone in the US for cellular-based traffic monitoring solutions.” 17 Dec 2007. <http://www.cellint.com/news/cellint-atlanta.html> Accessed 29 Oct 2010.

Cervero, Robert. “Profiling profitable bus routes.”*Transportation Quarterly*, Vol. 44, No. 2, Pages 183-201: 1990.

Cervero, Robert. “Mixed land-uses and commuting: evidence from the American Housing Survey.” *Transportation Research Part A: Policy and Practice*, Vol. 30, No. 5, 361-377: Sep 1996.

Chen, Brian X. and Bilton, Nick. “Et Tu, Google? Android Apps Can Secretly Copy Photos.” Bits Blog, New York Times. <http://bits.blogs.nytimes.com/2012/03/01/android-photos/> Accessed 2 Mar 2012.

Chen, Peter John. “Gov 2.0: Online engagement or a neo-liberal Trojan horse?” Parliamentary Library Lecture Series, Australian Parliament House, Canberra: 22 Jun 2011.

Chapleau, Robert, Martin Trépanier, and Ka Kee Chu. “The Ultimate Survey for Transit Planning*:* Complete Information with Smart Card Data and GIS.” *International Conference on Survey Methods in Transport*, Annecy, France: 2008

Chicago Transit Authority. “Chicago Transit Maps” <http://www.transitchicago.com/maps/> Accessed 29 Feb 2012.

Chicago Transit Authority. “Red Line Extension Project Documents.” <http://www.transitchicago.com/redeis/documents.aspx > Accessed 29 Feb 2012.

Chira-Chavala, T. and B. Coifman. “Impacts of Smart Cards on Transit Operators: Evaluation of I–110 Corridor Smart Card Demonstration Project.” *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1521, Pages 84-90: 1996.

Cho, Siu-Yeung and Tommy W.S. Chow. “A Fast Neural Learning Vision System for Crowd Estimation at Underground Stations Platform.” *Neural Processing Letters*, Vol. 10, No. 2, 111-120: 1999.

City-Go-Round. “Transit App Gallery.” <http://www.citygoround.org/apps/> Accessed 28 Nov 2012.

Computer Fraud and Security. "Mobile users more likely to fall victim to phishing." *Computer Fraud and Security*, Vol. 2011, No. 1, Page 20: Jan 2011.

comScore. "comScore Reports September 2010 U.S. Mobile Sucscriber Market Share." 3 Nov 2010. <http://comscore.com/Press_Events/Press_Releases/2010/11/comScore_Reports_September_2010_U.S._Mobile_Subscriber_Market_Share> Accessed 20 Nov 2011.

comScore. "Smartphone Adoption Reaches 40 Percent in Canada." 30 Nov 2011. <http://www.comscore.com/Insights/Press_Releases/2011/11/Smartphone_Adoption_Reaches_40_Percent_in_Canada> Accessed 28 Nov 2012.

comScore. "2012 Mobile Future in Focus." 23 Feb 2012. <http://www.comscore.com/Insights/Presentations_and_Whitepapers/2012/2012_Mobile_Future_in_Focus> Accessed 28 Nov 2012.

Davidov, Eldad. "Explaining Habits in a New Context: The Case of Travel-Mode Choice." *Rationality and Society*, Vol. 19, No.3, Pages 315-334: Aug 2007.

De Cristofaro, Emiliano, and Anthony Durussel, and Imad Aad." Reclaiming Privacy for Smartphone Applications." *2011 IEEE International Conference on Pervasive Computing and Communications (PerCom)*, Seattle: 21-25 Mar 2011.

decaWave. <http://www.decawave.com/scensor.html> Accessed 29 Apr 2010.

Deng, Julia. "Chatsworth Train Tragedy Anniversary Declared 'Don't Text and Drive Day.'" Annenberg TV News, 12 Sep 2011. <http://www.atvn.org/news/2011/09/three-years-later-chatsworth-train-tragedy-declared-dont-text-and-drive-day> Accessed 18 Jan 2012.

Doctorow, Cory. "Android lets apps secretly access and transmit your photos." BoingBoing, 2 Mar 2012. <http://boingboing.net/2012/03/02/android-lets-apps-secretly-acc.html> Accessed 2 Mar 2012.

Dossey, Larry. "Plugged In: At What Price? The Perils and Promises of Electronic Communication." *EXPLORE: The Journal of Science and Healing*. Vol. 5, No. 5, Pages 257-262: Sep-Oct 2009.

Dourish, Paul, Ken Anderson and Dawn Nafus. "Cultural Mobilities: Diversity and Agency in Urban Computing." *Human-Computer Interaction – INTERACT 2007,* *Lecture Notes in Computer Science*, Volume 4663, Pages 100-113: 2007.

