ABSTRACT

Title of Document: TRAVELER RESPONSES TO REAL-TIME TRANSIT PASSENGER INFORMATION SYSTEMS

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In recent years, a considerable amount of money has been spent on Real-time Transit Passenger Information Systems (RTPISs), which provide timely and accurate transit information to current and potential riders to enable them to make better pre-trip and en-route decisions. Understanding traveler responses to real-time transit information is critical for designing such services and evaluating their effectiveness. To answer this question, an effort is made in this dissertation to systematically conceptualize a variety of behavioral and psychological responses travelers may undertake to real-time transit information and empirically examine the causal effects of real-time information on traveler behavior and psychology.

This research takes ShuttleTrac, a newly implemented real-time bus arrival information system for UMD's Shuttle-UM service, as a case for empirical study. In Part 1 analysis, using panel datasets derived from three-waved online campus

transportation surveys, fixed-effects OLS models and random-effects ordered probit models are estimated to sort out causal relations between ShuttleTrac information use and general/cumulative behavioral and psychological outcomes. In addition, a two-stage instrumental variable model was estimated to examine the potential change in habitual mode choices due to real-time transit information use. The results show that with a few months of adjustment, travelers may increase their trip-making frequency as a result of real-time transit information use, and positive psychological outcomes are more prominent in both short and longer terms.

In Part 2 analyses, using the cross-sectional dataset derived from the onboard survey, OLS models and ordered logit models were estimated to examine the trip-specific psychological effects of real-time transit information. The results show that these trip-specific psychological effects of real-time transit information do exist in expected directions and they vary among user groups and in different scenarios. A finding consistent across two parts of analyses is that accuracy of information plays a greater role in determining traveler behavior and psychology than the mere presence.

This research contributes to the general discussion on traveler behavior under advanced information by 1) developing an integrative conceptual framework; and 2) providing useful insights into the issue with much empirical evidences obtained with revealed-preference data and sophisticated modeling techniques.

TRAVELER RESPONSES TO REAL-TIME TRANSIT PASSENGER INFORMATION SYSTEMS

By

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Dissertation submitted to the Faculty of the Graduate School of the
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Dedication

To my wife, Xiaodan and my son, Benjamin

Acknowledgements

It has been a long journey in which I didn’t travel at ease. Luckily I was never alone. There were times that I thought about giving up. It was many people’s invaluable help and supports that drove me overcoming difficulties and finally making it.

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Finally, I'm deeply indebted to my beloved wife, Ms. Xiaodan Wang. One thing I am certain about is that I would never make this achievement without her unconditional understanding and support. This dissertation is dedicated to her and our lovely two-year-old, Benjamin.

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Chapter 1: Introduction

1.1 Background

Public transit is widely recognized as an environmentally sustainable transportation mode. However, in the U.S. where low-density suburban expansion has prevailed for decades, transit's market share of urban travel has been continuing to fall, as it often fails to compete with the automobile which offers great convenience and flexibility. U.S. transit market share dropped to 1.51 percent of the total in 2005[1]. Facing the great challenge of providing adequate transit service in American cities, transportation researchers and policy-makers in this country have shown an increasing interest in learning from international experiences and exploring innovative approaches. One of the new strategies for high-quality transit service is the development of Real-time Transit Passenger Information Systems (RTPIS)[2] (Pucher, 2004). These systems provide timely and accurate transit information to current and potential riders to enable them to make better pre-trip and en-route decisions.

While the part of real-time traveler information systems accessed and used by the travelers is often relatively simple (e.g., a sign giving the next bus arrival time), the "system" behind what the user sees can be rather complex (Raman *et al.*, 2003). The high-view of a RTPIS is shown in Figure 1.1. Even though, as we will discuss in Chapter 3, a wide variety of transit-related information can be provided to travelers in

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[1] *U.S. Urban Personal Vehicle & Public Transport Market Share from 1900*. http://www.publicpurpose.com/ut-usptshare45.htm. Accessed July 10, 2007.
[2] An interchangeable term used in this dissertation is Real-time Transit Information System (RTIS).

real-time, the most frequently provided real-time transit information includes vehicle arrival times, and service disruptions and delays. In order to project vehicle arrival times, an Automatic Vehicle Location (AVL) system, mostly GPS-enabled, is needed to provide the real-time vehicle location data first. The system then uses the current vehicle location to compute the estimated arrival time at the upstream stops using data that may include vehicle speed, distance, travel time history, and traffic flow history. In many applications, a countdown to the arrival of the next vehicle (e.g., next bus in 5 minutes) is used. Note that these systems are typically integrated with transit management systems (see Figure 1.1).

The distribution of real-time transit information takes many forms and can be at any geographical and temporal point. Figure 1.1 has shown some major media for information dissemination, including Internet, wayside/at-stop kiosks and Dynamic Message Signs (DMS), landline or cell phones, and wireless devices. Thanks to the variety and ubiquitousness of these Information and Communication Technologies (ICT)-enabled information dissemination media, travelers are able to access the real-time transit information at any time point during a journey. In other words, pre-trip, en-route, or even post-trip information acquisition is possible and travel decisions can be altered according to the information anytime in the course of the trips.

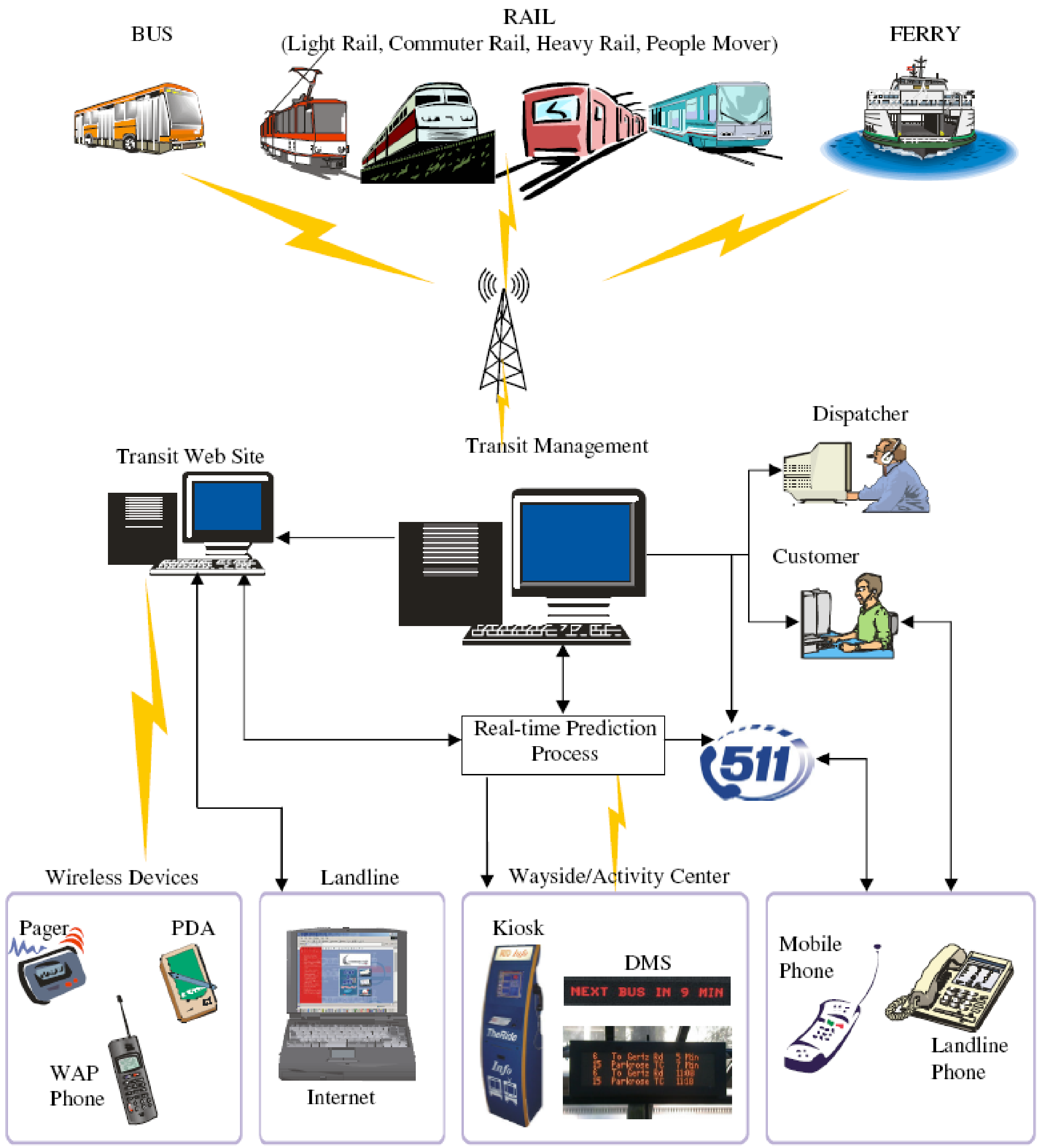


Figure 1.1 Real-time Transit Information System (integrated with the Transit Management System) (Source: Raman et al., 2003)

A considerable amount of money is being spent on real-time transit information systems all over the world (Cham *et al.*, 2006). The underlying reasons for deploying this kind of system include both economic and social considerations. Transit agencies in particular expect these systems to boost the ridership, and hence revenues, by attracting new passengers and increasing transit usage of existing patronage. From transit users' perspective, the travel time savings caused by real-time transit information use is certainly an economic benefit. Besides, transit agencies may want to boost their public images by making such visible efforts to improve their service. Also from the perspective of users, they may greatly improve their personal waiting and riding experience during transit trips due to the presence of real-time information. Perhaps a deeper social consideration is that social inequity in American cities, worsened by suburbanization and segregation, may be narrowed to some extent by improving transit service for the disadvantaged population who are largely captive transit riders.

Accompanying the implementation of such, often expensive, real-time information systems, many authorities are conducting their own evaluations to learn about the effects and to justify their investments. All underlying considerations presented above, either from providers' or users' point of views, can be ultimately attributed to the question of how individual travelers will use such systems and respond to them accordingly. The changes in travel behaviors and psychology at an individual level, no matter how small individually, can be summed up to show rather considerable aggregate changes in the market. As we will review in Chapter 2, understanding of such question to this date is very much sparse and inconclusive. The primary goal of this research is to develop a generic framework of traveler's behavioral and psychological responses to real-time transit information and empirically examine the causal relationships between these behavioral and psychological outcomes and real-time transit information.

1.2 Research Question

Relating to the general question of traveler behavior in the presence of real-time transit passenger information, there involves a number of closely interrelated sub-questions from the perspective of service users (adapted from Lappin and Bottom, 2001):

- Need of information: what types of information would passengers want to access under what scenario?
- Willingness-to-pay: how much would they be willing to pay to acquire the information?
- Use of information: what are determinants of use or acquisition of real-time transit information when provided?
- Response to information use: how would travelers respond to the information they acquire, at once and in iteration?

Each sub-question listed above is no doubt worth a certain amount of investigations in order to ascertain the real effects of RTPISs. The overarching research question this dissertation is particularly interested in is actually the last one:

- **What are the traveler's behavioral and psychological responses to real-time transit information?**

The critical importance of this particular question lies in its direct relation to tangible and intangible effects and benefits of RTPISs at both disaggregate and aggregate levels. The network-level impacts of RTPISs can be determined by aggregating the individual responses of many travelers to the information, but in doing this the interactions of the travelers on the transit network must also be taken into account. For example, individual travelers' behavior under information may cause changes in transit network conditions (e.g. transit network assignment, congestion), and in turn affect other travelers' behavior. Therefore, this dissertation is aimed at addressing this particular research question in order for providing theoretical basis for evaluation of the real-time transit information systems as well as providing some empirical insights into understanding of such issue.

1.3 Research Objectives

There have been a relatively small number of studies in recent years intended to answer above research question and explore the effects of real-time transit information. A detailed discussion of related literature is provided in Chapter 2. While all these studies offer some interesting features, as discussed in Section 2.2, they all embed major drawbacks in terms of drawing systematic causal relations between real-time transit information and traveler behavior/psychology. The main objective of this study, as we have mentioned above, is to develop a generic framework of traveler's behavioral and psychological responses to real-time transit information and then empirically investigate the causal relationships between these behavioral and psychological outcomes and real-time transit information. More specifically, there are some sub-objectives that are:

- To review the critical points of the current knowledge concerning traveler behavior and psychology under advance traveler information in general and real-time transit information in particular. This review will provide sound theoretical basis and useful insights for understanding the topic of this research.

- To develop a generic, comprehensive conceptual framework of individual traveler's responses to real-time transit information, taking into account traveler behavior and psychology as well as different response time frames (general/cumulative vs. trip-specific responses). This framework will identify major components of effects, conceptually formulate linkages between real-time transit information and these effects, and provide a basis for empirical investigation of this study and potential future research.
- To empirically analyze the traveler's general/cumulative behavioral and psychological responses with a quasi-experimental research, as well as traveler's trip-specific psychological responses to real-time transit information, using revealed-preference data.

1.4 Research Scope

The scope of this research is specified as follows:

The RTPISs are briefly introduced in Section 1.1. The information such systems distribute to the public has more than one dimensions in terms of its contents, costs, places, and quality. The conceptual framework presented in Chapter 3 is a generic one in that the four dimensions of RTPIS are incorporated in such framework. However, the empirical investigation was actually limited to only one type of real-time transit information – real-time *bus* arrival information – and its accuracy, due to the characteristics of the real-world case I look at. Real-time bus arrival information (e.g. a countdown to the arrival of the next vehicle in this case) is perhaps provided most frequently with a RTPIS, and how this kind of information influences traveler decisions is of primary interest to the studies in the related literature. In comparison of other public transportation modes (rail mostly), bus is somewhat special in that the quality of real-time bus arrival information is highly dependent on the complexity of road transportation. Nevertheless, our research will shed some lights on how real-time transit information, in a general sense, will affect traveler's behavior and psychology.

This research acknowledges that a large portion of effects of real-time transit information system are more of a psychological nature. In other words, even if traveler behaviors hardly change as a result of real-time transit information acquisition, they will still make some changes in psychological conditions, which bring along some intangible benefits. In this regard, in addition to travel behavior, travel psychology under real-time transit information is particularly conceptualized and investigated in this research.

It is generally agreed that there are two stages before effects of real-time transit information occur: first travelers must acquire the information and second the acquired information must lead to some behavioral and psychological changes of travelers. Information acquisition/use is referred to as that information is searched for or paid attention to by travelers and processed by her (Chorus *et al.*, 2006a). The question of what determines people's decision of acquiring information is an important issue too. And as a premise to traveler's responses, the use of real-time transit information may directly determine the existence and/or magnitude of effects of real-time information.

However, in order to sharpen the focus of research, this dissertation is only concentrated on the second stage of this process. That is, I would like to investigate the behavioral and psychological change as a result of acquired real-time transit information, without explicitly accounting for the process of information acquisition. There is only one exception here: to address the potential self-selection bias, the process of information use was explicitly modeled as the first stage in the two-staged model for commuting mode choice. Please see Section 5.3 for details.

1.5 Organization of this Dissertation

The rest of dissertation is organized as follows. Chapter 2 provides a detailed review of a large body of literature concerning traveler behavior and psychology under advance traveler information in general and real-time transit information in particular. Chapter 3 presents a generic, integrative conceptual framework of traveler behavioral and psychological responses to real-time transit information, which lays down the foundation for understanding and examining behavioral and psychological effects of RTPISs. In Chapter 4, the research methodology of this dissertation is presented, including research design, surveys and measures, and analytical methods. Chapter 5 particularly looks at the general/cumulative behavioral and psychological responses of travelers, followed by Chapter 6, which turns to trip-specific psychological responses. Both chapters present results of a variety of empirical models and following discussions. The final chapter, Chapter 7, draws the conclusion of this study and presents recommendations for future research.

Chapter 2: Literature Review

2.1 Introduction

Chapter 2 is intended to review the critical points of the current knowledge concerning traveler behavior and psychology under advance traveler information in general and real-time transit information in particular. This chapter is organized as follows. First, drawing on three pieces of review articles, Section 2 presents a review of both the empirical and the conceptual literature concerning the use and effects of Advanced Traveler Information System (ATIS) service. It provides sound theoretical basis and useful insights for understanding travel behavior under real-time transit information system. Section 3 reviews the relatively small body of literature that is most relevant to this dissertation's topic and classifies them into two categories in terms of their methodological approaches. Advantages and disadvantages of two different approaches are discussed in this section. These two sections are mostly about travel behaviors and focuses on literature in the field of transportation. The following Section 4 turns to literature of psychology of waiting for service, trying to review the effects of providing information of waiting duration on customer psychology during waiting for services. Finally, based on reviews in previous sections, Section 5 points out several major gaps in the knowledge regarding this topic and provides this research with directions.

2.2 Traveler Behavior with Advanced Traveler Information

Advanced Traveler Information System (ATIS) makes use of a variety of information and communication technologies to deliver to a wide range of travelers static or real-time information on traffic conditions, schedules, road and weather conditions, special events, tourist information, and so on. Providing travelers with such information is generally acknowledged as enabling travelers to make better travel choice and support better use of transportation facilities. Nowadays ATIS is widely available and becoming more advance every year. Policy makers in many countries have fairly high expectations of the potential effects of ATIS service on altering traveler behaviors in ways that would reduce passenger transportation externalities such as congestion, greenhouse gas emission, noise, etc. (e.g. Commission of the European Communities, 2001; Dutch Department of Transport, 2002; UK Department of Transport, 2004). Not surprisingly there is a large body of literature which has, over the last two decades or so, investigated traveler's behavioral change under the ATIS service. Unfortunately, although ATIS does not necessarily exclude Real-time Transit Passenger Information System, only an extremely small portion of the literature is concerning traveler behavior with real-time transit information. Nevertheless, studies on traveler behavior under auto-oriented ATIS do provide with theoretical basis of and useful insights into that under transit-oriented ATIS. In this section, I will briefly review such topic by mainly drawing on three excellent review articles, i.e., Lappin and Bottom (2001), Chorus *et al.* (2006a), and Chorus *et al.* (2006b). All of them have reviewed a large number of relevant studies from the past 20 years or so and provided complete pictures in regard with traveler behavior with ATIS.

Relating to the general question of traveler behavior in the presence of real-time traveler information, there involves a number of closely interrelated sub-questions (Lappin and Bottom, 2001):

- Need of information: what types of information would travelers want to access?
- Use of information: what are determinants of ATIS use and information acquisition?
- Response to information use: how would travelers respond to the information they receive, at once and in iteration?
- Willingness-to-pay: how much would they be willing to pay to receive the information?

Chorus *et al.* (2006a) summarized some dominant theories on travelers' decision on information use, including utility maximization (Von Neumann and Morgenstern, 1947), satisficing (Simon, 1955), habit execution (Triandis, 1997), and effort-accuracy trade-off (Payne *et al.*, 1993, 1996). All the theories, according to them, have in common that the use of information, being it for alternative generation or assessment, can be framed as a cost-benefit decision.

Empirical findings related to ATIS use were reviewed by all works. A large number of variables have been identified as determinants of ATIS use, including:

- Travelers' socio-economic characteristics. For example, high tendency of ATIS use was found among male, highly educated, high-income travelers

(Petrella and Lappin, 2004), professionals (Emmerink *et al.*, 1996), groups who appear to attach greater importance to making an accurate choice (Hato *et al.*, 1999), and travelers who have mobile phones (Polydorpoulou and Ben-Akiva, 1998). Also distinct market segments were delineated among ATIS users based on their personal traits, such as control seekers, web heads, and so on (Mehndiratta *et al.*, 1999).

- Trip purpose and context. Commuter trips (Petrella and Lappin, 2004) and especially business trips (Emmerink *et al.*, 1996) seem to induce the search for and use of ATIS, perhaps mainly because they are arrival time-sensitive trips. Expected congestion or expected volatility in travel times (Hato *et al.*, 1999), traveling in peak hours (Peirce and Lappin, 2004), longer trips (Targa *et al.*, 2003), and bad weather during the trips (Polydoropoulou and Ben-Akiva, 1998) also increase the likelihood of ATIS use.
- Existence and characteristics of travel alternatives. Travelers tend to search for information regarding alternatives of which they are aware, refer or often use (Polak and Jones, 1993; Srinivisan *et al.*, 1999). Also, if the alternatives are viable and promising for the trips to be made, information will be actively searched for and acquired by travelers. In addition to travel time and costs, information of seemingly less tangible characteristics of travel alternatives, such as convenience, privacy and comfort, is of interest to travelers to acquire for decision-making (e.g. Steg *et al.*, 2001; Bos *et al.*, 2004; Steg, 2005)
- Characteristics of ATIS service. The importance of information quality is always emphasized. Specifically, reliability, timeliness and coverage of the

information provided are keys to ATIS use (Polydoropoulou and Ben-Akiva, 1998). Also, if the information use entails high prices or difficulty, the likelihood of ATIS service use is lower as the expected benefits of ATIS use may be outweighed by the costs (Chorus *et al.*, 2006a).

Next to information acquisition or use, it is natural to ask an adjacent question: how do travelers respond to such traveler information? Mainly based on empirical studies, Lappin and Bottom (2001) made a relatively complete list of potential responses to real-time traveler information at individual level, which can be classified into two categories: those involving trip-making context and those involving trip-making itself. According to them, trip context responses to ATIS include:

- Reduce stress and anxiety (see Khattak *et al.*, 1995; Lee and Douglass, 2000). This is actually the only psychological response they have mentioned in the review.
- Affect non-travel activities at the trip endpoints. For instance, a Mitretek study (Shah *et al.*, 2001) found that pre-trip ATIS use had reduced the number of late arrivals by 62% and the total late schedule delays by 72%.
- Adjust daily activity schedule. Reliable information on travel times and traffic conditions may allow people to eliminate some of the “slack” originally needed in their scheduling decisions to reduce the risk of disruptions due to worse-than-expected travel conditions.

- Adjust habitual trip-making behavior. For example, Uchida *et al.* (1994) found that a VMS that provided predicted travel time information may significantly affect traveler's strategic response (i.e., the change over time in selection of their habitual route). However, the reluctance to change habitual route is still strong, even when the VMS repeatedly showed it to be an inferior alternative.
- Adjust residence and/or employment location. A variety of changes brought by ATIS could in a longer run lead people to reconsider their residential and/or employment location choice. Through these kinds of effects, ATIS could ultimately have an impact on urban form and structure (Hamerslag and van Berkum, 1991). However, this kind of effect may not be noticeable with current scale of ATIS.

Also the tactical trip-making or trip-specific responses to ATIS are:

- Decision to travel or not. Information about sufficiently bad travel conditions or alternatives could make travelers cancel their intended trips, particularly discretionary trips (Khattak *et al.*, 1999).
- Choice of destination(s). A set of Internet-based stated preference survey was used to investigate the effects of ATIS on shopping trip destination and route choice (Krann *et al.*, 2000; Mahmassani *et al.*, 2003). They found that switching destination and route was prominent when information on traffic delays was presented.

- Departure time choice. Departure time choice may be influenced by pre-trip ATIS use since the reduced travel time variability caused by real-time information may change when travelers choose to leave origins. The perceived accuracy of pre-trip information is important in determining whether commuters take account of it in their decision-making, including departure time choice (Khattak *et al.*, 1991).
- Mode choice. Extremely unfavorable information about one mode, such as unexpected delays, may force travelers to turn to other modes. And very favorable information about one mode may, on the other hand, may induce travelers to shift from intended mode to it. Polydoropoulou and Ben-Akiva (1999) found a detectible effect of prescriptive recommendations to take public transport on mode shift, especially in situations of unexpected delay on roads predicted by ATIS.
- Route choice. Perhaps driving route change is the effect that ATIS use is most capable to generate (Khattak *et al.*, 1999). Considerable empirical evidence has been found regarding driver route choice responses to ATIS information (e.g., Khattak *et al.*, 1995).
- Incident diversion response. A special case of the route choice response occurs when a driver becomes aware of an incident or disruption affecting traffic conditions on the current route.
- Driving behavior. For example, the warning messages of adverse road conditions may reduce driving speed (Ng and Mannering, 2000).

- Parking search and choice. Parking guidance and information (PGI) systems inform drivers about the availability and locations of parking. Allen (1993) has summarized four types of benefits of PGI systems, which may be quantified in modeling traveler responses to such parking related information.

Not surprisingly, only few responses such as departure time choice, route choice, have received certain amount of empirical research attention. Others basically remained in the stage of conceptualization. Despite the number of publications in this field, Lappin and Bottom (2001) concluded, the understanding of traveler responses to ATIS is still in its initial stages. The current state of knowledge provides at best general qualitative conclusions. Nevertheless, two important messages were conveyed from the above review: 1) dynamic real-time information *does* make a difference in travelers' behaviors; and 2) Using appropriate methodology and data, the effects of real-time information can be measured quantitatively.

It is commonly acknowledged that information will not change the objectively measurable reality regarding travel alternatives, but rather affect a traveler's perception of this reality (e.g. BenkAkiva *et al.*, 1991) and in turn travelers base their travel choices, which include the traveler responses summarized above, on perceptions of, or beliefs regarding, reality instead of on the reality itself (e.g. Recker and Golob, 1976). Based on this theory, Chorus *et al.* (2006a) constructed two paths along which perceptions can be updated with information provision and further influence travel choices:

> *"[…]firstly, information on travel possibilities may serve in the process of generation of travel alternatives by updating a traveler's perception of availability (i.e. awareness) of travel alternatives, or in other words, his choice set. Secondly, information on travel costs may serve in the process of assessing the travel alternatives a traveler is aware of by updating his perception of characteristics of travel alternatives*."(Chorus *et al.*, 2006a, p.137)

Based on these ideas, the following iterative decision scheme was presented by them for a traveler's acquisition of travel information (Figure 2.1). Detailed explanation of this scheme can be found in the article. Similar scheme can also be found in early theoretical works (Ben-Akiva *et al.*, 1991). This scheme is a rather good, generic framework for explaining the mechanism of information acquisition and its effect on trip-specific choice making and execution. The trip-specific responses listed above can be substituted for the travel choice square in the diagram, to represent conceptually how these responses take place with real-time information provision.

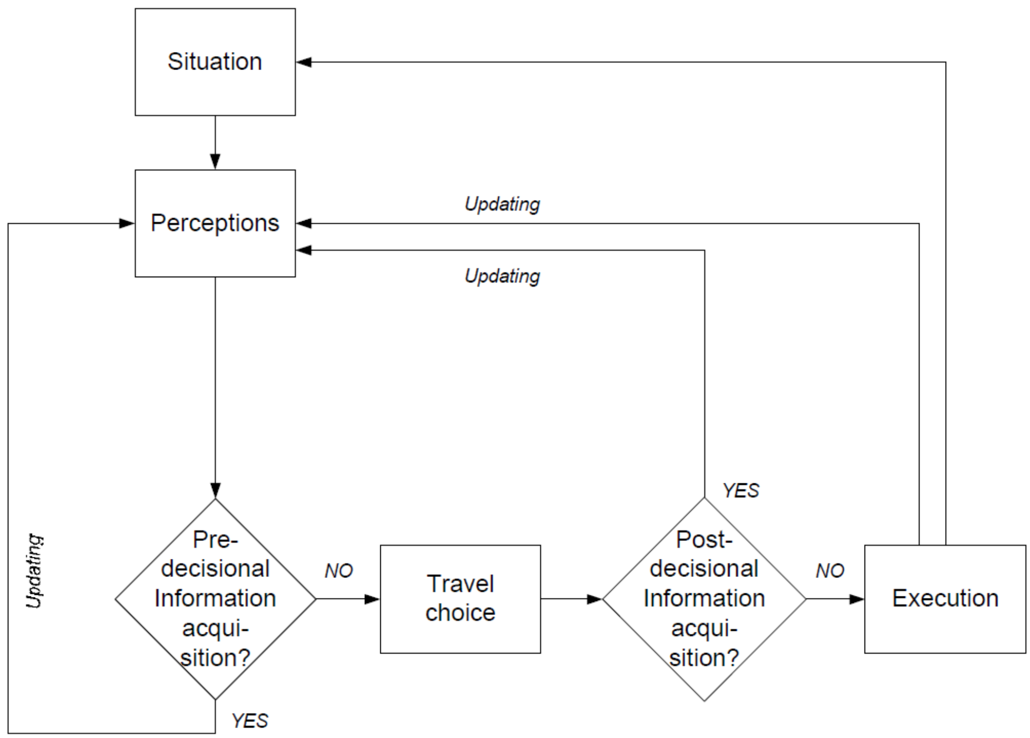


Figure 2.1 Traveler Information acquisition and effect on travel choice in iteration (Source: Chorus et al., 2006a)

Another literature review also by Chorus *et al.* (2006b) focused on three types of behavioral responses to ATIS that are expected to reduce passenger transport externalities: 1) mode shift from private car to public transportation 2) departure time change, and 3) route change. On a basis of the review on empirical evidences from more than 15 years of studies, the authors have derived a number of generic, integrative insights, including: "*it appears that our expectations with respect to the effects of information provision on travel choices in general may be mildly optimistic, particularly for behavioral changes not involving changes in mode-choice. In the longer term, the effects of information provision, when presented to travelers in suitable formats, are likely to be somewhat stronger than the short term effects, due to learning dynamics*." (Chorus *et al.*, 2006b, p.354)

A brief recap of these review articles, with a few hundred studies as backdrop, provides us with some sound theoretical basis and valuable insights for understanding travel behavior under real-time transit information, a special subset of ATIS service essentially.

2.3 Traveler Behavior with Real-time Transit Information: Two approaches

Traveler's behavior under auto-oriented ATIS has been studied for about two decades with a body of abundant literature, as demonstrated by our review in previous section. When it comes to real-time transit information, however, there exist only a small number of studies to date.

Parallel to what are asked regarding travel behavior with ATIS, from the traveler's perspective, several interrelated questions concerning travel behavior with real-time transit information have been asked by scholars: What kind of transit information is useful and attractive to users? What determines travelers' use of real-time transit information? What is the value, measured by traveler's willingness-to-pay, of this kind of information? And how travelers would actually respond to real-time transit information behaviorally and psychologically? Of particular interest to this dissertation is the last question. Previous studies addressing this question can be classified into two categories – effectiveness evaluation study and modeling study – in terms of their methodological approaches.

The first approach is the empirical evaluation of transit rider reactions to real-time transit information systems. When a RTPIS is being deployed in real world, the agency is likely to conduct some evaluation study in order to evaluate the effects and justify the investment. Typically both a before survey and an after survey among transit users were carried out by transit agencies to obtain information on individual characteristics, use of and attitude toward transit service, and use of and attitude toward real-time information. Based on such data, statistical comparisons of before-and-after aggregated indicators regarding effects of such systems are generally performed to see whether these systems have effectively generated some desirable outcomes.

For example, the landmark survey that measured people's reactions to the London Countdown system was reported by Smith *et al.* (1994). This survey covered perhaps one of the most complete sets of issues related to real-time information, including system reliability, bus service reliability, ergonomics, passenger behavior at stops, passenger perceptions and valuation of Countdown, and ridership and revenue generation. Several frequently cited key findings are 1) video survey and interview of passenger behavior at stops suggested much reduced stress; 2) the average perceived waiting time dropped from 11.9 minutes to 8.6 minutes; and 3) passenger valued Countdown at an average of 31cents.

Two well-known examples in the U.S. are Transit Watch (TW) in Seattle, Washington (Mehndiratta *et al.*, 2000), and Transit Tracker in Portland, Oregon (Science Applications International Corporation, 2003). The agencies responsible for these systems both carried out surveys to evaluate system effectiveness. One of the important findings from the TW satisfaction evaluation survey was that although TW and the improved information is perceived as a real benefit by its users, the users did not seem to think that it increased their overall satisfaction with the transit experience. Likewise, the Transit Tracker survey found no significant difference between satisfaction ratings before and after Transit Tracker was in place. It could be attributed to the fact that riders were already very satisfied before the deployment of Transit Tracker. In terms of ridership, the study found no changes in nighttime ridership at the bus stops as a result of deploying Transit Tracker.

A recent study focused on psychological effects of real-time train arrival information (Dziekan and Vermeulen, 2006). The authors collected a panel sample of travelers (N=53) for before-and-after time points. They found the perceived wait time decreased by 20 percent, while no effects on perceived security and ease of use were identified.

An even more recent study was the evaluation of OneBusAway, a real-time arrival information system operated by King County Metro in Seattle, Washington (Ferris *et al.*, 2010). The survey directly asked OneBusAway users to self-report how they respond to the system. Relying on respondents' self-reports, the study shows a set of behavioral and psychological positive outcomes: strongly increased overall satisfaction, decreased waiting time, increased transit trips per week, increased feeling of safety, and even a health benefit in terms of increased distance walked. The limitations of self-report bias and lack-of-control-group were actually recognized by authors.

The advantages of this type of studies are that they collect data in real-world environments and often look at both behavioral and psychological responses. However, these practice-oriented evaluation studies rarely make a careful experiment-like design or apply sophisticated modeling techniques to empirical data. As a result, one could hardly infer the causal effects of real-time information on the behaviors or perceptions because many confounding factors that influence the outcomes may very well exist.

The second approach is modeling study. Stated-preference survey or simulation was often applied to model the effects of real-time information on transit passengers at individual level. For example, two studies utilized stated-preference surveys to explore potential impacts of advanced transit information on mode preference (Abdel-Aty *et al.*, 1996; Abdel-Aty, 2001; Reed and Levine, 1997). Travelers were asked how likely they would consider transit use when given certain advanced transit information. Both studies found promising potential of advanced transit information (real-time schedule information in second case) in increasing the preference for transit.

Another kind of rider behavior that was researched was passenger path choice with real-time transit information. Hickman and Wilson (1995) developed one of the first dynamic path choice frameworks that take into account information on bus arrival at stops and its accuracy. It was assumed that the strategy of passengers to board a vehicle is to minimize total expected travel time, which can be informed to passengers through real-time information. To evaluate path choices and travel time benefits resulting from the information, the model was applied to a case study corridor, using a computer simulation to model vehicle movement and passenger path choice. The results suggest that real-time information yields only very modest improvement in passenger service measures such as the travel time and the variability of trip times, but significant changes in path assignments. Further they found improving information accuracy has only a slight effect in improving travel times.

A recent study by Gentile *et al.* (2005) developed a general framework for investigating passenger's path choice in transit networks when online information about carriers' arrival times at stops are available. They assumed that passenger's ultimate objective is to minimize the total travel time. The numerical example found drastic differences in terms of proportions of passengers boarding slow and fast common lines, while the differences on total travel times are less important yet relevant.

The study by Mishalani *et al.* (2000) is unique in that it took passenger utility as the dependent variable. The utility is assumed to be a function of the difference between the estimated waiting duration acquired by the passenger upon arriving at the bus stop and the actual time that passenger waits for the bus. Then passenger arrivals and transit bus operations were simulated as a stochastic system. Passenger utilities under different real-time information provision scenarios were computed based on simulation. The problem of this study is the vague definition of utility and unconvincing utility function. It is not clear as why utility was defined based solely on the consistency of predicted and actual waiting time.

A recent study by Chorus *et al.* (2006c) first presented a theoretical model of travel information use and effect by incorporating Bayesian updating into a regret-based framework of travel choice, and used numerical simulation to model non-habitual car drivers' mode choice with presence of real-time transit information. Their results showed that even in the case where transit information is acquired, and the message is favorable to transit, its impact on mode choices will be limited. Thus the study suggested conservative estimates of the impact of transit information provision on modal shifts.

With generally sound theoretical frameworks and sophisticated modeling techniques, these modeling studies have provided useful insights about how travelers would respond to real-time transit information. The major weakness of this kind of studies is that they used stated-preference and simulation methods rather than revealed-preference data, which is likely due to the lack of real-world cases of this emerging technology application. The stated-preference approach is characterized by the hypothetical nature of the exercise. Respondents are placed in unfamiliar situations in which complete information is not available. In reality, travelers would not necessarily respond in the ways stated-preferences and simulations suggest. Therefore this approach suffers from an inherent lack of external validity as no real-life behavior is observed.

The literature has painted a somewhat mixed picture at best. On the one hand, stated-preference and simulation studies generally found positive influences of real-time information on mode shift or other travel behavior. On the other hand, real-world applications have not provided definitive evidence of increase in ridership due to real-time transit information, although positive psychological responses were usually detected. Therefore, the small volume of empirical research completed to date and the disparities among the findings point to the necessity for further study.