Doyle, Mike. "CTA Bus Tracker vs. Union Negotiating Power," *Chicago Carless*. 20 Apr 2010. <http://www.chicagocarless.com/2010/04/20/cta-bus-tracker-vs-union-negotiating-power/> Accessed 25 Apr 2010.

Eaves, David. "The Economics of Open Data – Mini-Case, Transit Data & TransLink." Eaves.ca, 7 Nov 2011. <http://eaves.ca/2011/09/07/the-economics-of-open-data-mini-case-transit-data-translink/> Accessed 18 Jan 2012.

Essential Research. "Branded services will make smart phones." Jan 2010. <http://www.essentialresearch.co.uk/blog/2010/01/branded-services-will-make-smart-phones/> Accessed 28 Apr 2010.

Ericsson ConsumerLab. "Apps main reason for buying smartphones according to Ericsson ConsumerLab report." 17 April 2012. <http://www.ericsson.com/news/120417_apps_main_reason_for_buying_smartphones_244159019_c> Accessed 23 Nov 2012.

Evans-Cowley, Jennifer. "Planning in the Real-Time City: The Future of Mobile Technology." *Journal of Planning Literature*, Vol. 25, Pages 136-149: 2010.

Feldman, Amy. “Want to Improve Your City? There’s an App For That.” *TIME Magazine*. 21 Dec 2010. <http://www.time.com/time/specials/packages/article/0,28804,2026474_2026675_2039309,00.html> Accessed 23 Jan 2012.

Ferris, B., Watkins, K., and Borning, A. "OneBusAway: Results from Providing Real-Time Arrival Information for Public Transit." *Proceedings of CHI 2010.* Atlanta, GA, USA: 10-15 Apr 2010.

Ferris, B., Watkins, K., and Borning, A. "OneBusAway: Behavioral and Satisfaction Changes Resulting from Providing Real-Time Arrival Information for Public Transit." *Proceedings of the 2011 Transportation Research Board Annual Meeting*: 2011.

Ferris, Brian. “OneBusAway: Improving the Usability of Public Transit.” Doctor of Philosophy, University of Washington, 2011.

Fischer, Eric. “Paths through cities.” Flickr, 24 Jan 2012. <http://www.flickr.com/photos/walkingsf/sets/72157629014750905/detail/> Accessed 24 Jan 2012.

Ford, Nathaniel. “Parking meter changes may be coming to San Francisco.” *Parking*

Network. 31 Mar 2010. <http://www.parking-net.com/News/33223/Parking-meter-changes-may-be-coming-to-San-Francisco> Accessed 25 Apr 2010.

Foth, Marcus, Jaz Hee-jeong Choi, and Christine Satchell. “Urban Informatics.” CSCW '11, Proceedings of the *ACM 2011 Conference on Computer Supported Cooperative Work*: 2011.

Fouladvand, M. Ebrahim and Amir H. Darooneh. “Statistical analysis of floating-car data: an empirical study.” *Traffic and Granular Flow ’05*. Ed. Andreas Schadschneider et al. Springer Berlin Heidelberg: 2007.

Fujii, Satoshi, and Kitamura, Ryuichi (2003). “What does a one-month free bus ticket do to habitual drivers? An experimental analysis of habit and attitude change.” *Transportation*, Vol. 30, No. 1, Pages 81–95: 2003.

Gilbert, Peter, Byung-Gon Chun, Landon P. Cox, and Jaeyeon Jung. “Automating Privacy Testing of Smartphone Applications.” Duke University, Technical Report: 2011.

Goldmark, Alex. “Google Adds Real Time Transit Info to Maps.” 8 Jul 2011. <http://transportationnation.org/2011/06/08/google-adds-real-time-transit-info-to-maps/> Accessed 28 Nov 2012.

Goodman, William I. and Eric C. Freund. “Principles and Practice of Urban Planning.” Institute for Training in Municipal Administration by the International City Managers' Association: 1968.

Gosselin, Kadley. “Tech for Transit: Designing a Future System.” A Study By Latitude, in Collaboration With Next American City. <http://www.latd.com/2011/03/16/deprivation-study-finds-access-to-real-time-mobile-information-could-raise-the-status-of-public-transit/> Accessed 24 Jan 2012.

Graham-Rowe, Duncan. “Smartphone app monitors your every move.” *New Scientist*. 26 Nov 2010. <http://www.newscientist.com/article/mg20827885.300-smartphone-app-monitors-your-every-move.html> Accessed 7 Feb 2011.