2.4 Psychology of Waiting with Real-time Information

Waiting is an important component of transit experience. For a typical transit trip, 10-30% of travel time is spent waiting (VTPI, 2010). In transportation studies, total transit trip time is often decomposed into in-vehicle time and out-of-vehicle time (including walking time/access time and waiting time). As a major part of out-of-vehicle time, passenger waiting time is found to be more onerous than in-vehicle time and often cited as one of the most important factors that influence choice of transit modes (see Wardman (2004) for a review). However, waiting-time savings is not only of great economic importance, but also existence of other costs of a psychological nature associated with waiting should not be ignored.

2.4.1 Psychology of Waiting for Service

People regard time to be a valuable resource and actively consider time costs during decision makings. Perceptions and attitudes of consumers waiting time are of great importance for service industries in which consumer waiting has a significant impact on satisfaction and global evaluation of service quality (Durrande-Moreau and Usunier, 1999).

As noted by Katz, Larson, and Larson (1991), there are basically two ways for a service provider to manage waiting. The first is to decrease the actual length of wait through operation management techniques (e.g., increase bus frequency in transit setting). In addition, it has been argued that managing the psychological experience of a customer's waiting can reduce perceived waiting time and thus is as effective as reducing the wait time itself (Maister, 1985). A seminal article by Maister (1985) has theoretically proposed eight "propositions" of psychology of waiting lines. Two more propositions were incorporated later (Davis and Heineke, 1994; Jones and Peppiatt, 1996). Therefore, ten universally-recognized propositions on the psychology of waiting are as follows:

1) Unoccupied time feels longer

2) Pre-process/post-process waiting feel longer than in-process

3) Anxiety makes waiting seem longer

4) Uncertain waiting is longer than known, finite waiting

5) Unexplained waiting seems longer

6) Unfair waiting is longer than equitable waiting

7) People will wait longer for more valuable services

8) Waiting alone feels longer than in groups

9) Physically uncomfortable waiting feels longer

10) Waiting seems longer to new or occasional users

Building upon above conceptual propositions, researchers have identified a number of individual and situational factors that influence people's psychological responses to waiting. For many years, scholars have examined the effects of these situational factors empirically in order to provide implications for manipulation of waiting psychology. Durrande-Moreau (1999) surveyed 18 empirical studies on a comparative basis.

Prior studies (Taylor and Fullerton, 2000; Durrande-Moreau, 1999) have identified three levels of outcome variables of waiting experience. The first level is *perceived waiting time*, defined as the "*customer's perception of the length of time over which the person is engaged in waiting*" (Taylor and Fullerton, 2000, p.174). The second level is *affective reactions* to the wait, which is referred to as feelings and emotions people have toward the wait. Stress, anxiety, irritation, frustration, and boredom are commonly mentioned concepts of affective reactions in the context of waiting for service. The third level is consumer's evaluation of, or global satisfaction with, service quality provided. This service evaluation is often assessed as the ultimate dependant variable of service waits. And empirical results suggest that it is less sensitive to wait experience because the wait is just one element of the service delivery.

What is of great relevance to this dissertation is one of Maister's propositions that "*uncertain waiting feels longer than known waits*." Based upon this proposition, it is often hypothesized that providing information about waiting length would decrease the uncertainty, and thus generate positive effect on waiting experience. Theoretical discussions tend to favor this argument (Maister, 1985; Osuna, 1985; Larson, 1987). For instance, Osuna (1985) developed a theoretical basis for analyzing building up process of stress during the waiting period. The results gave theoretical support to the providing "real-time" information to people in waiting situations, particularly in the operation of public transportation systems.

But empirical evidence from a limited number of existing studies has been mixed so far. For example, Ahmadi (1984) found that when informed of waiting length, people tend to report shorter perceived waiting time for short waits of less than 5 minutes. Hui and Tse (1996), however, found duration information provision influenced perceived waiting time only in longer waits (15 minutes). Katz *et al.* (1991) in their field work in a bank found that providing wait time information reduced perceived waiting time but did not affect stress levels and satisfaction of customers. Similar results were reported by later empirical studies in other settings (Antonides *et al.*, 2002; Groth and Gilliland, 2006). Hui and Zhou (1996) even found no effect of providing waiting duration information on perceived waiting time. And according to them, the more favorable attitude toward service due to waiting duration information can be attributed to increased sense of control over wait and higher acceptance level of wait.

Besides several laboratory experiments, most field experiments were carried out in settings of post offices, shops, banks, hospitals, or telephone services. Very little has been focused on psychologies of waiting for public transportation.

2.4.2 Passenger Actual and Perceived Waiting Time

As concerns the study of waiting time, there are two interrelated concepts involved: actual waiting time and perceived waiting time. The definitions of two concepts are as follows (Durrande-Moreau and Usunier, 1999).

- Actual waiting time: objective time individual spends in waits, based on reality, as measured by clocks, watches, and chronometers.
- Perceived waiting time: subjective time individual experiences in waits, based on perceptions. Subjective time is often depicted as perceptual, flexible, changeable, and elastic, susceptible to various factors.

In transportation field, objective time is of primary interest to researchers and practitioners, as time savings is one of the major economic incentives for transportation policy and projects.

Passenger waiting times, in objective sense, depend on patterns of passenger arrivals and bus arrivals at boarding stops. The latter is directly influenced by the schedule.

Traditional model suggests that expected passenger waiting time is one-half of the transit headway (Hall, 2001). This is based on the following assumptions: (a) passengers arrive at stops randomly; (b) passengers get on the first vehicles that come; and (c) the service is reliable, i.e. the vehicles arrive regularly. When service reliability is considered a problem, it is found that the average passenger waiting time is expected to be longer. Therefore, when the third assumption is relaxed, the well-known model was developed to estimate the expected waiting time shown as follows (Mohring, *et al.*, 1972):

$$W = h \times \frac{\left(1+\frac{S^2}{h^2}\right)}{2} \tag{2.1}$$

Where

W is expected passenger waiting time,

h is mean headway between vehicles, and

S^2 is variance of headway between vehicles.

Empirical results show that the first assumption (i.e. random distribution of passenger arrivals at stops) holds true when headway is small (e.g., random arrivals dominate below a short headway threshold between 5 and 10 min; Jolliffe and Hutchinson, 1975). When headway becomes longer or transit service is more infrequent, it is expected that some passengers might plan their arrivals at the stops according to timetables to reduce their waiting times. That is, passenger arrivals would become less random as headway increases.

In this regard, it is generally theorized that passengers fall in two classes, those who are aware of schedules and plan their arrivals (“aware” passengers), and those who are not (“unaware” passengers) and arrive at random (Jolliffe and

Hutchinson, 1975; Turnquist, 1978; Bowman and Turnquist, 1981). Empirical evidences show that those aware passengers arrive by non-stationary patterns, with peak arrival rates a few minutes before scheduled vehicle departures. In coordinating their arrivals with timetables, “aware” passengers implicitly trade-off the risk of missing their buses against the added time of allowing larger safety margins (Hall, 2001).

There appears to be little research on how trip characteristics, passenger demographics and stop environment are related to passenger arrival patterns and waiting time at stops. Fan and Machemehl (2009) developed an OLS model investigating the relationship between observed passenger waiting time and a set of explanatory variables including bus headway, service reliability, location, traffic periods, gender, ethnicities, and access modes. Hall (2001) also built an OLS model with reported waiting time as a function of a host of trip and rider characteristics. Their results show that, in addition to traditionally recognized determinants (i.e. service frequency and reliability), some of the trip and passenger characteristics may significantly influence passenger waiting time (either actual or reported), such as driving as access mode, need of arriving by a set time. In Hall’s study, knowledge of schedule has a highly significant and negative effect on reported waiting time, meaning that “aware” passengers tend to experience shorter waiting times.

Literature of psychology has shown that, although highly dependent of each other, actual time may not be readily translated into perceived time. Psychologists have found a number of temporal and non-temporal variables that might account for the differences in time perception. Allan (1979), on the basis of a few early experiments, has concluded that a linear function probably exists between perceived and subjective time. It has been consistently shown by empirical studies that the function between subjective and objective time represents that the subject's response is a simple linear transformation of perceived time. Other factors that may influenced perceived durations include non-temporal characteristics of activities (e.g. the nature of the activity, personal enjoyment from the activity), personal characteristics (e.g. male vs. female), or spatial schemes (Hornik, 1984).

There exist a small number of studies that examine the correlation between actual and perceived waiting times in the context of public transportation. Moreau (1992) found that passengers overestimate the average waiting time (of 3.5 minutes) by 14%. The shorter people waited, the greater the overestimation of the waiting time. With 5-minute waiting time, the perceived waiting time is reported correctly, and with up-to-15-minute waiting time, the perceived time is slightly underestimated. The same pattern is reported in Van Hagen *et al.* (2007). Collecting a small-sized sample from a stop (N=83), Mishalani *et al.* (2006) reported a 14.6% overestimation of mean perceived waiting times (6.61 vs. 5.77 minutes).

2.4.3 Summary

Psychology of waiting for service is a subfield that has been explored for many years. Theoretical discussions agree that providing information about waiting duration will decrease the perceived waiting time, positively influence affections of waiting, and in turn increase customer’s overall satisfaction with service. Empirical investigations of this proposition give mixed information so far, suggesting that the aforesaid benefits of providing information of waiting duration may not occur or may take place under certain conditions.

Public transportation is a kind of special service provided to the public by transit agencies. Waiting for transit service constitutes a crucial component of transit trips. Transportation researchers and practitioners mostly concentrate their eyes on actual waiting time as time savings in waiting are one of major benefits of transport policies and projects. Thus they tend to neglect psychological aspects of waiting for transit service. When it comes to real-time transit passenger information provision, using before-and-after indicators, many project evaluation studies have shown that real-time transit vehicle arrival information may decrease perceived waiting times and cast positive psychological effects on passengers (See Dziekan and Kottenhoff, 2006 for a summary).

However, so far there exists little study that draws on psychological framework to model impacts of transit information on passenger waiting psychology.

2.5 Chapter Summary

From above review of relevant literature, several knowledge gaps in understanding traveler behavioral and psychological responses to real-time transit information can be identified as follows:

- Although there is a fairly large body of literature on traveler behavior with ATIS, the real-time transit information, as a subset of ATIS service, and its effects on travelers have only been studied with a limited number of studies. And the research to date employed two types of approaches, either of which has intrinsic weaknesses in inferring real and realistic causal relationships between travel decisions and real-time transit information. And a mixed picture has been painted so far based on previous research on this topic. Research using revealed-preference empirical data collected in real-world settings, valid research design, and sophisticated inference techniques is needed so badly, if we want to deepen our understanding of such particular question.

- There is a lack of an integrative, comprehensive conceptual framework for understanding such issue. Effects of real-time transit information were put forward fragmentally. An integrative, comprehensive conceptual framework linking real-time transit information with all major potential effects in a logic, systematic way is needed as a basis for further investigations.
- Psychological responses are largely neglected in the previous research framework of traveler behavior with ATIS, probably with stress reduction as an exception. However, when it comes to real-time transit information, its potential psychological effects are not ignorable since travelers' responses to such information may of a psychological nature mostly. Also some of those psychological effects were identified in practice-oriented system evaluations, psychological outcomes of real-time are hardly incorporated into the framework as well as in scientific examination in the transportation field.
- Literature on psychology of waiting for service has provided some theoretical basis and empirical evidences regarding psychological costs and outcomes of providing real-time information to customers in waits. However, very little is set in the context of public transportation.

This dissertation aims at filling in some, if not all, of these gaps by 1) proposing an integrative conceptual framework, 2) carefully designing research structure and collecting revealed preference data from a case of real-world real-time transit passenger information system; 3) modeling both behavioral and psychological responses to such information with sophisticated modeling techniques.

Chapter 3: Conceptual Framework

3.1 Introduction

Potential traveler behavioral and psychological changes due to real-time transit information were put forward and explored by a variety of studies, including, but not limited to, modal shift (Abdel-Aty *et al.*, 1996; Reed and Levin, 1997; Abdel-Aty, 2001; Chorus *et al.*, 2006c), path choice (Hickman and Wilson, 1995; Gentile *et al.*, 2005), increased transit trips (Ferris *et al.*, 2010), adjusted behavior such as utilization of wait time and stop change (Nijkamp *et al.*,1996); reduced perceived waiting time (Smith *et al.*, 1994; Infopolis2, 1998; Dziekan and Vermeulen, 2006), increased feeling of security (Infopolis2, 1998; Dziekan and Vermeulen, 2006), increased ease-of-use (Stradling, 2002; Dziekan and Vermeulen, 2006), reduced stress or anxiety (Schweiger, 2003; Smith *et al.*, 1994), increased customer satisfaction (Mehndiratta *et al.*, 2000; Science Applications International Corporation, 2003).

However, effects of real-time transit information put forward by previous research were fragmental at best, rather than under an integrative, systematic framework. Dziekan and Kottenhoff (2007) tried to use a mind map to depict seven possible main effects of at-stop real-time information displays (Figure 3.1). This mind-map format framework is insightful yet incompetent to systematically capture the relationships among real-time transit information and potential traveler behaviors and psychology.

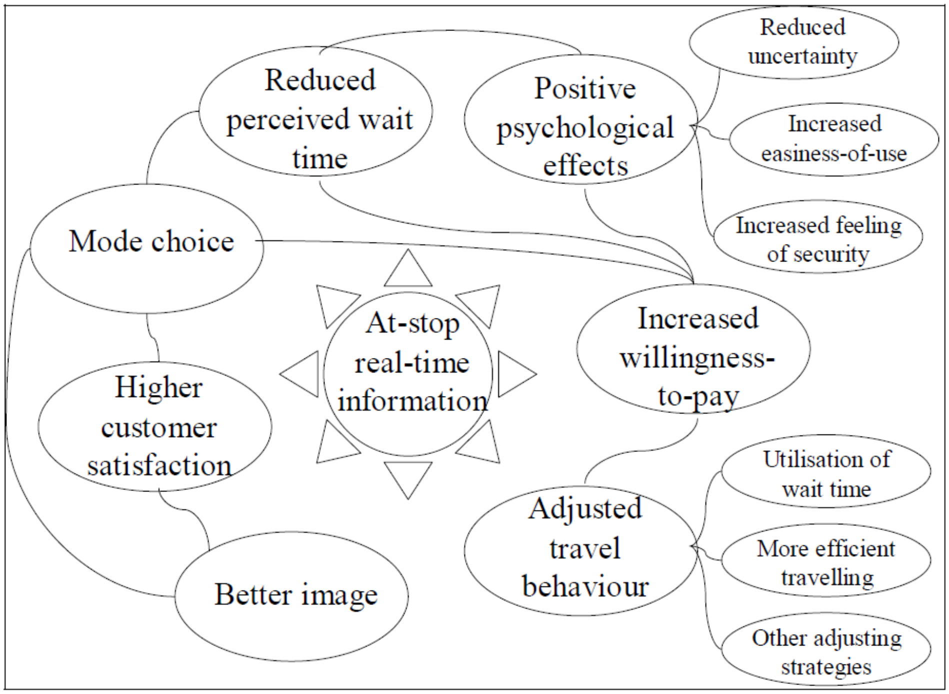


Figure 3.1 Mind map on possible effects of at-stop real-time information displays (Source: Dziekan and Kottenhoff, 2007)

This chapter is aimed at presenting a conceptual framework for understanding and examining behavioral and psychological effects of real-time transit information. The organization of this chapter is as follows: the overarching conceptual framework and hypotheses are presented in Section 2, followed by two sections elaborating traveler trip-specific responses as well as general or cumulative responses in details respectively. Finally, section 4 summarizes this chapter.

3.2 Overarching Framework and Hypotheses

The conceptual framework contains the key factors, the variables and presumed relationships amongst them (Miles and Huberman, 1994). The overarching conceptual framework is presented in Figure 3.2.

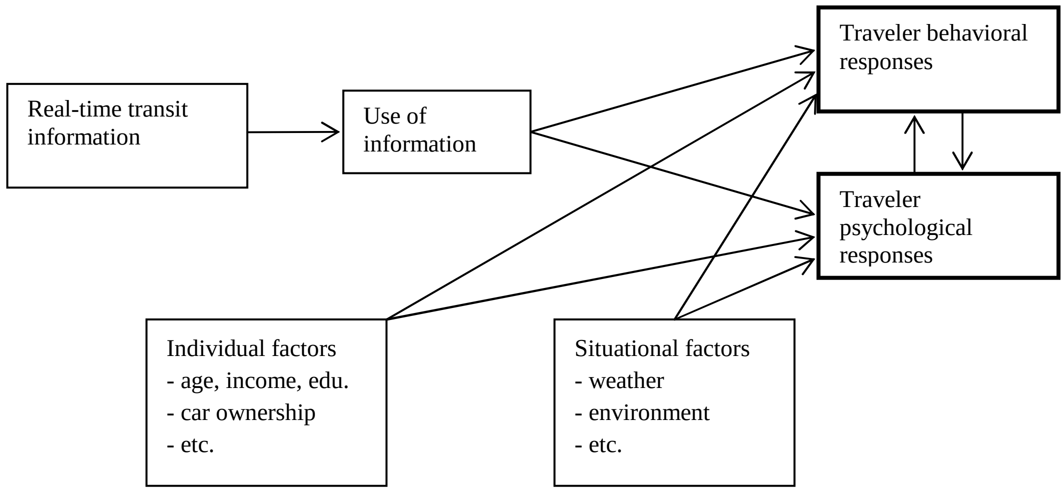


Figure 3.2 Overarching conceptual framework of traveler responses to real-time transit information (Source: Author)

Let us suppose that some transit agency provides travelers with real-time information about transit service (e.g real-time bus arrival information, bus seat-availability information) with intention to induce a change of travel-related behavioral change in ways that are beneficial to the transportation system and generate positive change in attitudes towards and perception of public transit service. In order for such change to occur, first travelers must acquire the information and then the acquired information must lead to the desirable behavioral and psychological outcomes. Information acquisition/use is referred to as that information is searched for or paid attention to by travelers and processed by her. However, this dissertation, as I describe in Chapter 1, is only focused on the second stage of this process. That is, I would like to examine the behavioral and psychological change as a result of acquired real-time transit information, without accounting for the process of information acquisition.

Traveler responses to real-time transit information are classified into two constructs – traveler *behavioral* responses and traveler *psychological* responses. The former refers to what travelers physically act upon real-time information. The latter means the traveler's change in psychological outcomes (e.g., attitudes and perceptions) concerning transit trips and service due to real-time transit information. It has been generally acknowledged by scholars and practitioners that, unlike ATIS for drivers, a large portion of effects of real-time transit information system are considered to be more of a psychological nature (Dziekan and Vermeulen, 2006). Bearing that in mind, many transit agencies paid particular attention to psychological benefits when they considered deploying the systems and many evaluation studies tried to assess these psychological benefits. This dissertation joins these scholars and practitioners by arguing that traveler's psychological responses should be conceived as an indispensible component of traveler responses to real-time transit information, when it comes to considering and assessing effects of real-time transit passenger information systems.

Further, each type of responses is divided into two categories in terms of the response time frame. Real-time information directly influences a transit user's behavioral decisions and psychological conditions around specific transit trips he or she engages in. *Trip-specific behavioral* and *psychological responses* comprise the first category.

Given a much longer response time frame, with cumulative experience from a certain number of stand-alone journeys, traveler's general travel behavior and general perceptions on transit service may adapt due to acquisition of real-time transit information. This is what I call *general traveler responses*. The general activity-travel behaviors can be either a simple accumulation of deliberate trip-specific travel decisions or some change in habitual travel behaviors. For example, for every trip, a traveler deliberately shifts the mode choice from intended private car to transit because of favorable information. Her cumulative number of trips by transit mode increases accordingly. Alternatively, a few trials of transit under real-time information may make people aware of the attractiveness of transit, break their bad travel habit (e.g., driving to work), and then build a new habit in favor of transit.

As for psychological responses, psychological literature suggests that the choice of temporal reference period (i.e. response time frame) shall be an important consideration in assessing the psychological conditions (Terry *et al.*, 2005). Details about trip-specific and general responses will be elaborated in the following two sections.

The construct of real-time transit information has several major dimensions:

1) *Information content*.

Abdel-Aty (2001) has found that commuters seek several types of transit information using a stated-preference survey, including information about operating hours, frequency of service, fare, transfers, seat availability, walking time. Many types of such transit information are potentially able to be provided real-time to transit users. The white paper on real-time transit information issued by FTA (2002) provides a summary of various types of real-time information that can be provided, such as (adapted from FTA (2002)):

- Estimated arrival or departure times for, or “countdown” to, the next vehicles,
- Vehicle locations,
- Service disruption/delay information,
- Seat availability for the next vehicles,
- General information on service area, fares, routes, and travel times,
- Information on transfers and other local/regional transportation services,
- Other real-time information, such as date, time, and weather, and
- Peripheral information, such as advertisements, security related information and updates during terrorist/emergency events, and other general events in the local area.

It is a fact that the first type of real-time information (i.e., predicted real-time transit vehicle arrival times) is most often referred to when real-time transit information is mentioned and comprehended. And this dissertation does focus on this type of advanced transit information. In spite of that, it is noteworthy that other types of real-time information may also very much influence traveler’s choice and psychology. For instance, a recent study by Kim *et al.* (2009) has shown that real-time seat availability information does have an effect on passenger choice of a bus.

2) *Place of information*.

Thanks to the advancement of modern information and communication technologies, real-time transit information can be disseminated via a variety of media. The white paper by FTA (2002) has summarized those interactive or non-interactive media including Internet, Dynamic Message Signs (DMS), Interactive voice response

(IVR) via telephone, video monitors, interactive/non-interactive kiosks, PDAs, Wireless Application Protocol (WAP)-enabled mobile telephones, cable television, and Short Message Service (SMS). Peng and Jan (1999) assessed some of the means of advance transit information delivery. And a recent stated-preference research (Caulfield and O'Mahony, 2009) shows that providing real-time transit information via a mobile phone short message service (SMS) can give riders very high utility.

However, it is believed by the author that, what matters most to use and effect or real-time transit information is where such information is disseminated by media and acquired by travelers, rather than the dissemination media per se. The variety of media for information dissemination offers high flexibility of place of information use. Two fundamentally different types of information acquisition places are *pre-trip* information acquisition and *en-route* information acquisition (e.g. access, at-stop, onboard, and at-transfer-point information acquisition). Specifically, travelers can search for pre-trip information to update perceptions and make pre-trip travel choices (such as mode, path, departure time); or they can acquire information in the course of trip, and thus modify their behaviors and psychology accordingly. Of course, one can argue that post-trip information acquisition is also possible. But generally speaking, the use and effects of such post-trip information are marginal.

3) *Cost of information*.

The literature generally states that there is among travelers a low willingness-to-pay for information provided via ATIS service (e.g. Khattak *et al.*, 2003), especially for transit information among passengers (Molin and Chorus, 2004), as transit riders mostly feel they have already paid for such information by purchasing tickets. In addition to monetary costs of information, searching for or acquiring information may also entail other costs depending on the ease-of-use or accessibility of the system, such as time costs and psychological costs associated with information acquisition and comprehension. Those monetary and non-monetary costs of real-time transit information are expected to not only determine whether information is going to be used, but also affect traveler's choice and perceptions of transit service after using it.

4) *Information quality*.

Almost every study on ATIS stresses the importance of information quality. Accuracy, reliability, timeliness and coverage of the information are conceived as the key to ATIS use and traveler's responses. A DOT's white paper on data quality in ATIS applications (Ahn *et al.*, 2008) defines six measures: accuracy, completeness, validity, timeliness, coverage, and accessibility. The accuracy of real-time information is always one of the top concerns for ATIS service. For example, a stated-preference study (Fox and Boehm-Davis, 1998) showed that 40 percent accuracy of traffic information would not support user trust and compliance, but that 60 percent accuracy probably would. The white paper (Ahn *et al.*, 2008) also recommends only 10-17% error range for travel time estimation in terms of prediction accuracy. The distinction between accuracy and another seemingly similar measure, accessibility, was given by Schweiger (2003): accuracy refers to whether or not the information presented is correct, and reliability refers to whether or not the information is presented consistently (e.g., updated on a regular basis to be timely).

The key to accurate predictions of real-time transit vehicle arrival times is two-fold: the prediction algorithm or model, and the data that are used as input to the algorithm (Schweiger, 2003). The bus arrival time prediction models have been generally based on historical arrival time patterns and/or other explanatory variables correlated with the arrival time, including historical arrival time (or travel time), schedule adherence, weather condition, time-of-day, day-of-week, dwell time and road-network condition (e.g. Lin and Zeng, 1999; Shalaby and Farhan, 2004). Accuracy of real-time transit information is more of an issue for bus than for train because of the higher complexity and dynamics of road conditions.

Parallel to findings in the field of traffic-related ATIS, I would like to hypothesize that quality of real-time transit information is also a key to travel behavior and psychology under such system.

Other factors that influence traveler behaviors and psychologies are classified into two categories: individual factors and situational factors. Individual factors refer to individual or household socio-economic characteristics, such as age, income, car ownership, etc. Situational factors are those that are not able to be controlled by individuals, including travel time and cost, weather, built environment, and so on.

The causal links among constructs are illustrated as well in the diagram. Note that traveler behavior and psychology are causally interrelated. On the one hand, it is well documented that travelers' perceptions of environment is actually in the middle between the object, measurable environment and the actual travel choices (Chorus *et al.*, 2006a). On the other hand, travelers' behavioral adjustment will also directly change their psychology on travel and travel service. These interactions take place in iterations, as illustrated in Figure 2.1.

Based on above framework, two general hypotheses are proposed:

H1: Travelers will modify their travel behavior according to high-quality real-time transit information use in ways that their travel becomes more efficient and in favor of public transit in general.

H2: High-quality real-time transit information will positively affect passengers' psychology on public transit.

3.3 Trip-specific Responses to Real-time Transit Information

3.3.1 Trip-specific Behavioral Responses

This sub-section presents a behavioral framework for a transit trip under real-time transit information provision. Passenger's dynamic travel behaviors concerning a specific transit trip with real-time transit information acquisitions can be represented by a hierarchy of pre-trip and en-route choices as illustrated in Figure 3.4. Similar framework for dynamic driver behavior under real-time driver information system can be found in Ben-Akiva *et al.* (1991). As a basis of proposed behavioral framework, I adopt the generic framework by Chorus *et al.* (2006a) for traveler's decision process.

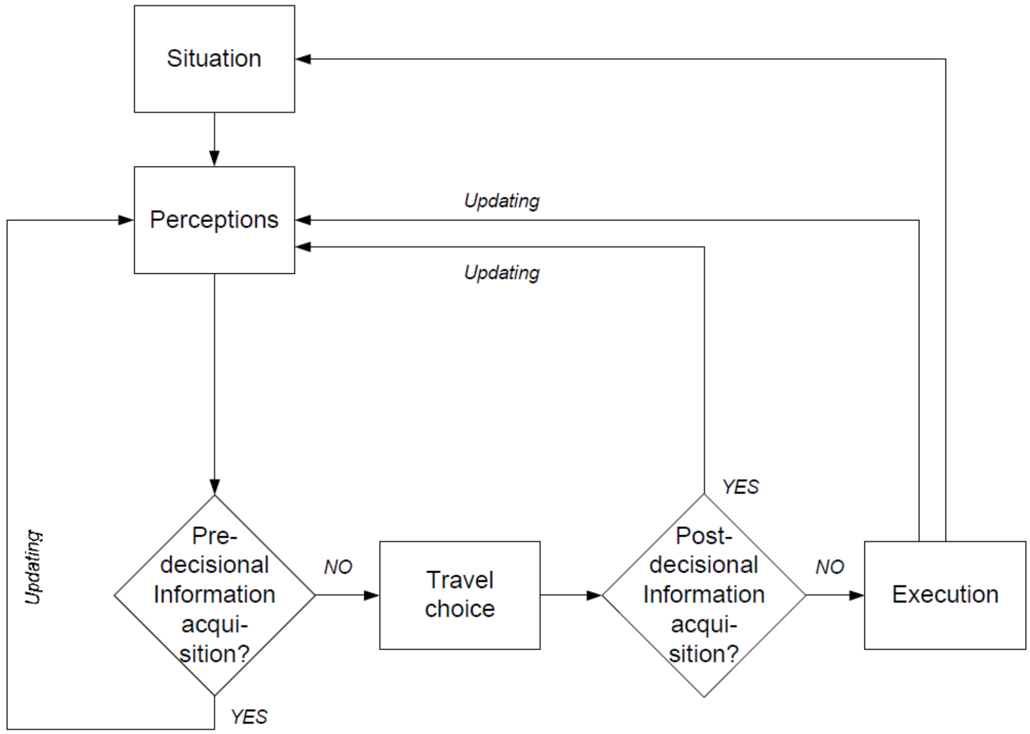


Figure 3.3 Traveler Information acquisition and effect on travel choice in iteration (Source: Chorus et al., 2006a)

In this framework, a transit trip (either repetitive or non-repetitive) is separated into two phases, namely a pre-trip phase and an en-route phase. Pre-trip information acquisition updates the perceptions of alternatives regarding available paths, stops, and departure times. Based on the updated perceptions, passengers make up the choices of intended path, stop and departure time. Note that alternatives among paths or stops may not be always available. When there is a transit network with *common lines* facing a passenger, she may choose between lines with different arrival times and travel times. With pre-trip real-time carrier arrival information, one may choose the express line even the bus comes after the slow one. Also, with more than one transit stops available for a passenger to access, she may choose the one with more desirable environment (e.g., more sheltered, lightning) even if it is further from where she begins the trip, because she acquires and processes the real-time information and is sure that there is no risk missing the coming bus. Be aware that the passenger may choose the slow bus or undesirable stop if the real-time arrival information is unfavorable to the express line or desirable stop.

After the passenger reaches the intended stop, she can acquire the at-stop real-time information to update her perceptions for the first time (is she did not acquire pre-trip information) or again (if she did acquire pre-trip information). Note that this at-stop information acquisition can take place any time between the arrival of the passenger and the vehicle, and can take place multiple times. For example, Nijkamp *et al.*, (1996) found from the case of the STOPWATCH in Southampton, UK, that more than 50% passengers looked at the at-stop electronic information several times. In this sense, the perceptions of travel choice sets may be updated more than one time. On a basis of the updates of perceptions of alternatives, a series of choices are to be made by the traveler:

(1) *Trip quitting* or *modal shift*. The traveler may forgo the trip (especially when this trip is not mandatory) or turn to another mode when she is aware of a long wait time from the real-time information acquisition. For instance, Nijkamp *et al.* (1996) report that in case of a long wait time as indicated by the at-stop displays, of the people who leave the stop, about 39% walked all the way, and 7% hailed a taxi/lift. In either way, the transit trip is put in an end.

(2) *Stop change*. Facing the long wait as suggested by the real-time information, if the passenger chooses to continue the trip with transit mode, she can make another decision to tackle the long wait – walking to a different stop. Again in

the case of STOPWATCH, Nijkamp *et al.* (1996) report that of those who leave the stop, 30% walked to another stop. Also in a stated-preference survey (Ferris *et al.*, 2010), 78% respondents reported they were more likely to walk to a different stop, of whom about 70% would like to walk to a different route, 50% further down the route, and 25% back up the route. Passengers make this stop change decision for various reasons. The most prominent one is obviously to turn to a presumably faster route in order to reduce the waiting time and total travel time. If the real-time information for alternative routes is acquired at the stop and it turns out to be favorable (e.g. much less waiting time), it makes more sense to turn to that route by walking to other stop. Other reasons for walking to a different stop are 1) choosing a stop with desirable environment (e.g., with shelters, lights, seats) to address some concerns (e.g. comfort, safety); 2) walking backward the route to beat the waiting crowd and increase a chance of getting a seat in bus; 3) walking downward the route for exercise or just for occupying the waiting time. Mathematicians have tried to compute some mathematically optimal "bus waiting strategy" (e.g. Saniee, 1987; Chen *et al.*, 2008). However, with real-time arrival information, waiting strategy may be even more truly optimal.

(3) *Diversionary activities around stop*. This is another choice a passenger can make to cope with a long wait. When a passenger is aware of the bus arrival time, she may leave the stop to undertake various activities nearby and return when the bus is due (Science Applications International Corporation, 2003). In the case of STOPWATCH, around 20% of those who leave stop walked to

a shop or bank nearby (Nijkamp *et al.*, 1996). A variation of this behavior would be that if the passenger acquires bus arrival time via other media (e.g., phone, SMS, WAP website) on her way to the stop and is aware of the long wait, she can drop by some shops or banks before arriving at the stop.

(4) *Path choice*. There are two scenarios when a passenger may divert from her intended transit path. First, as discussed above, long wait time suggested by real-time information induces the passenger to walk to another route with faster speed or less waiting time. Second, when there are two common lines – an express line and a slow line, the passenger is often faced with the problem of choosing between either to board the arriving slow bus or to wait for a express one. If with real-time information system the passenger knows that the express bus is only 1-2 minute after the slow bus, chances are that the passenger will skip the slow bus coming first to wait for the express bus, in order to minimize the total travel time. This scenario has actually been simulated by Hickman and Wilson (1995) and Gentile *et al.*, (2005). Both frameworks hold the assumption that a passenger's strategy is to minimize her total travel time. Drastic differences of the passenger loads on express and slow lines were found.

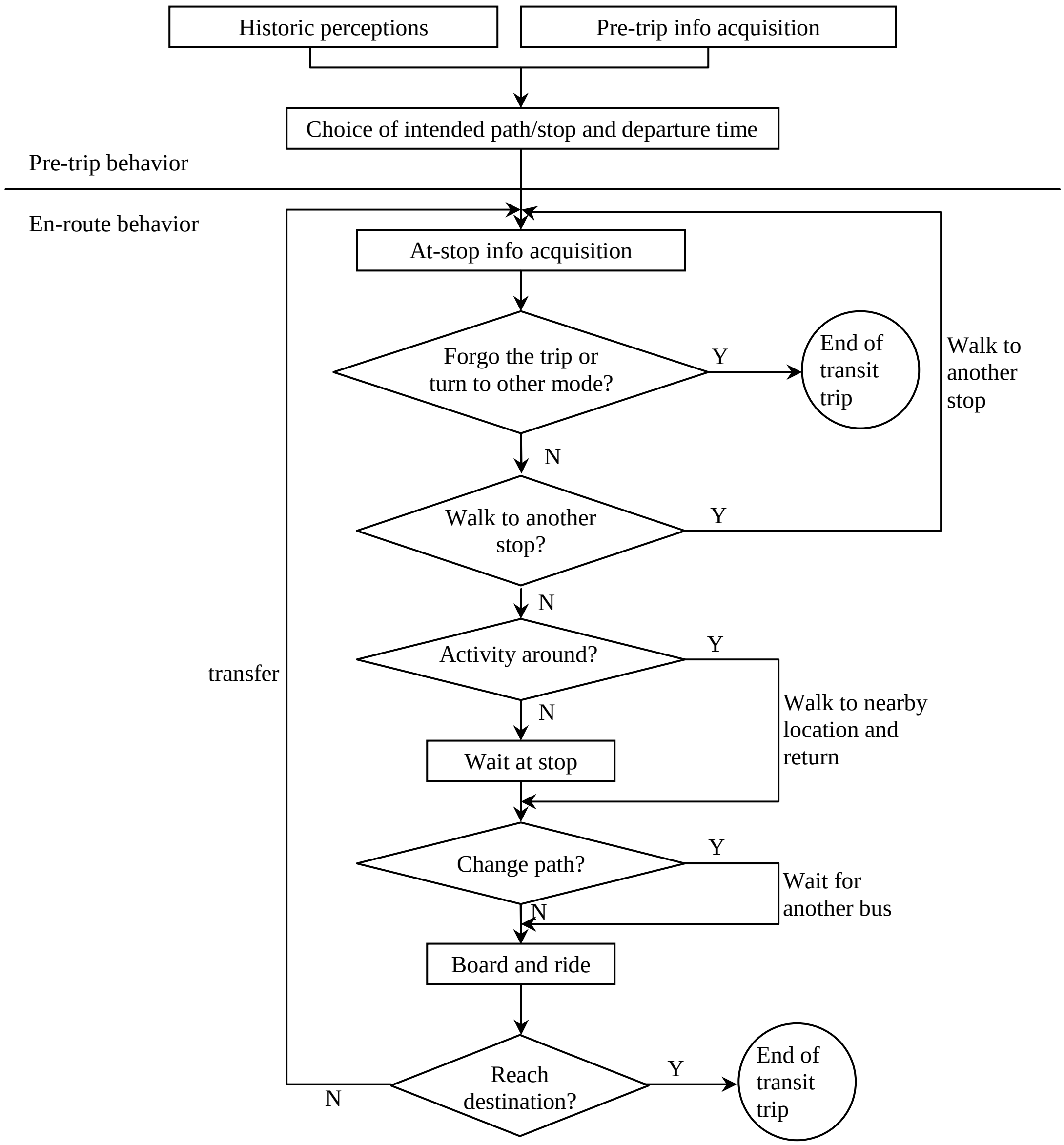


Figure 3.4 Trip-specific travel behaviors with real-time transit information (Source: Author)

The dynamic nature and complexity of these en-route travel behaviors under real-time information is noteworthy. As mentioned above, multiple information acquisitions and perception updates are possible. Thus at any point before the passenger boards a vehicle, she can always go through the process of acquiring information, updating perceptions, and making and executing any of these choices, again and again. In addition, these choices are arranged in the framework with a plausible, logical sequence. However, one can argue that these decisions are being made simultaneously and some of the choices are even alternatives to each other. For instance, in face of an expected long wait for the intended bus, the following decision tree is possible for the passenger (Figure 3.5). Another note related to the general hypothesis H1 is as follows. Some of the changes in trip-specific behavior presented above may seem not to be in favor of transit (e.g. trip quitting, modal shift). However, in all cases either travel efficiency is achieved (e.g., less waiting time, less travel time, better use of time) or some concerns are addressed (e.g., comfort, safety). Therefore, higher utility associated with specific trip-making is almost always the consequence when high-quality real-time information is acquired and travel behavior is adjusted accordingly.