Guo, Zhan, Nigel H M Wilson, and Adam Rahbee. “Impact of Weather on Transit Ridership in Chicago, Illinois.” *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2034, No. 1, Pages 3-10: 2007.

Gurstein, Mike. “Open Data: Empowering the Empowered or Effective Data Use for Everyone?” Gurstein’s Community Informatics, 2 Sep 2010. <https://gurstein.wordpress.com/2010/09/02/open-data-empowering-the-empowered-or-effective-data-use-for-everyone/> Accessed 19 Jan 2012.

Hammerle, Meghan, Michael Haynes, and Sue McNeil. “Use of Automatic Vehicle Location and Passenger Count Data to Evaluate Bus Operations.” *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1903: 2005.

Hasu, Tero. “ContextLogger2 - A Tool for Smartphone Data Gathering.” Helsinki Institute for Information Technology HIIT, HIIT Technical Reports 2010-1: 2010.

Hayton, James and Malos, Stan. “The Impact of Telecommuter Rail Cars on Modal Choice.” Mineta Transportation Institute: May 2005.

Hess, Daniel Baldwin, Brown, Jeffrey and Shoup, Donald. “Waiting for the Bus.” *Journal of Public Transportation*, Vol. 7, No. 4: 2004.

Hoback, Alan, Scott Anderson, and Utpal Dutta. “True Walking Distance to Transit.” *Transportation Planning and Technology*, Vol. 31, No. 6, 681-692: Dec 2008.

Hollands, Robert G. “Will the real smart city please stand up?: Intelligent, progressive or entrepreneurial?” *City*, Vol. 12, No. 3, Pages 303-320: 2008.

Hunt, John Douglas, Paul McMillan, Kevin Stefan, and Dianne Atkins. “Nature of Weekend Travel by Urban Households.” *Paper Prepared for Presentation at the Emerging Best Practices in Urban Transportation Planning (A) Session of the 2005 An-*

nual Conference of the Transportation Association of Canada, Calgary, Alberta: Sep 2005.

Immordino-Yang, Mary Helen, Andrea McColl, Hanna Damasio, and Antonio Damasio. “Neural correlates of admiration and compassion.” 20 Apr 2009, Proceedings of the National Academy of Sciences. <http://www.pnas.org/content/early/2009/04/17/0810363106.abstract> Accessed 26 Jan 2012.

Jack, William and Suri, Tavneet. “The Economics of M-PESA.” National Bureau of Economic Research Working Paper No. 16721: Jan 2011.

Jenny Chan and Ngai Pun. 2010. “Suicide as Protest for the New Generation of Chinese Migrant Workers: Foxconn, Global Capital, and the State.” *The Asia-Pacific Journal*, Vol. 37, No. 2: 2010.

Johnson, Nathanael. “How San Francisco is building bike lanes with the iPhone.” *San Francisco Bay Area News*. 3 Mar 2010. <http://kalwnews.org/audio/2010/03/03/how-san-francisco-building-bike-lanes-iphone_202117.html> Accessed 25 Apr 2010.

Joint Monitoring Program for Water Supply and Sanitation. “Improved Drinking-Water Sources.” March 2010. <http://www.wssinfo.org/fileadmin/user_upload/resources/KEN_wat.pdf> Accessed 23 Jan 2012.

Jones, Matt. “The Robot-Readable World.” BERG, 3 Aug 2011. <http://berglondon.com/blog/2011/08/03/the-robot-readable-world/> Accessed 19 Jan 2012.

Jonietz, Erika. “Finding a Parking Space Could Soon Get Easier.” *Technology Review*. 8 Feb 2010. <http://www.technologyreview.com/communications/24497/page1/> Accessed 25 Apr 2010.

Jordan, David. “City of Vancouver.” BCBusiness, 4 Apr 2011. <http://www.bcbusinessonline.ca/2011/04/04/city-of-vancouver> Accessed 19 Jan 2012.

Katz, Karen L., Blaire M. Larson and Richard C. Larson. "Prescription for the Waiting-in-Line Blues: Entertain, enlighten, and engage." *Sloan Management Review*, Pages 44-53: Winter 1991.

Kelly, Kevin. *What Technology Wants*. Viking Adult: 2010.

Kim, Sunyoung and Paulos, Eric. “inAir: Measuring and Visualizing Indoor Air Quality.” Ubicomp ’09, *Proceedings of the 11th International Conference on Ubiquitous Computing*: 2009.