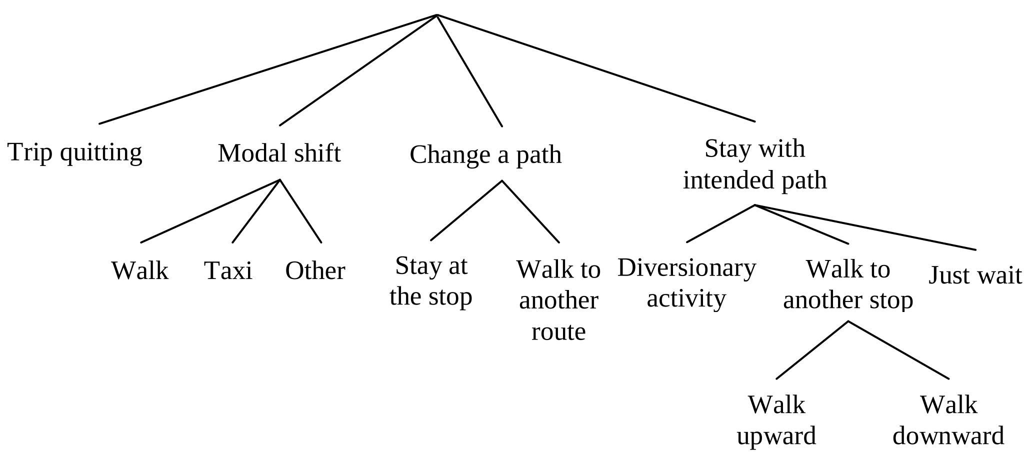


Figure 3.5 A possible decision tree when long wait is expected (Source: Author)

3.3.2 Trip-specific Psychological Responses

The proposed conceptual model for trip-specific psychological responses to real-time passenger information system is illustrated in Figure 3.6.

This model is based on the theoretical framework that research on psychology of waiting for service has built, taking into account the distinctions of public transportation. The outcome variables are classified into three levels as suggested by prior work. The lower levels of outcomes may influence the high levels of outcomes.

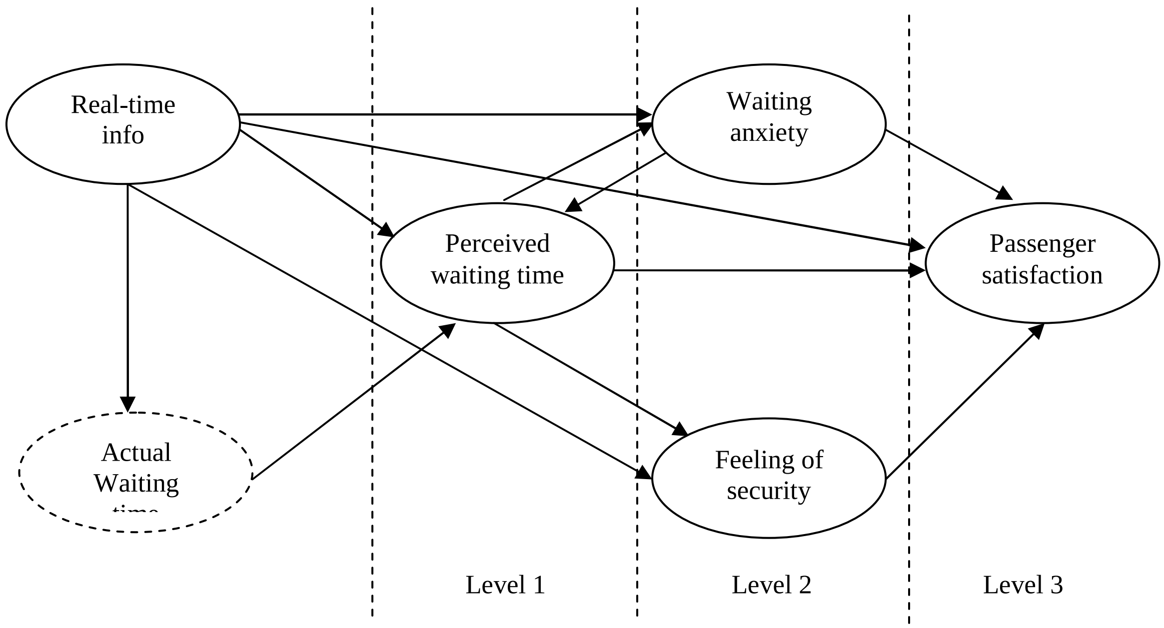


Figure 3.6 Conceptual framework for trip-specific psychological responses to real-time passenger information (Source: Author)

The first level is perceived waiting time. Real-time transit information has actually direct and indirect effects on this critical psychological response. The intermediate construct along the indirect path is actual waiting time, which is no doubt one of determinants of perceived waiting time. In fact, psychological literature suggests a linear function between perceived and actual waiting time (Allan, 1979). Passengers who acquire real-time transit information may adjust their behavior to reduce their actual waiting time. In turn, passenger perceived waiting time is reduced. The direct link between real-time information and perceived waiting time suggests that, even if actual waiting time is the same, providing real-time bus arrival information may psychologically address the problem of exaggeration of perceived waiting time. Mishalani et al. (2006) even assumed that passengers take the predicted bus arrival times, which are indeed the actual waiting times if accurately predicted, as their perceived waiting times.

The second level is affective reactions to the waits. Anxiety is one of commonly mentioned affective reactions. While waiting for the coming transit vehicles, as the clock ticks, passengers easily feel stressed or anxious about such threats as missing the vehicles, missing the connections, being late to the appointments, until they board on the right vehicles and make sure that the vehicles will get to the destinations within their schedule. It is generally accepted that after having to wait for a certain amount of time, anxiety and stress start to build up in an individual, due both to the sense of waste and the uncertainty involved in a waiting situation (Osuna, 1984). Real-time information is presumed to lower this waiting anxiety by significantly reducing the uncertainty associated with waiting. The backward link from anxiety to perceived waiting time is derived from Maister's third proposition: *Anxiety makes waiting seem longer*.

Another outcome of the second level, feeling of security, is a special one to the public transportation service. Since waiting for transit service mostly takes place at outside transit stops, passengers are subject to incidental crimes. In the model, it is hypothesized that decrease in perceived waiting time caused by real-time information use will increase passenger's feeling of safety. In addition, just the mere existence of such an information feedback system creates a general sense of trust in the public transport system (Dziekan and Kottenhoff, 2007).

The ultimate outcome variable is the passenger satisfaction with this trip-specific transit service offered by the operators. Unlike attitudes which exist prior to and subsequent to encounters with a product or service, satisfaction is a direct response to a product or service (Friman and Gärling, 2000). Outcomes of previous two levels contribute to this overall satisfaction. Besides, the mere provision of arrival information boosts passenger satisfaction with transit service consumed by passengers for particular transit trips.

3.4 General Responses to Real-time Transit Information

Two major general travel behaviors with real-time transit information are identified in the framework: *transit trip increase* and *habitual mode shift*.

Ridership increase is always one of the main reasons for transit agencies to invest in real-time transit passenger information system, because this kind of increase can be directly translated into revenues (Schweiger, 2003). Nijkamp *et al.* (1996) listed various induction effects of STOPWATCH on new transit traffic. To summarize their propositions among others, ridership effect of real-time transit information is actually twofold: either travelers shift from other modes to public transportation (especially for new or infrequent transit riders), or they make more trips than before with transit as the mode for additional trips (more likely for frequent transit riders). In either way, from the standing point of individual travelers, their transit trip-making frequency is hypothesized to increase because of real-time transit information use.

The habitual travel choice is defined as repeated choice of a travel behavior without deliberation (Gärling and Axhausen, 2003). For instance, travelers may repeat his commuting mode everyday without deliberately search for alternatives, which can be referred to as *habitual mode choice*. Any attempt at influencing the travel choice may fail if choices are habitual. At least it takes additional measures to make the choices deliberate before they can be changed (Dahlstrand & Biel, 1997). Fujii *et al.* (2001) found that a forced change of a routine mode choice (driving to work) did make people aware of the attractiveness of other alternatives (public transportation). Providing travelers with real-time transit information is also hypothesized to have the potential of making travelers deliberately choose transit first and then use transit as their habitual mode with a certain period of adaption.

A variety of service quality attributes/factors of public transportation have been identified by different studies (e.g., Andreassen, 1995; Eboli & Mazzulla, 2007) including, but not limited to, service availability, frequency, reliability, time traveling, cost, information, safety, quality of vehicle (see TRB(1999) for an example list of 48 transit service quality measures). Theoretical and empirical studies suggest that transit rider's perceptions of these quality areas influence their overall satisfaction with transit service to various degrees (see a model in Figure 3.7). Customer satisfaction is the accumulated experience of a customer's purchase and consumption experiences. Assuming that the customer is capable of evaluating the service quality, the result is compared to expectations prior to purchase or consumption. Any discrepancy leads to disconfirmation; i.e. positive disconfirmation increases or maintains satisfaction and negative disconfirmation creates dissatisfaction (Andreassen, 1995).

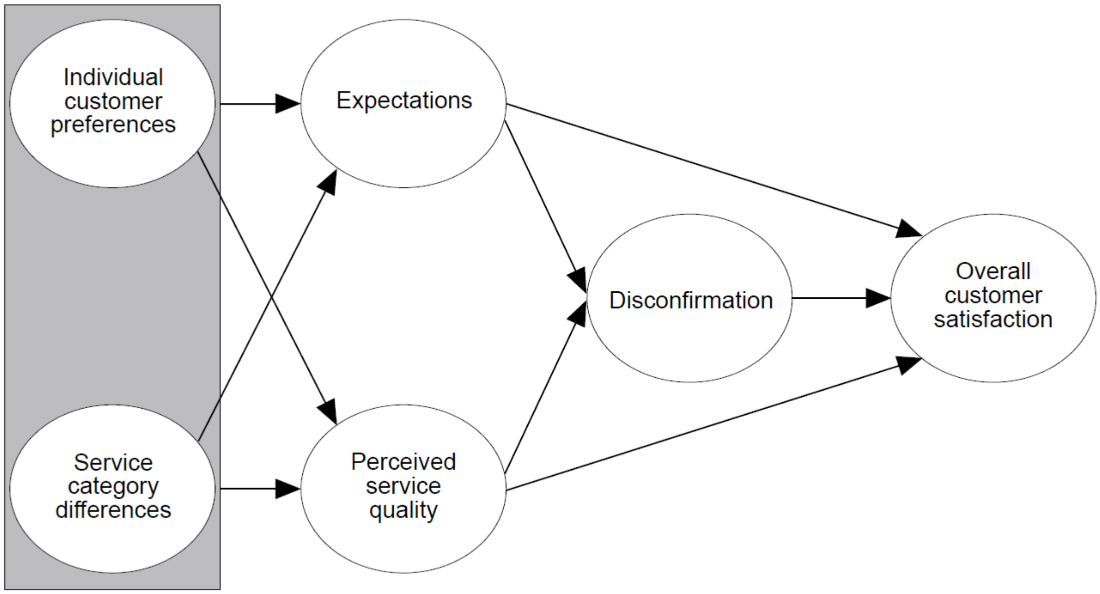


Figure 3.7 A (dis)satisfaction model (Source: Andreassen, 1995)

We know that real-time transit information does not change the objective service quality attributes, except for the information availability. Rather it may change or update rider's perceptions of some quality measures, and in turn these changes may contribute to higher overall satisfaction. Perceived service quality attributes that may be modified by use of real-time transit information are identified as follows. Note that we focus on general perceptions accumulated from specific trip experiences that may be influenced by real-time transit information every time.

1) *Increased general feeling of security*. Real-time traveler information contributes to an increased general feeling of security against crimes at public transport stops in general and especially after dark (Dziekan & Vermeulen, 2006). The reasons are multifaceted: first, reduced perceived waiting time makes passengers feel less time of exposure to potential danger or crime; second, when real-time arrival information is provided, travelers may choose to adjust her behavior in order for obtaining higher safety, such as walking to

a different stop, turning to a different mode; third, even if waiting is inevitable, reduced uncertainty with knowledge of real-time but arrival time may boost travelers' sense of security, especially at night or at unsavory stops.

2) *Increased perceived on-time performance*. Schedule adherence or on-time performance refers to the level of success of the transit service remaining on the published schedule. The GPS-enabled real-time information system may virtually improve the on-time performance since dispatcher can monitor for any route or time deviations and provide the drivers with guidance in real time. On the other hand, even if the on-time performance keeps unchanged, the passenger may have a feeling of increased adherence of bus service, with real-time information provision.

In addition to the change in perceptions of service quality, there is a special type affective reaction to experience of waiting for public transportation, which is:

3) *Decreased general waiting anxiety*. Cumulatively, stress or anxiety passengers build up while waiting for transit in the course of specific transit trips will lead to a general level of anxiety. By hypothesis, real-time information use will lower the general waiting anxiety, which will generate some health benefit.

4) And finally, the ultimate construct of general psychological response, *higher overall satisfaction* (or *cumulative satisfaction*). Two conceptualizations of satisfaction are presented by literature in psychology and business – transaction-specific satisfaction and cumulative satisfaction (Johnson *et al.*, 1995). Overall satisfaction is viewed as "a cumulative, abstract construct that describes customers' total consumption experience with a product or service

to date" (Johnson and Fornell, 1991). Satisfaction, in this view, is not a transient perception of how happy a customer is with a product or service at any given point in time. It is a customer's overall evaluation of his or her purchase and consumption experience to date. Because this cumulative satisfaction directly affects customer loyalty and subsequent profitability, it serves as a common denominator for describing differences across firms and industries. In sum, while a transaction-specific view of satisfaction provides valuable insight into particular, short-run product or service encounters, cumulative satisfaction is a fundamental indicator of a market's (or firm's) current and long-run performance. This has depicted exactly the difference between the trip-specific satisfaction and the overall satisfaction with transit service in the context of public transportation. Parallel to previous discussion, the effect of real-time transit information on overall satisfaction may take two paths: The *direct path* is that the provision of real-time information per se is considered as a type of effort the transit agencies make to improve the transit service, and passengers generally appreciate this effort and feel more satisfied with overall service. The *indirect path* is that use of real-time transit information first updates passenger's psychological outcomes of lower levels (e.g. feeling of security, perception of on-time performance, anxiety), and in turn boosts the global satisfaction.

3.5 Chapter Summary

This chapter presents an integrative, systematic conceptual framework for exploring major behavioral and psychological effects of real-time transit information system. This framework takes into account changes in both traveler behavior and psychology in different response time frames. In addition to the overarching framework, trip-specific and general responses were elaborated as well. This chapter has provided with a solid basis for analyzing effects of real-time transit information with empirical data.

Chapter 4: Methodology

<u>4.1 Introduction</u>

The purpose of this dissertation is to empirically examine behavioral and psychological effects of real-time transit information acquisition with revealed-preference data. The research methodology is presented in this chapter with following organization. Section 2 presents the detailed research design, with justification of revealed-preference approach, introduction to the case for study, and elaboration of a quasi-experimental design for studying general responses. Section 3 details about a number of surveys conducted for collecting first-hand empirical data. Section 4 presents a variety of variables that measure the key constructs in the conceptual framework, followed by a brief summary of analytical methods in Section 5. Finally, Section 6 summarizes this chapter.

<u>4.2 Research Design</u>

4.2.1 Consideration of Data Collection

When considering the issue of data collection for travel behavior analysis, arguably there are three main categories of data-types that together represent the bulk of the theoretical and empirical research efforts in this field:

1) *Simulated data*. Hypothetical travelers who have certain personality traits, such as preferences, decision styles, knowledge levels, are created. By simulating their travel choices, insights can be gained into the working of behavioral models at the individual level, or even at a network level. Thanks to the low costs and high

flexibility, simulated data have been quite popular throughout the years, especially as a first step towards empirical model validation and estimation when services are not yet available. For example, a behavioral model of transit path choice built by Hickman and Wilson (1995) was tested with simulated data and the effect of real-time arrival information was then explored.

2) *Stated-preference (SP) data*. SP survey presents participants with hypothetical alternatives, and asks them to indicate which of the available alternatives they would choose in real life, or asks them to state their needs, willingness to pay for, or preferences for the alternatives. The advantage of SP-methods also first lies in their low-cost, flexibility and efficiency. For example, it is possible, by careful design, to control experimental conditions in such a way that variations in choices or preferences can be efficiently attributed to each of the explanatory variables being studied. Another advantage of SP-approach, also shared with simulation approach, is the capability to evaluate the demand for products and services that are not yet available in the market at the time of the investigation. The principal drawback of SP approach is its limited external validity: individuals' stated preferences may not correspond closely to their actual preferences. They may diverge because of systematic bias in SP responses or because of difficulty in carrying out the SP survey (Wardman, 1988). Examples of SP approach include early studies by Abdel-Aty *et al.* (1996) and Reed and Levine (1997), mostly because of unavailability of real-time transit information systems at that time.