Kimpel, Thomas J., Kenneth J. Dueker, & Ahmed M. El-Geneidy. “Using GIS to measure the effects of service areas and frequency on passenger boardings at bus stops.” *Journal of the Urban and Regional Information Systems Association,* Vol. 19, No. 1, Pages 5-11*:* 2007.

Kindberg, Tim, Matthew Chalmers; and Eric Paulos. “Guest Editors' Introduction: Urban Computing.” *Pervasive Computing*. Vol. 6, No. 3, Pages 18-20: Jul-Sep 2007.

Klein, Lawrence A, Milton K. Mills, and David R.P. Gibson. “CHAPTER 1. INTRODUCTION.” *Traffic Detector Handbook: Third Edition—Volume I*: Oct 2006. <http://www.fhwa.dot.gov/publications/research/operations/its/06108/01.cfm> Accessed 25 Jan 2012.

Kopp, Christopher, Joseph A. Moriarty, and Mark E. Pitstick. “Transit Attractiveness: Systematic Approach to Transit Performance Measurement.” *Transportation Research Board*, Vol. 1986, Pages 11-20: 2006.

Koskinen, S and Koskinen, K. "Architecture for a Smartphone Driver Information System." *Proceedings of the 13th ITS World Congress*, London: 8-12 Oct 2006.

Lane, Wilburn and Manner, Chris. "The Impact of Personality Traits on Smartphone Ownership and Use." *International Journal of Business and Social Science*, Vol. 2, No. 17: Sep 2011.

Lee, Ulchin and Mario Geria. "A survey of urban vehicular sensing platforms." *Elsevier Computer Networks Journal*, Vol. 54, No. 4, Pages 527-544: Mar 2010.

Levinson, Marc. *The Box: How the Shipping Container Made the World Smaller and the World Economy Bigger.* Princeton University Press: 2008.

Li, Bo and Im, Eul Gyu. "Smartphone, promising battlefield for hackers." *Journal of Security Engineering*, Vol. 8, No. 1: 2011.

Li, Xun et al. "Smartphone Evolution and Reuse: Establishing a More Sustainable Model." *Second International Workshop on Green Computing (GreenCom), in Conjunction with ICPP'10*, Sep 2010, San Diego.

Lichenstein, Richard, Daniel Clarence Smith, Jordan Lynne Ambrose, and Laurel Anne

Moody. “Headphone use and pedestrian injury and death in the United States: 2004-2011).” *Injury Prevention*: 2012.

Ling, Rich, and Leslie Haddon. "Mobile telephony, mobility and the coordination of everyday life.” *Machines That Become Us: The Social Context of Personal Communication Technology*, Pages 245-66, Ed. By J. E. Katz, Edison, NJ: Transaction Publishers: 2006.

Lohr, Steve. “Smartphone Rises Fast From Gadget to Necessity.” *New York Times*, 9 Jul 2009. <http://www.nytimes.com/2009/06/10/technology/10phone.html> Accessed 26 Jan 2012.

Long, Katherine. "Tech tools for Metro riders fall flat." *Seattle Times*. 22 Nov 2010. <http://seattletimes.nwsource.com/html/localnews/2013498259_transit23m.html> Accessed 1 Dec 2010.

Lu, Hong, Jun Yang, Zhigang Liu, Nicholas D. Lane, Tanzeem Choudhury, and Andrew T. Campbell. “The Jigsaw Continuous Sensing Engine for Mobile Applications.” *SenSys ‘10 Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems*: 2010.

Lu, Huapu. “Complexity of Public Transport Networks.” *TsinghuaScience&*

Technology, Vol. 12, No. 2, Pages 204–213: Apr 2007.

Maiman, Theodore H. *The Laser Odyssey*. Laser Press: 2000.

Maisonneuve, Nicolas, Matthias Stevens, Maria E. Niessen, and Luc Steels. "NoiseTube: Measuring and Mapping Noise Pollution With Mobile Phones." *Environmental Engineering, Environmental Science and Engineering*, Part 2, Pages 215-228: 2009.

Manaugh, Geoff. "Drone Landscapes, Intelligent Geotextiles, Geographic Countermeasures." Bldgblog, 7 Jan 2012. <http://bldgblog.blogspot.com/2012/01/drone-landscapes-intelligent.htm> Accessed 19 Jan 2012.

Masnick, Brian. "Berlin Metro Demands Removal Of Free iPhone Timetable App." Techdirt, 6 Nov 2008. <http://www.techdirt.com/articles/20081106/0148582753.shtml> Accessed 18 Jan 2012.

Masnick, Brian. "Railroad Says Train Schedule iPhone App Violates Copyright." Techdirt, 4 Mar 2009. <http://www.techdirt.com/articles/20090304/0152573986.shtml> Accessed 18 Jan 2012.

Masnick, Brian. “Train Operators Around The World Stopping Others From Helping Riders... Due To Intellectual Property.” Techdirt, 27 Mar 2009. <http://www.techdirt.com/articles/20090326/1211254264.shtml> Accessed 18 Jan 2012.

Melanson, Mike. “Combatting the Hype: 76% Don’t Access the Mobile Internet.” *ReadWriteWeb*. 25 Jan 2010. <http://www.readwriteweb.com/archives/combatting_the_hype_76.php> Accessed 28 Apr 2010.

Mohan, Prashanth, Venkata N. Padmanabhan, and Ramachandran Ramjee. “TrafficSense: Rich Monitoring of Road and Traffic Conditions using Mobile Smartphones.” Indian Institute of Science, Bangalore: Feb 2008.

Montreal Gazette. “Scan ‘n’ ride revolution.” 3 Mar 2007. <http://www.canada.com/montrealgazette/news/saturdayextra/story.html?id=da65eaaa-e4fc-4a81-bd5f-9626b6d5f1c8> Accessed 30 Apr 2010.

Morency, Catherine, Martin Trepanier, and Bruno Asgard. “Measuring transit use variability with smart-card data.” *Transport Policy*, Vol. 14, No. 3, Pages 193-203: May 2007.

Moss, Mitchell L., Josh Mandell, and Carson Qing. “MOBILE Communications and TRANSPORTATION in Metropolitan Regions.” The Rudin Center for Transportation Policy and Management, New York University: Jul 2011.

Multisystems. “Strategies for Improved Traveler Information.” Transit Cooperative Research Program. Report 92, Page 17: 2003.

Murray, Alan T. and Wu, Xiaolan. “Accessibility tradeoffs in public transit planning.” *Journal of Geographic Systems*, Vol. 5, No. 1, Pages 93-107: 2003.

Nafus, Dawn and Tracey, Karina. “Mobile phone consumption and concepts of personhood.” *Perpetual Contact: Mobile Communication, Private Talk, Public Performance*. Ed., James E. Katz and Mark Aakhus. Cambridge University Press: 2002.

Network Security Newsletter. "Cyber attacks increasingly target wealthy smartphone users, says Cisco." *Network Security*, Volume 2009, No. 8, Page 1: Aug 2009.

O’Neil, Kevin. “Bus Tracker second most popular local Google search for 2009.” *CTA Tattler*. 2 Dec 2009. <http://www.chicagonow.com/blogs/cta-tattler/2009/12/bus-tracker-second-most-popular-local-google-search-for-2009.html> Accessed 25 Apr

2010.

O’Reilly, Tim. “Gov 2.0: It’s All About The Platform.” TechCrunch, 4 Sep 2009. <http://techcrunch.com/2009/09/04/gov-20-its-all-about-the-platform/> Accessed 19 Jan 2012.

Ophir, Eyal, Clifford Nass, and Anthony D. Wagner. “Cognitive control in media multitaskers.” 24 Aug 2009, *Proceedings of the National Academy of Sciences*. <http://www.pnas.org/content/early/2009/08/21/0903620106.abstract> Accessed 26 Jan 2012.

Ory, David T., Patricia L. Mokhtarian and Gustavo O. Collantes. "Exploring the Cognitive and Affective Mechanisms Behind Subjective Assessments of Travel Amounts." *Environment and Behavior*, Vol. 39, No. 4, Pages 494-528: Jul 2007.

Oulasvirta, Antti, Mikael Wahlström, and K. Anders Ericsson. "What does it mean to be good at using a mobile device? An investigation of three levels of experience and skill." *International Journal of Human-Computer Studies*. Vol. 69, No. 3, Pages 155-169: Mar 2011.

Outram, Christine, Carlo Ratti, and Assaf Biderman. "The Copenhagen Wheel: An innovative electric bicycle system that harnesses the power of real-time information and crowd sourcing." MIT SENSEable City Lab: 26 Mar 2010.

Park, Jin Young, Dong-Jun Kim, and Yongtaek Lim. "Use of Smart Card Data to Define Public Transit Use in Seoul, South Korea." *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2063: 2008.

Park, Yangil and Chen, Jengchung V. **"**Acceptance and adoption of the innovative use of smartphone." *Industrial Management & Data Systems*, Vol. 107, No. 9, Pages 1349 – 1365: 2007.

Paulos, Eric, RJ Honicky, and Ben Hooker. "Citizen Science: Enabling Participatory Urbanism." *Handbook of Research on Urban Informatics: The Practice and Promise of the Real-Time City*. Hershey, PA: IGI Global. 414-36.