3) *Revealed-preference (RP) data*. RP-surveys collect data concerning choices that are actually made, or behaviors that are actually performed, by travelers in the

real world. The advantage of RP data is that it is based on actual decisions, which gives RP data high reliability and face validity. The notable disadvantages to the use of RP-data, when compared to SP, are the following: Firstly, sometimes RP-data simply do not exist as the service is not available in real life. Secondly, as the level of experimental control is low, RP-data often suffer from little variation in, and collinearity among, explanatory factors; therefore, a large number of observations might be needed in order to obtain meaningful parameter estimates. Another flaw of RP-data is that the service, which is to be evaluated, may not be randomly used by travelers. The non-stochastic nature of treatment in RP data may threaten the validity of results.

As we have reviewed in Chapter 2, the majority of scientific studies to this date employed either simulated or SP data, since probably the real-time transit passenger information systems were not ubiquitous when these studies were conducted. Therefore, the external validity of these studies is presumably low.

Recently, the real-time transit passenger information systems are being more and more popular in many countries. Thus it is more feasible to collect RP data in order for gaining higher external validity. This dissertation is intended to fill in the gaps and utilize revealed-preference approach as data collection methodology. The case of Real-time Transit Passenger Information System (RTPIS) that is to be examined is the ShuttleTrac system deployed and operated by Departments of Transportation Services (DOTS) at University of Maryland, College Park.

4.2.2 A Case of ShuttleTrac System

University of Maryland, College Park operates a Shuttle-UM system with a 60-vehicle fleet, serving College Park campus and commuters from nearby communities. The students, faculty and staff of the university may use Shuttle-UM free of charge[3]. During summer 2006, the University's DOTS started to implement a GPS-based Real-Time Passenger Information System, named ShuttleTrac. For this project, DOTS contracted with transit technology integrator Connexionz, Ltd., based in New Zealand, to develop a Real-time Tracking and Passenger Information (RTPI) system. The cost of this venture was $350,000 (UMCP, 2007).

The ShuttleTrac system is composed of five components (Figure 4.1):

1) 30 touch-enabled BusFinder terminals at select on-campus and off-campus stops. These terminals are battery powered and receive tracking information via radio signals. A passenger simply pushes the button for the particular route of interest, and the terminal displays the estimated arrival time of the next bus on that route at that respective bus stop.
2) A large display screen at an activity center, Stamp Student Union. Nearly all shuttle lines either depart from this stop or pass by it. Arrival information for routes that pass next to the Stamp Student Union is displayed on this screen, much like an airport arrival & departure screen.
3) An Interactive Voice Response (IVR) system for telephone inquiry. The passengers may contact an Interactive Voice Response (IVR) system,

[3] In fact, students have to pay for the Shuttle-UM service as a portion of mandatory fees charged every semester. The Shuttle-UM student fee is $61.5 per semester in Fiscal Year 2006, and $65.7 per semester in Fiscal year 2007. However, these are essentially hidden costs.

enter the passenger stop number, and receive the estimated arrival times of buses scheduled to arrive at that stop within the next 30 minutes.

4) A website for Internet inquiry. Passengers may visit the website by following a link from the main DOTS website (www.dot.umd.edu). He or she will then choose which route they wish to ride, and the passenger stop at which they wish to board, and the system will display arrival times for buses arriving at that stop within the next 30 minutes.

5) A website for WAP-enabled handheld inquiry. The user simply points his or her browser to www.shuttle.umd.edu and enters the passenger stop number to acquire the arrival times of shuttles for that stop within the next 30 minutes.

Therefore, travelers can acquire real-time shuttle arrival information (estimated arrival times of buses scheduled to arrive at that stop within the next 30 minutes) via various media both pre-trip and en-route.

Figure 4.1 Five ways to use ShuttleTrac (Source: www.dot.umd.edu)

Figure 4.2 Online query of real-time Shuttle arrival information (Source: www.dot.umd.edu)

Each bus is equipped with a GPS and radio transmitter BusPack which is constantly in communication with the Real-time Tracking server (RTT). This information, coupled with data from the Historical server, is used to estimate arrival times. After the BusPacks were installed during the summer of 2006, timing/schedule adherence data was gathered on each route throughout the fall semester and first half of the spring semester. This extensive data gathering and fine tuning of the route schedules allow the system to increase accuracy of arrival predictions. The Shuttle-UM dispatchers use an automatic vehicle location (AVL) application to track the buses on their routes and monitor for any route or time deviations. Although since December 2006 ShuttleTrac has been accessible via Internet and telephones, it has been fully functional only since the early April of 2007. All in all, this system represents the-state-of-practice of real-time transit passenger information system.

There are several advantages and disadvantages in utilizing this system as the case study. One of the advantages is pertinent to timing of this dissertation research. This research was proposed right before the deployment of systems and therefore a carefully designed before-and-after research was applicable so that higher validity can be obtained. One special feature of ShuttleTrac system is that acquisition of real-time bus arrival information requires a certain amount of effort, such as pushing the buttons on BusFinder, getting online or calling the phone number. One good thing about it is that not all of travelers will make the effort, even if the system is available for a while. Therefore, two groups of travelers, either with (users) or without treatment (non-users), can be easily differentiated. However, the downside of this feature is that we have to take into account the non-randomness of ShuttleTrac use in our research design and analysis, so as to increase the validity of our results.

Another inevitable challenge to this case is the generalizability of research findings concerning such system in the context of a special transit system (i.e. ShuttleUM). It is obvious that Shuttle-UM system differs from other typical urban public transportation systems in many aspects including fares, coverage, to name a few. The principle difference lies in the population of service: Shuttle-UM serves only the university community, whose travel behaviors and preferences are likely to be different from general public. This issue will be discussed in details in the final chapter.

Nevertheless, ShuttleTrac system provides a good opportunity to be selected as the case for studying traveler responses to the real-time shuttle arrival information.

4.2.3 Quasi-experimental Design

Different research designs were employed to study general and trip-specific traveler responses to real-time passenger information. As discussed in Chapter 3, general responses are accumulated from response in individual encounters or experiences. It is then feasible to measure the cumulative behavioral and psychological variables before and after the deployment of ShuttleTrac system and infer the causal effects of such system out of the before-and-after comparison. Therefore, the *quasi-experimental design*, more specifically, a *pretest posttest nonequivalent group design*, was utilized in this research in this natural-experiment setting, as illustrated in Figure 4.3.

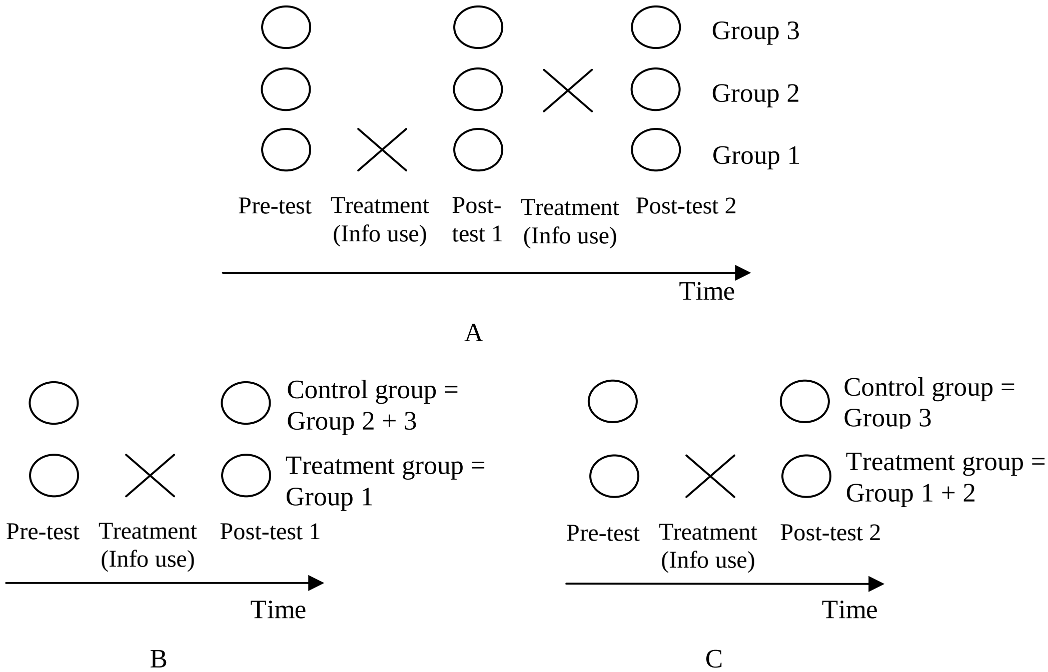


Figure 4.3 Quasi-experimental design of research on general responses (Source: Author)

As shown in the diagram, the "treatment" of our interest is the real-time information use. Hypotheses proposed in Chapter 3 state that, with use of real-time transit information, travelers modify their behaviors in favor of transit (i.e., as for general response, increase transit trip-making frequency and shift habitual mode to transit) and positively change their perceptions of and attitudes towards transit. In terms of information use, there are two groups: information users in the treatment group and non-information users in the control group. In our research design, if one traveler reports in the survey that he or she ever used ShuttleTrac at least once, he or she is then assigned into the treatment group. Efforts demanded for making the actions to acquire real-time information ensure that the number of persons in each group is comparable with each other. If some Variable Message Signs were installed at every stop, people in treatment group will very likely outnumber people in control group as information ease-of-use is much higher in this case.

In this quasi-experimental design, one pre-test (Pre-test, i.e. Wave1) and two post-tests (Post-test 1, i.e. Wave2; and Post-test 2, i.e. Wave3) are proposed in order to ascertain effects of real-time transit information at different time points. Because the treatment (first ShuttleTrac use) can take place either between Pre-test and Post-test 1 or between Post-test 1 and 2, three groups can be identified as follows (see Figure 4.3A): Group 1 contains travelers whose first use of ShuttleTrac is before Post-test 1; Group 2 contains travelers who use ShuttleTrac between Post-test 1 and Post-test 2; and Group 3 consists of those travelers who never use ShuttleTrac.

To examine the effects of ShuttleTrac use at Wave2, the treatment and control groups can be identified (see Figure 4.3B): Group 1 is equivalent to treatment group as travelers in this group use ShuttleTrac before the time point; and Group 2 and 3 comprise the control group. Similarly, if we turn to examine the effects of ShuttleTrac use at Wave3, the treatment group is then composed of Group 1 and 2, and Group 3 comprises the control group (see Figure 4.3C).

The Quasi-experimental designs are considered better than pre-experimental studies in that they employ a means to compare groups. They fall short, however, on one very important aspect of the experiment: randomization of treatment (Campbell and Stanley, 1963). In our case, conceivably the ShuttleTrac use, as the treatment on travelers, is unlikely to randomly occur among travelers. Some types of travelers are inherently more inclined to acquire real-time shuttle arrival information. In other words, self-selection bias may occur in this case as those travelers, whose travel behaviors and preferences favor Shuttle-UM, deliberately sort themselves into the

ShuttleTrac user group. Different statistical approaches are utilized to try to address this potential self-selection problem in the next Chapter.

Note that so far what we are talking about is only traveler's general/ cumulative responses to real-time information. As far as trip-specific responses are concerned, I did not propose a similar quasi-experimental design framework because of two reasons. Firstly, collecting information concerning trip-specific decisions and feelings normally involves on-site surveys. It is simply not feasible to find the same group of respondents (a panel) who can fill out the questionnaires two times. The best one can do is to collect two repeated cross-sectional datasets for pre- and post-deployment time points. Secondly, trip-specific behaviors and perceptions are binding to each specific trip, and thus behaviors and psychologies concerning specific trips before real-time information systems may not constitute good references for after using the real-time information. After all, these decisions or feelings are very much trip-dependent. As a matter of fact, in travel behavior studies rarely are panel data used to model trip-specific travel decisions.

As a result, one cross-sectional dataset after the deployment of ShuttleTrac is sufficient to conduct a research to examine how real-time transit information influence traveler's behavior and psychology for specific shuttle trips.

4.3 Survey

To examine travelers' responses to new ShuttleTrac system and evaluate its effectiveness, DOTS at the University of Maryland, College Park sponsored a comprehensive study which consists of three types of surveys –three-waved panel online campus transportation surveys, two-waved panel one-day travel diary surveys, and repeated two-waved cross-sectional shuttle onboard surveys, all designed and administered by the author. Data used in this dissertation were extracted from the three-waved online surveys and the cross-sectional onboard survey in Wave2 (See Figure 4.4). The Wave1 and Wave2 surveys were conducted within an academic year of 2006-07, and Wave3 survey was conducted in the first semester of academic year 2007-08. There was no other major change regarding shuttle service such as scheduling or routing. This makes the surveys more valuable in sorting out the effects of ShuttleTrac.

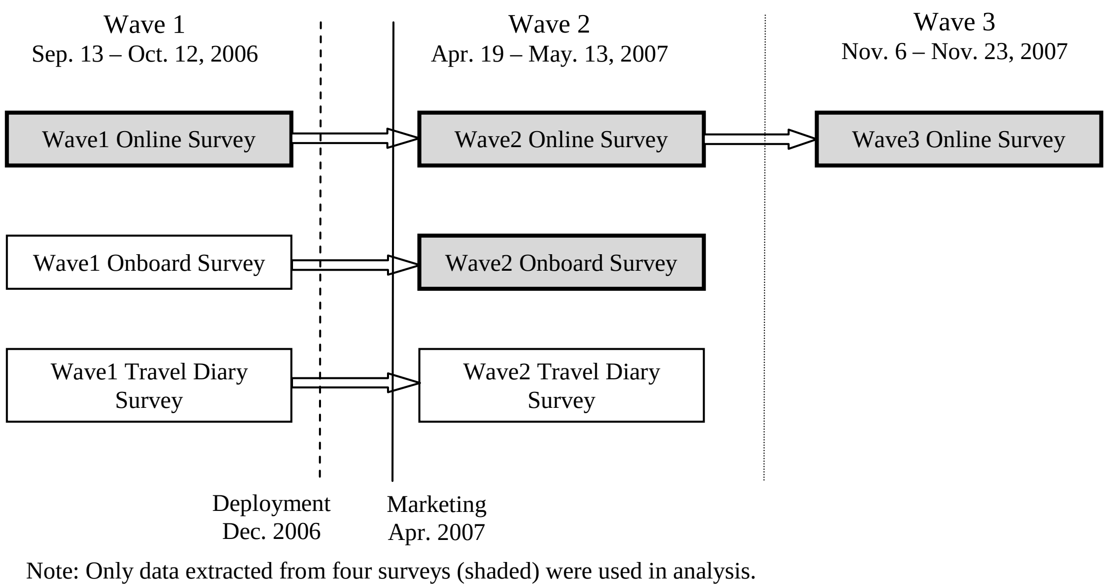


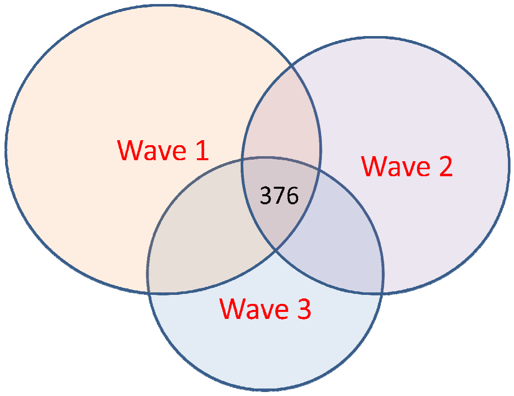
Figure 4.4 Surveys conducted by author and used for this research (Source: Author)

4.3.1 Campus Transportation Survey

The online Campus Transportation Survey was conducted for pre- and post-ShuttleTrac periods. Wave 1 started on September 13, 2006 and ended on October 12, 2006. Wave 2 started on April 19, 2007, two weeks after campus-wide marketing of ShuttleTrac, and ended on May 13, 2007. Wave 3 started on November 6, 2007, and ended on November 23, 2007. The purpose of the before-and-after survey is to explore potential shuttle trip increase, and overall attitude/perception change because of real-time shuttle arrival information.

Questions in the online questionnaires for all three waves asked about three types of information: 1) commuting pattern for off-campus residents, 2) use and perceptions of Shuttle-UM, and 3) personal characteristics. Additional questions about awareness and use of ShuttleTrac (if any) were presented in Wave2 and Wave3 questionnaire (see Appendix 1).

The sampling strategy is as follows: in wave1, online recruiting methods were used targeting the entire university community, including 1) recruiting emails sent to various campus email-lists three times, 2) recruiting message published on campus-wide daily online FYI system twice, and 3) advertisement on DOTS website. To ensure adequate presence of shuttle riders grouping the sample, some supplementary recruiting methods were used, including 1) posters at two campus shuttle shelters, 2) fliers handed out at a major shuttle hub, and 3) advertisement on shuttle onboard survey forms. In wave 2, we sent out emails directly to the respondents of Wave1 survey three times, trying to recruit them for Wave2 survey. Meanwhile, new participants were recruited using similar methods as in wave 1. In Wave3, only emails were directly sent to respondents of Wave1 and Wave2 three times in order to recruit as many respondents from previous two waves as possible. No new respondents were recruited this time. Because it was impossible for us to keep the record of the number of people who received the recruiting message, there is no way to calculate the response rate[4].



Sample	Size
Wave 1	1679
Wave 2	1367
Wave 3	1089
Wave 1+2 panel	623
Wave 1+3 panel	750
Wave 2+3 panel	715
Wave 1+2+3 panel	376

Figure 4.5 Samples of Three-waved Online Surveys (Source: Author)

The sample sizes of Wave1, Wave2, and Wave3 are 1679, 1367, and 1089. Out of 1679 Wave1 respondents, 623 (37%) participated in Wave2 survey, 715 (42.6%) participated in Wave3 survey (see Figure 4.6). A large number of Wave 1 respondents did not participate in Wave 2 or Wave 3 survey because they were not required to make the commitment of doing it again in the first place. We assume that the attritions from the study were random.

Different panel datasets was used for analysis in this dissertation. Panel data analysis becomes more and more popular in transportation research because of its advantages over cross-sectional data. Not only panel data are particularly useful in answering questions about the dynamics of change, but also they provide stronger evidence for causal inference than cross-sectional data because unobserved heterogeneity was controlled for.

[4] Total population of the university in Academic Year 2006-07 is 39,414 (breakdowns: Undergraduate student: 24,776; Graduate student: 8,149; Faculty: 2,410; Staff: 4,079) (source: http://www.asg-architects.com/comparing/campuses/illustrations/umcp.html)

A concern of wave2 survey is that it started only two weeks after extensive marketing of the ShuttleTrac service and insufficient time had passed adequately to test the impact of the intervention. Some components of ShuttleTrac had already been functional and available to the public before the marketing of ShuttleTrac. For instance, phone numbers and Internet had worked since the beginning of the spring semester. But it was not until early April that the busfinders were deployed and extensive marketing was run. Therefore, travelers may not have enough time to adjust their behaviors and perceptions. Nonetheless, we consider Wave2 survey data as an adequate empirical basis for understanding how travelers respond to the ShuttleTrac system in a short run. To complement Wave2 survey, Wave3 survey was conducted to further understand the responses in a longer run.

4.3.2 Shuttle-UM On-board Survey

The Shuttle-UM on-board survey was administered between April 24 and May 10 by the author to ascertain riders' trip-specific responses to ShuttleTrac. The author has done the most of field survey with help from some friends as surveyors. All 17 shuttle lines were covered in the survey. A questionnaire was distributed on-board buses in paper form (see Appendix 2). As passengers boarded the bus and sat down, the surveyor announced the survey before asking each passenger whether they want to fill out a brief survey about their trips. The registration to win an iPod shuffle was offered to those who completed a survey as the incentive. Because most of the passengers are UMD students who are willing to help, the response rate is between 90% and 100%. The questionnaire consists of 32 questions, and was designed to be completed in about five minutes, making it feasible for most riders to finish the survey during the course of their ride.

The focus of the questionnaire was on ShuttleTrac usage and accuracy, along with rider's psychological conditions while waiting. It included questions concerning:

1) Trip characteristics, such as boarding and alighting stops, origin, destination, access modes, and purpose;
2) Perceived waiting time at the boarding stop;
3) ShuttleTrac usage (when, where, and what media) and perceived accuracy;
4) Perception of on-time performance of the bus;
5) Activities passengers were engaged in while waiting;
6) Passenger's general attitudes towards Shuttle-UM and ShuttleTrac; and
7) Personal characteristics.

The sample size of Wave2 onboard survey is 686. Even though the total number of riders approached by surveyors was not kept track of, from the observation it is safe to say that the response rate of onboard survey is fairly high (about 80%-90%) as Shuttle-UM riders were generally very cooperative.

In the original research plan for this dissertation, on-board surveys and travel diary surveys were proposed to capture some, if not all, of trip-specific behavioral choices induced by real-time information, as conceptually discussed in Chapter 3. However, it turned out that the trip-specific behaviors are not feasible to be examined in our case because: 1) the Shuttle-UM has only little common lines, thus path choice may not be a feasible decision for riders to make; 2) onboard surveys were inherently limited in only interviewing riders on the vehicle, so some choices (e.g. trip quitting, modal shift) made by non-riders cannot be captured; 3) Wave2 travel diary survey only gave a very small number of ShuttleTrac users, perhaps because of the timing of Wave2 survey. As a result, there will be no empirical analysis in trip-specific behavioral responses to real-time transit information in this dissertation, and it will remains in conceptualization. This is one of the major limitations of this research acknowledged by the author. Details about this limitation and future research toward this issue will be discussed in the final chapter.

4.4 Measures

The objective of my analysis is to figure out the relationships between real-time bus arrival information acquisition and the behavioral and psychological responses as hypothesized in the conceptual framework in Chapter 3. Before I turn to the analytical methods, the measures of the constructs I propose in the conceptual framework are presented in this section. The measures are all derived from the self reports of respondents in surveys.

Considering the special properties of ShuttleTrac, two sets of variables are operationalized to measure different dimensions of the construct of real-time transit information for examination of general responses and trip-specific responses respectively (see Table 4.1).

Table 4.1 Measures of Real-time Transit Information

Dimension	Variable	Type
For general responses		
Information acquisition	Whether traveler has used ShuttleTrac anytime before survey	Dummy
Information accuracy	Whether traveler perceives that the ShuttleTrac is 50% or below accurate	Dummy
For trip-specific responses		
Information acquisition and place	Whether rider used the ShuttleTrac to acquire pre-trip information for this trip	Dummy
	Whether rider used the ShuttleTrac to acquire at-stop information for this trip	Dummy
Information accuracy	Whether rider thinks the bus was early against ShuttleTrac prediction for this trip	Dummy
	Whether rider thinks the bus was late against ShuttleTrac prediction for this trip	Dummy

Our principle interest is in the effect of ShuttleTrac use. For study on general response to ShuttleTrac use, firstly a dummy explanatory variable was extracted from the Wave2 and Wave3 online surveys to indicate whether or not the shuttle rider has ever used one of the devices of the new ShuttleTrac system to acquire real-time information. Although respondents told us how many times they have used ShuttleTrac, the frequency of ShuttleTrac usage was not directly incorporated in models to avoid likely endogeneity, which is caused by reverse causality – more shuttle trips and positive perceptions on shuttle cause more ShuttleTrac use.

Secondly, another variable is the perception of ShuttleTrac accuracy. Based on ShuttleTrac user's reply to the question regarding their general perceived accuracy of ShuttleTrac prediction (five categories are always accurate, mostly accurate, 50% accurate, rarely accurate, and never accurate), a dummy variable was generated to show whether the individual real-time information user perceives that that the accuracy of ShuttleTrac is 50% or below (i.e. respondents checked 50% accurate, rarely accurate or never accurate). Naturally, the reference group is those who checked always accurate or mostly accurate. According to the hypothesis, this kind of user perception of “mis-information” would negatively influence their behavior and psychology.

Four measurable variables were derived from the Wave2 onboard survey to capture ShuttleTrac information use and perceived accuracy. There are five means for passengers to find out real-time bus arrival time. In the onboard survey questionnaire, passengers were asked whether they acquired real-time bus arrival information before trip or at stop. Two dummy variables of our principle interests are generated accordingly to capture the acquisition of pre-trip and at-stop real-time bus arrival information. Based on the conceptual framework, it is hypothesized that acquiring pre-trip and at-stop real-time information will generate positive effect on their at-stop psychology, i.e., increasing feeling of security at stop, decreasing waiting anxiety, and increasing satisfaction with transit service.

Not only is presence of information important, but also quality of information is essential to information users for specific transit trips. The accuracy of real-time bus arrival information is more of an issue than that of train arrival information because of the higher complexity and dynamics of road conditions. Passengers were asked, in comparison to the real-time bus arrival time they initially acquired, whether they think the bus arrived early, within +/- 1 minute, or late. Based on their answers, three variables were formulated to represent the accuracy of real-time bus arrival information perceived by users. The consistency of these three accuracy variables was checked with the real-time information acquisition variables. Statistical tests show that the real-time information acquisition at stop is significantly correlated with the accurate perception. Therefore, to eliminate the problem of multicollinarity, the variable “within +/1 minute accurate” is dropped.

Table 4.2 Measures of Traveler Responses to be Examined

Traveler Response	Variable	Type
General responses		
Transit trip increase	Number of monthly shuttle trips	Continuous
	Number of monthly campus-based shuttle trips	Continuous
Habitual mode shift	Dominant commuting mode of transportation	Nominal (4 alternatives)
Increased feeling of security	General feeling of security about riding shuttle at day	Ordinal (1-5)
	General feeling of security about riding shuttle at night	Ordinal (1-5)
Increased perception of on-time performance	General perception of on-time performance of shuttle service	Ordinal (1-5)
Reduced waiting anxiety	General anxiety while waiting for shuttle	Ordinal (1-5)
Increased overall satisfaction	Overall satisfaction with Shuttle-UM service	Ordinal (1-5)
Trip-specific responses		
Reduced perceived waiting time	Perceived waiting time	Continuous
Increased feeling of security	Feeling of security at the stop while waiting for shuttle	Ordinal (1-5)
Reduced waiting anxiety	Anxiety while waiting for shuttle at the stop	Ordinal (1-5)
Increased satisfaction	Satisfaction with shuttle service at the stop	Ordinal (1-5)

In the online survey respondents rated their frequency of shuttle use for past month to take part in eight different activities (i.e. going to class, going to work, shopping, personal business, going to meals, social/recreational activities, returning to home, and others5) by choosing among 6 options: “never”, “less than once a month”, “less than once a week”, “1-2 days a week”, “3-4 days a week”, and “5 or more days a week”. Based on their answers, a continuous variable named “monthly frequency of shuttle use” was generated by assuming a middle value for each category and aggregating trip counts for all purposes.

[5] There is actually one more type of activity: connect to Metro. Assuming that riders ride Shuttle to connect to the nearby College Park Metro Station, those trips do not count as Shuttle trips.

In addition, I further hypothesize that the number of campus-based shuttle trips will increase since the ShuttleTrac system mainly serves the campus (e.g., 24 out of 30 Busfinders are installed at on-campus stops). More specifically, with real-time arrival information, university students or faculty/staff members may use shuttle more to engage in campus-based non-mandatory (maintenance or discretionary) activities such as going shopping, meeting friends, having meal, etc. Therefore, trip counts for those activity purposes (shopping, personal business, meal, social/recreational) were aggregated to generate a new dependent variable named "monthly campus-based shuttle trip-making frequency." Note that shuttle trips for maintenance or discretionary activities are not necessarily campus-based. One can of course take the shuttle from an off-campus site to another for maintenance or discretionary purposes. But it rarely happens because all shuttle routes start from the campus and it is not convenient to travel between two off-campus sites unless they are on the same route.

Respondents who live off-campus were asked in online surveys about their primary commuting mode to campus every day in past week. The question noted that if respondent used more than one mode of transportation during a commuting trip, the primary mode for this day was the one used for most of the distance. Eight options were provided as the candidates of primary commuting modes: "Drive along", "Carpool", "Shuttle-UM", "Metrobus or other bus system", "Metro, MARC or other rail system", "Walk", "Bicycle", and "Other". Consistency was checked to ensure that the sum of answers to such question is equal to the answer to a prior question of "In the past week, how many days did you travel from where you live to the College Park campus."

Based on answers to this question, we can construct a nominal dependent variable representing the dominant mode of transportation for commuting to the UMD campus. To make the alternatives more manageable and, more importantly, to ensure the property of Independence of Irrelevant Alternatives (IIA), eight options presented in the question were collapsed into four modes of transportation, namely "Car" (the first two options), "Shuttle-UM", "Transit" (fourth and fifth options), and "Non-motorized mode" (sixth and seventh options). Respondent's dominant commuting mode is the one out of four by which one used for the largest number of days in past week. For instance, a respondent commuted to the campus for 5 days in past week. He used car (either drive along or carpool) as his primary mode for 4 days, and transit for 1 day. In this case, car is considered as his dominant commuting mode to travel from where he lives to the university campus. When two or more modes were used for the same number of days (e.g. car for 2 days, shuttle for 2 days, transit for 2 days), I selected dominant mode according to a priority list: non-motorized mode > shuttle > transit > car. The main reason for doing so is to make sure that there are sufficient numbers of respondents using modes other than private vehicles. Conceivably, this variable of dominant commuting mode measures the habitual commuting mode. A more preferable way of dealing with this problem is to randomly select the dominant mode when two or more modes have the same number of days. However, because of the already uneven distribution of modes, this may cause a problem of underrepresentation of non-private-car modes.

The five psychological dependent variables are feeling of security about riding shuttle during the day time, feeling of security about riding shuttle at night, perception of shuttle on-time performance, general anxiety level while waiting for shuttle, and overall satisfaction level of shuttle service. They measure shuttle riders' general/cumulative perceptions on shuttle service. In survey questionnaires, questions for the first four of these variables were presented using 5-point likert scales with only the lowest and highest points labeled. Question for overall satisfaction level was presented using a 10-point likert scale. For the sake of comparability, I collapsed satisfaction ratings into 5 levels. Another transformation is the order reverse of waiting anxiety level. Originally, 1 means "not anxious at all" and 5 "extremely anxious".

Perceived waiting time is a continuous variable, transformed from the categorical answers in the onboard survey using the middle point value (e.g. 1.5 for "1-2 minutes", 30 for "more than 30"). If a passenger reports that she boards on the bus without waiting, her perceived waiting time is 0.

Three variables that measure passengers' psychology at boarding stops are derived directly from three questions in the on-board survey: "feeling of security at the boarding stop", "anxiety level while waiting" and "satisfaction with service at the boarding stop". Note that because of the survey was conducted onboard, there is no way one can give you her satisfaction rating for the service during entire journey. Therefore, respondents were asked to rate level of satisfaction with at-stop service instead. In survey questionnaires, questions for these three variables were presented using 5-point likert scales with only the lowest and highest points labeled (i.e. Feeling of security: 1=very unsafe, 5=very safe; anxiety level: 1=not anxious at all, 5=extremely anxious; satisfaction level: 1= extremely dissatisfied, 5=extremely satisfied). Note that the order is reversed for waiting anxiety level in order to guarantee the consistency with other two variables (i.e., highest means most desirable). After the reverse, 1 means “extremely anxious” and 5 “not anxious at all”.

In terms of measures of other individual and situational factors, I will cover them in details in the corresponding sections in the following two chapters.

4.5 Analytical Methods

The major analytical methods used in this dissertation are statistical multivariate regression models that were estimated to find out causal relationships between dependent variables of traveler responses and independent variables of real-time information, controlling for other individual or situational factors (see Figure 4.3). Details about modeling techniques and specifications will be elaborated in corresponding chapters. Note that the potential self-selection bias in models for general responses is to be addressed using different approaches (see Chapter 5).

Table 4.3 Analytical Methods

<table>
<tr><th>Dependent variable</th><th>Dataset</th><th>Statistical modeling method</th></tr>
<tr><td colspan="3">For general responses</td></tr>
<tr><td>Monthly Shuttle-UM trip-making frequency (total and campus-based)</td><td>Wave 1+2 full panel dataset
Wave 1+3 full panel dataset
Wave 1+2+3 full panel dataset</td><td>Fixed-effects linear regression (OLS) model</td></tr>
<tr><td>Dominant commuting mode</td><td>Wave3 commuter cross-sectional dataset</td><td>Two-stage instrumental conditional logit model</td></tr>
<tr><td>Feeling of security about riding shuttle (at day or night)</td><td rowspan="4">Wave 1+2 rider panel dataset
Wave 1+3 rider panel dataset
Wave 1+2+3 rider panel dataset</td><td rowspan="4">Random-effects ordered probit model</td></tr>
<tr><td>Perception of general on-time performance</td></tr>
<tr><td>General waiting anxiety</td></tr>
<tr><td>Overall satisfaction with shuttle service</td></tr>
<tr><td colspan="3">For trip-specific psychological responses</td></tr>
<tr><td>Perceived waiting time</td><td rowspan="4">Wave2 onboard survey rider cross-sectional dataset</td><td>Linear regression (OLS) model</td></tr>
<tr><td>Feeling of security</td><td rowspan="3">Ordered logit model</td></tr>
<tr><td>Waiting Anxiety</td></tr>
<tr><td>Satisfaction with at-stop service</td></tr>
</table>

4.5 Chapter Summary

This chapter is a complete presentation of research methodology adopted in this dissertation. This research takes a real-world case of a real-time transit information system, ShuttleTrac, and collects revealed-preference data. In addition, a quasi-experimental design was proposed for studying traveler's general/cumulative responses to real-time information. All these conditions lead to a higher validity of this study than previous research regarding this issue. What is more, surveys, measures and analytical methods are presented before the empirical findings are reported in following chapters.

Chapter 5: General Responses to Real-time Transit Information

5.1 Introduction

In the online Campus Transportation Surveys, respondents answered questions about their use and perception of Shuttle-UM for one pre-ShuttleTrac and two post-ShuttleTrac periods. Therefore, it is possible for us to examine both behavioral and psychological effects of ShuttleTrac using the panel datasets. In this chapter, three behavioral variables and five psychological variables measuring traveler's general responses to real-time transit information were modeled to be a function of real-time transit information use. This chapter is organized according to the dependent variables: models for trip-making frequency, dominant commuting mode, and psychological variables are presented respectively, followed by the summary of empirical findings and discussion.

5.2 Monthly Trip-making Frequency

5.2.1 Datasets and Variables

According to the conceptual framework, real-time transit information may entice drivers away from their cars and encourage patrons to ride buses more. In this case study, as discussed in Chapter 4, I constructed two variables to measure the shuttle trip-making frequency – monthly number of shuttle trips, and monthly campus-based shuttle trips. The specific hypothesis, based on the general *H1*, is that

ShuttleTrac use would increase monthly frequency of shuttle use of university travelers, no matter they are existing riders or not.

The datasets utilized in this analysis are three panel datasets – Wave1+2, Wave1+3, and Wave1+2+3. Note that here “full dataset” means that all travelers are included in the datasets, no matter whether they have used Shuttle-UM before or not. Conceivably, the non-Shuttle riders (or potential riders) may be enticed to use Shuttle as the mode of transportation in some trips due to the use of real-time transit information. Descriptive statistics of three full panel datasets are displayed in Table 5.1, Table 5.2, and Table 5.3. Note that there are some missing values for different variables, which are excluded from all calculations.

A number of individual characteristics were incorporated into regression models as independent variables. Variables that do not vary among three surveys are time-invariant variables, which in our case are sex (male=1), race (white=1), and citizenship (foreign=1). As shown later in the discussion of model specification, time-invariant variables will be canceled out in fixed-effects models. Age is dropped too because everyone has the same one year increment. Note that age square was included in five psychological models to capture possible non-linear effect of age on psychological dependent variables.

Three vehicle-related variables indicate whether a respondent has a valid driver license, regular car access, and a campus parking permit. All three are hypothesized to be negatively related to number of shuttle trips. Correlation tests show that they are not highly correlated. In addition, model sensitivity test further proves that there is no problem of multicollinearity among them.

Based on the question of “how far is where you live from the nearest shuttle stop”, I derived three dummy variables to indicate their accessibility to shuttle service – “less than 5 min walk”, “5-10 min walk”, and “10-20 min walk”. The baseline category is “more than 20 min walk” and “don’t even know”, indicating the shuttle is not accessible from where respondent lives. Presumably, nearer to shuttle stops, more shuttle trips.

Another important locational variable is whether a respondent live on campus or off campus. On-campus students very likely ride shuttle more often than off-campus commuters, especially for various non-mandatory activities. One more locational characteristic is the number of commuting-to-campus days in past week for commuters, ranging from 0 to 7. More commuting days possibly bring more shuttle commuting trips. But more likely, since all shuttle lines are campus-based, more commuting days mean more days on campus and consequently more shuttle use. Because students living on campus skipped this question, a reasonable transformation is to consider them commuting to campus 7 days a week. This way we did not have to lose a large number of cases of on-campus students. This variable is dropped in the psychological models because of the problem of multicollinearity.