PR Newswire. "Smartphone Owners Concerned and In the Dark About Mobile Security." 25 Jan 2012. <http://www.prnewswire.com/news-releases/smartphone-owners-concerned-and-in-the-dark-about-mobile-security-138033368.html> Accessed 25 Jan 2012.

Press, Elizabeth. "A Case for Open Data in Transit." Streetfilms. 29 Jul 2010.

<http://www.streetfilms.org/a-case-for-open-data-in-transit/> Accessed 18 Jan 2012.

Privat, Ludovic. "Nielsen: US Smartphone Penetration to Be over 50% in 2011." GPS Business News. 30 Mar 2010. <http://www.gpsbusinessnews.com/Nielsen-US-Smartphone-Penetration-to-Be-over-50-in-2011_a2154.html> Accessed 15 Nov 2011.

Pucher, John R. "Discrimination in Mass Transit." *Journal of the American Planning Association*, Vol. 48, No. 3, Pages 315-326: Sep 1982.

Quick, Chris. “With Smartphone Adoption on the Rise, Opportunity for Marketers is Calling,” Nielsen Wire. September 15, 2009. <http://blog.nielsen.com/nielsenwire/online_mobile/with-smartphone-adoption-on-the-rise-opportunity-for-marketers-is-calling/> Accessed 18 Nov 2011.

Raento, Mike, Antti Oulasvirta and Nathan Eagle. "Smartphones: An Emerging Tool for Social Scientists." *Sociological Methods Research*. Vol. 37, No. 3, Pages 426-454: Feb 2009.

Reades, Jonathan, Francesco Calabrese, Andres Sevstuk, and Carlo Ratti. “Cellular Census: Explorations in Urban Data Collection.” *Pervasive Computing*, Vol. 6 No. 3, Pages 30 – 38: Jul-Sep 2007

Rehrl, Karl, Nicolas Göll, Sven Leitinger, and Stefan Bruntsch. “Combined indoor/outdoor Smartphone navigation for public transport travelers.” *Location Based Services & Telecartography - Proceedings of the Symposium 2005*.

Repas, Robert. “Wireless Sensor Network Aids Travelers in Parking Their Cars and Trucks.” *Machine Design*: 8 Sep 2009. <http://machinedesign.com/article/wireless-sensor-network-aids-travelers-in-parking-their-cars-and-trucks-0908> Accessed 28 Apr 2010.

Repenning, Alexander and Ioannidou, Andri. “Mobility agents: guiding and tracking public transportation users.” *AVI ’06: Proceedings of the Working Conference on Advanced Visual Interfaces*, Pages 127–134. ACM: 2006.

Rogerson, Simon. "What is wrong with mobile phones?" *IMIS Journal*, Vol. 13, No. 5: Oct 2003.

Roth, Matthew. “How Google and Portland’s TriMet Set the Standard for Open Transit Data.”

LA.Streetsblog.Org. <http://la.streetsblog.org/2010/01/08/how-google-and-portland’s-trimet-set-the-standard-for-open-transit-data/> Accessed 18 Jan 2012**.**

S. J. Barbeau, P. L.Winters, R. Perez, M. Labrador, and N. Georggi. “Travel Assistant Device.” US Patent App. 11/464,079: 11 Aug 2006.

Sage, Simon. “U.S. Smartphone Penetration Highest Among Asian/Pacific Islanders.” IntoMobile: 21 February 2011. <http://www.intomobile.com/2011/02/01/amaericanasians-hispanics-most-likely-to-own-smartphone/> Accessed 20 Nov 2011.

Schäfer, Ralf-Peter, Kai-Uwe Thiessenhusen, and Peter Wagner. “A trafficinformation systembymeansofreal-timefloating-cardata” *Proceedings of the ITS World Congress*: Oct 2002.

Schaller, R.R. “Moore's law: past, present and future.” *Spectrum*, Vol. 34, No. 6, Pages 52-59: Jun 1997.

Scott, Darren M., Kenneth Bruce Newbold, Jamie E.L. Spinney, Ruben Mercado, Antonio Paez, and Pavlos S. Kamaroglou. "New Insights into Senior Travel Behavior: The Canadian Experience." *Growth and Change*: Vol. 40, No. 1, Pages 140-168: Mar 2008.

Shaheen, Susan and Charlene Kemmerer. “Smart Parking Linked to Transit: Lessons Learned from the San Francisco Bay Area Field Test.” *Transportation Research Board*, 2008.

Sheller, Mimi and John Urry. “The City and the Car.” *International Journal of Urban and Regional Research*, Vol. 24, No. 4, Pages 737-757: December 2000.

Slee, Tom. “What Else Is Wrong With Government 2.0.” Whimsley, 16 Nov 2010. <http://whimsley.typepad.com/whimsley/2010/11/what-else-is-wrong-with-government-20.html> Accessed 19 Jan 2012.

Smith, Aaron. “35% of American adults own a smartphone,” Pew Research Center. 11 Jul 2011. <http://pewresearch.org/pubs/2054/smartphone-ownership-demographics-iphone-blackberry-android> Accessed 20 Nov 2011.

Song, Chaoming, Zehui Qu, Nicholas Blumm, and Albert Laszlo Barabasi. “Limits of Predictability in Human Mobility.” *Science*, Vol. 327, No. 5968, Pages 1018-1021: 19 Feb 2010.

Standage, Tom. *The Victorian Internet: The Remarkable Story of the Telegraph and the Nineteenth Century's On-line Pioneers*. Berkley Trade: 1999.

Standora, Leo. “MTA trains its anger at subway Web site.” *New York Daily News*, 26 Mar 2009. <http://www.nydailynews.com/news/mta-trains-anger-subway-web-site-article-1.360238> Accessed 18 Jan 2012.

Stanford Design School. “mobile + africa.” d.News. <http://dschool.typepad.com/news/2010/10/mobile-africa.html> Accessed 17 Jan 2012.

Steg, Linda. “Car use: lust and must. Instrumental, symbolic and affective motives for car use.” *Transportation Research Part A: Policy and Practice*, Vol. 39, No. 2-3, Pages 147-162: Feb-Mar 2005.

Sterling, Bruce. “42 Major Countries Ranked By Smartphone Penetration Rates.” Wired Magazine. 16 Dec 2011. <http://www.wired.com/beyond_the_beyond/2011/12/42-major-countries-ranked-by-smartphone-penetration-rates/> Accessed 16 Jan 2012.

Stradling, Stephen, Michael Carreno, Tom Rye, and Allyson Noble. “Passenger perceptions and the ideal urban bus journey experience.” *Transport Policy*, Vol. 14, No. 4, Pages 283-292: Jul 2007.

Takeuchi, Kiichi and Patrick J. Kennelly. “iSeismometer: A geoscientific iPhone application.*”* *Computers and Geosciences*, Vol. 36, No. 4, Pages 573-575: Apr 2010.

Ter Hofte, G.H. “What’s that hot thing in my pocket? SocioXensor, a smartphone data collector.” *Proceedings of the e-Social Science 2007, the Third International Conference on e-Social Science*: 7-9 Oct 2007.

Tertoolen, Gerard, Dik van Kreveld, and Ben Verstraten. “Psychological resistance against attempts to reduce private car use.” *Transportation Research Part A: Policy and Practice*, Vol. 32, No. 3, Pages 171-181: Apr 1998.

Thiagarajan, Arvind, James P. Biagioni, Tomas Gerlich, and Jakob Eriksson. "Cooperative Transit Tracking Using GPS-enabled Smart-phones." *Sensys 2010*, Zurich, Switzerland, Nov 2010.

Thorndyke, Perry W and Barbara Hayes-Roth. “Differences in spatial knowledge acquired from maps and navigation.” *Cognitive Psychology*, Vol. 14, No. 4, Pages 560-589: Oct 1982.

Timmermans, Harry J.P. and Zhang, Junyi. "Modeling household activity travel behavior: Examples of state of the art modeling approaches and research agenda." *Transportation Research Part B*, Vol. 43, No. 2, Pages 187–190: 2009.

Tossell, Chad C., Jo R. Jardina, Philip T. Kortum, S. Camille Peres, Clayton W. Shepard, Ahmad Rahmati and Lin Zhong. “Effects of Socioeconomic diversity on iPod

Touch Device Use in Real-World Environments." *Proceedings of the Human Factors and Ergonomics Society Annual Meeting,* Vol 55, No. 1, Pages 1293-1297: Sep 2011.

Townsend, Anthony. Ed. by Foth, Michael. *Handbook of Research on Urban Informatics: The Practice and Promise of the Real-Time City*, IGI, Hershey, PA: 2009.

Toyama, Kentaro and M. Bernardine Dias. "Information and Communication Technologies for Development." *Computer*, Vol. 41, No. 6, Pages 22-25: Jun 2008.

Trepanier, Martin, Nicolas Tranchant, and Robert Chapleau. "Individual Trip Destination Estimation in a Transit Smart Card Automated Fare Collection System." *Journalof IntelligentTransportationSystems*, Vol. 11, No. 1, 1 – 14: Jan 2007.

TriMet App Center. "Transit Tools for the Web and Mobile Devices." <http://trimet.org/apps/index.htm> Accessed 25 Apr 2010.

United States v. Jones. Supreme Court of the United States. Legal Information Institute. Cornell University Law School. 23 Jan. 2012. <http://www.law.cornell.edu/supremecourt/text/10-1259>. Accessed 23 Jan 2012.

Valentino-Devries, Jennifer. "'Stingray' Phone Tracker Fuels Constitutional Clash." *Wall Street Journal*, 22 Sep 2011. <http://online.wsj.com/article/SB10001424053111904194604576583112723197574.html> Accessed 20 Jan 2012.

Valentino-Devries, Jennifer. "Google Defends Way It Gets Phone Data." *Wall Street Journal*, 23 Apr 2011. <http://online.wsj.com/article/SB100014240527487033879045762794510015937 60.html> Accessed 20 Jan 2012.

Verkasalo, Hannu, Carolina Lopez-Nicolas, Francisco J. Molina-Castillo, and Harry Bouwman. "Analysis of users and non-users of smartphone applications." *Telematics and Informatics*, Vol. 27, No. 3, Pages 242-255: Aug 2010.

Warzala, Dan. "Vehicle Telematics for Novice Teenage Driver Support System - Smartphone Based Novice Teenage Driver Support." Minnesota Department of Transportation: 2008. <http://rip.trb.org/browse/dproject.asp?n=27213> Accessed 28 Jan 2012.

Watkins, Kari Edison, Brian Ferris, Alan Borning,, G. Scott Rutherford, and David Layton. "Where Is My Bus? Impact of mobile real-time information on the perceived and actual wait time of transit riders." *Transportation Research Part A:*

Policy and Practice, Vol. 45, No. 8, Pages 839–848: Oct 2011.

Weeels. “Social Transit: Engineering Vehicle Effiency via Systems Design.” <http://weeels.org/> Accessed 25 Nov 2010.

Wilson, NHM, D Nelson, A Palmere, T H Grayson, and C Cederquist. “Service-Quality Monitoring For High-Frequency Transit Lines.” *Transportation Research Record*, No. 1349, Pages 3-11: 1992. <http://trid.trb.org/view.aspx?id=370840>

Winters, Chris. “Mismatch on the South Side between housing and job opportunities leads to long commute times for many South Siders.” University of Chicago Map Collection: Jun 2008.

Wissenschaftszentrum Berlin für Sozialforschung. "Call-a-Bike — Results of the Intermodi Research Project.” 10 Oct 2008. <http://www.wzb.eu/callabike/1_callabike.html> Accessed 25 Nov 2009.

Work, Daniel B. and Alexandre M. Bayen. "Impacts of the Mobile Internet on Transportation Cyberphysical Systems: Traffic Monitoring using Smartphones." *National Workshop for Research on High-Confidence Transportation Cyber-Physical Systems: Automotive, Aviation and Rail*. Washington, DC, 18-20 November 2008.

Worldchanging Team. “Principle 8: Leapfrogging.” *Worldchanging*. 15 May 2007. <http://www.worldchanging.com/archives/006700.html> Accessed 29 Apr 2010.

Wronski, Richard. “South Side hopes Olympics bring a CTA ‘Gold Line.’” Chicago Tribune, 7 Jul 2009. <http://articles.chicagotribune.com/2009-07-07/news/0907060938_1_olympic-venues-red-line-rapid-transit> Accessed 29 Feb 2012.

Yardi, Sarita and Bruckman, Amy. “Income, Race, and Class: Exploring Socioeconomic Differences in Family Technology Use.” *Proceedings of the ACM Conference on Human Factors in Computing Systems* (CHI `12). Austin, Texas: 5-10 May 2012.

Yin, Sara. "RIM Loses Ground to Google's Android, comScore Says." PCMag.com, 3 Nov 2010. <http://www.pcmag.com/article2/0,2817,2372096,00.asp> Accessed 15 Nov 2011.

Zhao, Fang. “GIS analysis of the impact of community design on transit accessibility.” *Proceedings of the ASCE South Florida Section Annual Meeting*, Sanibel Islands: Sep 1998.

Fang, Zhao, Lee-Fang chow, Min-Tang Li, Ike Ubaka, Albert Gan. "Forecasting Transit Walk Accessibility: Regression Model Alternative to Buffer Method." *Transportation Research Board of the National Academies*, Vol. 1835: 2003.

Zhao, Yilin. *Vehicle Location and Navigation Systems: Intelligent Transportation Systems*. Artech House: 1997.