Table 5.1 Descriptive Statistics of Wave1+2 Full Panel Dataset

	Wave1 (Pre-test)					Wave2 (Post-test1)				
Variables	N	Min	Max	Mean	SD	N	Min	Max	Mean	SD
# of shuttle trips a month	623	0	116	10.92	17.82	623	0	154	10.33	17.75
# of campus-based shuttle trips	623	0	94	2.85	7.21	623	0	94	2.68	7.06
Use of ShuttleTrac	N/A					623	0	1	0.413	0.49
Perceived inaccuracy	N/A					623	0	1	0.069	0.25
Age	610	16	72	30.94	11.94	610	17	73	31.94	11.94
Male	615	0	1	0.4	0.49	time-invariant				
Foreign citizen	618	0	1	0.17	0.37	time-invariant				
White	614	0	1	0.68	0.47	time-invariant				
Student	622	0	1	0.64	0.48	619	0	1	0.63	0.48
Driver license	616	0	1	0.94	0.24	612	0	1	0.95	0.21
Car access	623	0	1	0.76	0.43	620	0	1	0.78	0.42
Campus parking permit	623	0	1	0.56	0.50	620	0	1	0.56	0.50
Live on campus	623	0	1	0.15	0.36	623	0	1	0.15	0.36
# days of commuting to campus a week	623	0	7	5.09	1.49	623	0	7	5.08	1.61
<5 min walk to nearest stop	623	0	1	0.37	0.48	623	0	1	0.37	0.48
5-10 min walk to stop	623	0	1	0.1	0.3	623	0	1	0.09	0.29
10-20 min walk to stop	623	0	1	0.07	0.26	623	0	1	0.06	0.24

Table 5.2 Descriptive Statistics of Wave1+3 Full Panel Dataset

	Wave1 (Pre-test)					Wave3 (Post-test2)				
Variables	N	Min	Max	Mean	SD	N	Min	Max	Mean	SD
# of shuttle trips a month	750	0	92	10.67	18.20	750	0	94	7.45	14.73
# of campus-based shuttle trips	750	0	62	2.33	5.77	750	0	48	1.34	4.18
Use of ShuttleTrac	N/A					750	0	1	0.43	0.50
Perceived inaccuracy	N/A					750	0	1	0.07	0.25
Age	729	17	74	31.60	12.04	729	18	75	32.60	12.04
Male	737	0	1	0.41	0.49	time-invariant				
Foreign citizen	744	0	1	0.17	0.38	time-invariant				
White	737	0	1	0.69	0.46	time-invariant				
Student	749	0	1	0.63	0.48	746	0	1	0.61	0.49
Driver license	742	0	1	0.94	0.24	745	0	1	0.96	0.21
Car access	750	0	1	0.78	0.42	746	0	1	0.83	0.38
Campus parking permit	750	0	1	0.58	0.49	746	0	1	0.59	0.49
Live on campus	750	0	1	0.13	0.33	750	0	1	0.11	0.31
# days of commuting to campus a week	750	0	7	5.1	1.39	750	0	7	4.82	1.72
<5 min walk to nearest stop	750	0	1	0.34	0.47	750	0	1	0.32	0.47
5-10 min walk to stop	750	0	1	0.12	0.32	750	0	1	0.09	0.29
10-20 min walk to stop	750	0	1	0.06	0.24	750	0	1	0.65	0.25

Table 5.3 Descriptive Statistics of Wave1+2+3 Full Panel Dataset

	Wave1 (Pre-test)					Wave2 (Post-test1)					Wave3 (Post-test2)				
Variables	N	Min	Max	Mean	SD	N	Min	Max	Mean	SD	N	Min	Max	Mean	SD
# of shuttle trips a month	376	0	89	11.43	17.99	376	0	154	10.88	18.82	376	0	94	7.80	14.56
# of campus-based shuttle trips	376	0	42	2.35	5.40	376	0	80	2.36	6.76	376	0	28	1.21	3.34
Use of ShuttleTrac	N/A					376	0	1	0.28	0.45	376	0	1	0.49	0.50
Perceived inaccuracy	N/A					376	0	1	0.06	0.23	376	0	1	0.07	0.25
Age	371	18	72	32.46	12.57	371	19	73	33.46	12.57	371	19	73	33.46	12.57
Male	374	0	1	0.40	0.49	time-invariant					time-invariant				
Foreign citizen	374	0	1	0.17	0.37	time-invariant					time-invariant				
White	372	0	1	0.69	0.46	time-invariant					time-invariant				
Student	376	0	1	0.61	0.49	372	0	1	0.60	0.49	374	0	1	0.59	0.49
Driver license	370	0	1	0.95	0.23	367	0	1	0.95	0.21	373	0	1	0.96	0.19
Car access	376	0	1	0.76	0.43	372	0	1	0.77	0.42	374	0	1	0.81	0.39
campus Parking permit	376	0	1	0.56	0.50	372	0	1	0.55	0.50	374	0	1	0.58	0.49
Live on campus	376	0	1	0.14	0.35	376	0	1	0.14	0.35	376	0	1	0.11	0.31
# days of commuting to campus a week	376	0	7	5.08	1.46	376	0	7	5.11	1.52	376	0	7	4.90	1.67
<5 min walk to nearest stop	376	0	1	0.37	0.48	376	0	1	0.36	0.48	376	0	1	0.32	0.47
5-10 min walk to stop	376	0	1	0.09	0.29	376	0	1	0.10	0.30	376	0	1	0.09	0.28
10-20 min walk to stop	376	0	1	0.07	0.26	376	0	1	0.06	0.24	376	0	1	0.09	0.28

5.2.2 Model Specifications

Two behavioral dependent variables, total number of shuttle trips per month and number of campus-based shuttle trips per month, were transformed by adding .5 to all scores and then taking the natural logarithm. This transformation was chosen because it both reduced the skewness of the distribution of trip counts and ensured that the model did not predict trip counts less than zero. An alternative approach would be to assume that number of shuttle trips has a Poisson distribution. This was not chosen because results from the Poisson analysis and the log-linear OLS analysis were virtually identical in the two-period case (Allison, 1994).

For each time point, we have one linear equation for a sample of individuals labeled i=1,…, n. In our two-wave case, we have the following two-equation model:

$$Y_{i1} = \mu \qquad + \gamma W_{t1} + \beta Z_i + \alpha_i + \varepsilon_{i1} \qquad (5.1)$$

$$Y_{i2} = \mu + \delta X_i + \gamma W_{t2} + \beta Z_i + \alpha_i + \varepsilon_{i2} \qquad (5.2)$$

Here, Y_{it} is the transformed number of trips for individual *i* at wave *t*, *Z* is a vector of measured explanatory variables that are constant over time (time-invariant variables), *W* is a vector of measured explanatory variables that vary with time, and β and γ are vectors of coefficients. Our principle interest is in δ, which may be regarded as the effect of the event *X*, which, in our case, represents the use of ShuttleTrac. Some of these individuals experience the event (use of ShuttleTrac) between two measurements (X_i=1), other do not (X_i=0). The ε_s are time-specific random disturbances that are assumed to be independent of the explanatory variables, and of α_i. It is permissible for ε_1 to be correlated with ε_2 in our two-period case. Therefore, no autocorrelation test is necessary for the two-wave models. The α_i represents unobserved differences across individuals (unobserved heterogeneity) that are constant over time.

The main reason for collecting panel data is to deal with the unobserved heterogeneity α_i. One approach, called within transformation, is to time-demean the data. Specifically, we average equations 5.1 and 5.2, subtract the averaged equation from equation 5.1 and 5.2, and obtain two equations as follows:

$$Y_{i1} - \overline{Y_i} = -0.5\delta X_i + \gamma\left(W_{i1} - \overline{W_i}\right) + (\varepsilon_{i1} - \overline{\varepsilon_i}) \quad (5.3)$$

$$Y_{i2} - \overline{Y_i} = 0.5\delta X_i + \gamma\left(W_{i2} - \overline{W_i}\right) + (\varepsilon_{i2} - \overline{\varepsilon_i}) \quad (5.4)$$

Consequently, time-constant unobserved heterogeneity α_i was cancelled out and no longer a problem. Then equations 5.3 and 5.4 can be pooled to estimate coefficients δ and γ with the OLS estimator. The OLS estimator with time-demeaned data is normally called fixed-effects (FE) estimator or within estimator. One character of the within transformation is that all time-invariant variables Z are canceled out too.

An alternative to fixed-effects model is random-effects (RE) model. It is assumed that α_i is random variables and is not correlated with any independent variable (i.e. W, Z and X). Here α_i is no longer a problem, but serial correlation is. A pooled GLS estimator, namely random-effects estimator, can be used to deal with serial correlation.

I chose the FE estimator over the RE one based on the theoretical considerations and the statistical test. RE estimator demands the assumption that unobserved heterogeneity is uncorrelated with explanatory variables. In randomized experiments, the possibility of correlation between treatment and unobserved heterogeneity is reduced by random assignment. In that case, RE estimator is appropriate. In non-experimental scenarios, however, the possible biasing effects of "unmeasured selectivity" or "self-selection" could be a serious problem (Allison, 1994). It is commented by many scholars that the fixed-effects estimator is nearly always preferable for estimating causal effects of events with non-experimental data. Essentially our data is quasi-experimental in that the treatment (use of ShuttleTrac) is not randomized among riders. Therefore, theoretically the FE estimator is preferable in our case. Moreover, the Hausman specification test were performed to test the null hypothesis that the coefficients estimated by the RE estimator are the same as the ones estimated by the consistent FE estimator. If the *p*-value is significant, random-effects estimator can be deemed to be biased. In all models for two trip-making frequency dependent variables, the *p*-values from Hausman tests are all highly significant, suggesting that FE estimators are superior to RE estimators in all cases.

For three-wave dataset, linear equations for a sample of individuals labeled i=1,…, n for three waves could be formulated as follows:

$$Y_{i1} = \mu \qquad\quad + \gamma W_{t1} + \beta Z_i + \alpha_i + \varepsilon_{i1} \qquad (5.5)$$

$$Y_{i2} = \mu + \delta X_{i2} + \gamma W_{t2} + \beta Z_i + \alpha_i + \varepsilon_{i2} \qquad (5.6)$$

$$Y_{i3} = \mu + \delta X_{i3} + \gamma W_{t3} + \beta Z_i + \alpha_i + \varepsilon_{i3} \qquad (5.7)$$

Where X_{i2} denotes whether the individual i used ShuttleTrac between Wave1 and Wave2, X_{i3} denotes whether the individual i used ShuttleTrac between Wave1 and Wave3. Presumably, if X_{i2}=1, then X_{i3}=1.

Using the within transformation introduced above, we can obtain:

$$Y_{i1} - \overline{Y_i} = -\frac{1}{3}\delta(X_{i2} + X_{i3}) + \gamma\left(W_{i1} - \overline{W_i}\right) + (\varepsilon_{i1} - \overline{\varepsilon_i}) \qquad (5.8)$$

$$Y_{i2} - \overline{Y_i} = \frac{1}{3}\delta(2X_{i2} - X_{i3}) + \gamma\left(W_{i2} - \overline{W_i}\right) + (\varepsilon_{i2} - \overline{\varepsilon_i}) \qquad (5.9)$$

$$Y_{i3} - \overline{Y_i} = \frac{1}{3}\delta(2X_{i3} - X_{i2}) + \gamma\left(W_{i3} - \overline{W_i}\right) + (\varepsilon_{i3} - \overline{\varepsilon_i}) \qquad (5.10)$$

In this case, the unobserved heterogeneity α_i which is constant across three waves was also cancelled out.

As discussed in Chapter 4, endogeneity caused by self-selection is potentially a problem to the models. To represent this problem using the equations listed above, X_{it} as the non-randomly assigned treatment might be correlated with the two components of unobserved disturbances – α_i and ε_{it}. A nice thing about FE estimator is that unobserved individual differences (α_i) as a part of unobserved disturbance are canceled out. If we assume that the endogenous variable X_{it} is only correlated with the unobserved individual heterogeneity α_i, the self-selection is no longer a problem with FE estimators. This assumption seems to be reasonable because literature review in Chapter 2 has suggested that use of real-time information to an extent can be attributed to individual differences (see Section 2.1).

5.2.3 Modeling Results

Results for modeling two trip-making frequency dependent variables using panel datasets are displayed in Table 5.4 and 5.5. Since the fixed-effects (FE) estimator was chosen, four time-invariant variables are dropped, including age, gender, race, and foreign citizenship. Note again that the dependent variables are natural logarithm of trip counts.

Table 5.4 Estimated Results for Number of Monthly Shuttle Trips

# Monthly Shuttle Trips	Model 1-1 Wave 1+2		Model 1-2 Wave 1+3		Model 1-3 Wave 1+2+3	
Independent varaibles	*Coef.*	*t*	*Coef.*	*t*	*Coef.*	*t*
Wave 2 dummy	-0.042	-0.69	N/A		-0.104	-1.47
Wave 3 dummy	N/A		**-0.371[a]**	**-5.54**	**-0.504[a]**	**-6.30**
Use of ShuttleTrac	0.034	0.35	**0.231[b]**	**2.27**	**0.245[b]**	**2.46**
Accuracy of ShuttleTrac: 50% or less	0.185	0.95	**-0.593[a]**	**-2.90**	-0.051	-0.27
Age	dropped		dropped		dropped	
Male	dropped		dropped		dropped	
Foreign citizen	dropped		dropped		dropped	
White	dropped		dropped		dropped	
Student	0.021	0.05	0.008	0.02	0.178	0.48
Driver license	-0.452	-1.45	-0.528	-1.53	**-0.540[c]**	**-1.77**
Car access	0.124	0.65	**-0.838[a]**	**-5.00**	**-0.339[b]**	**-2.03**
Campus Parking permit	**-0.617[a]**	**-3.50**	**-0.622[a]**	**-4.72**	**-0.551[a]**	**-3.99**
Live on campus	-0.137	-0.51	-0.253	-1.24	**-0.525[b]**	**-2.48**
# commuting days a week	**0.070[c]**	**1.86**	**0.067[c]**	**1.83**	0.053	1.53
<5 min walk to stop	**0.413[b]**	**2.05**	**0.682[a]**	**4.29**	**0.615[a]**	**3.84**
5-10 min walk to stop	0.067	0.32	**0.463[b]**	**2.48**	0.257	1.36
10-20 min walk to stop	0.287	1.47	**0.360[c]**	**1.87**	0.176	1.00
_cons	**1.247[a]**	**2.89**	**1.869[a]**	**4.89**	**1.639[a]**	**4.41**
within R^2	0.046		0.214		0.149	
Overall R^2	0.359		0.416		0.465	
# obs	1196		1419		1097	
# groups	606		713		372	

NOTE: Significant values are boldfaced.
a: $p<0.01$; b: $p<0.5$; c: $p<0.1$

Table 5.5 Estimated Results for Number of Monthly Campus-based Shuttle Trips

# Monthly campus-based Shuttle trips	Model 2-1 Wave 1+2		Model 2-2 Wave 1+3		Model 2-3 Wave 1+2+3	
Independent varaibles	*Coef.*	*t*	*Coef.*	*t*	*Coef.*	*t*
Wave 2 dummy	-0.042	-0.74	N/A		-0.022	-0.41
Wave 3 dummy	N/A		**-0.174**[a]	**-3.59**	**-0.274**[a]	**-4.59**
Use of ShuttleTrac	0.109	1.20	0.006	0.09	0.066	0.89
Accuracy of ShuttleTrac: 50% or less	**-0.337**[c]	**-1.88**	**-0.533**[a]	**-3.62**	-0.093	-0.67
Age	dropped		dropped		dropped	
Male	dropped		dropped		dropped	
Foreign citizen	dropped		dropped		dropped	
White	dropped		dropped		dropped	
Student	-0.139	-0.38	0.241	1.03	0.243	0.88
Driver license	-0.256	-0.89	-0.178	-0.72	0.043	0.19
Car access	-0.219	-1.24	**-0.679**[a]	**-5.61**	**-0.538**[a]	**-4.32**
Campus Parking permit	-0.202	-1.24	**-0.203**[b]	**-2.13**	**-0.242**[b]	**-2.36**
Live on campus	**0.896**[a]	**3.58**	**0.268**[c]	**1.82**	**0.357**[b]	**2.26**
# commuting days a week	-0.008	-0.24	0.020	0.78	-0.009	-0.36
<5 min walk to stop	-0.004	-0.02	**0.203**[c]	**1.77**	0.135	1.13
5-10 min walk to stop	**-0.402**[b]	**-2.08**	**0.350**[b]	**2.59**	0.056	0.40
10-20 min walk to stop	-0.088	-0.49	**0.230**[c]	**1.66**	0.063	0.48
_cons	**0.754**[c]	**1.90**	0.448	1.62	0.409	1.48
within R^2	0.052		0.175		0.119	
Overall R^2	0.243		0.326		0.374	
# obs	1196		1419		1097	
# groups	606		713		372	

NOTE: Significant values are boldfaced.
a: p<0.01; b: p<0.5; c: p<0.1

First of all, the wave3 dummy variables in Model 1-2 and Model 2-2 are found to be significantly related to number of shuttle trips. The negative sign suggests that, everything else being equal, travelers tend to use Shuttle-UM less in November 2007 than in September 2006. This systematic change may be due to seasonal factors. On the other hand, wave2 dummy variables in Model 1-1 and 2-1 have insignificant coefficients, implying that no systematic changes between wave1 and wave2, if everything else are kept unchanged.

The variable of our primary interest, ShuttleTrac use, has shown interesting patterns in three models regarding monthly shuttle trip rate. ShuttleTrac use dummy shows a positive effect on monthly shuttle trip-making frequency at a significant level of .05 in Model 1-2 and 1-3, but not in Model 1-1 (see Table 5.4). The insignificant coefficient in Model 1-1 suggests that, between wave 1 and 2, travelers may not increase their number of shuttle trips in response to use of real-time bus arrival information. In contrast, the significant coefficient in Model 1-2 shows that, between wave 1 and 3, the use of ShuttleTrac is to increase the number of monthly shuttle trips by 23.1%, other factors being fixed.

Conceivably it is the adjustment period and learning dynamics that makes a difference in two models. For this natural experiment, the treatment is use of real-time bus arrival information system. Therefore, individual travelers have various adjustment periods, starting precisely from the day they first use ShuttleTrac to the survey time points. An apparent explanation for the insignificant effect between wave 1 and 2 is that our wave 2 survey was only about 2 weeks (less than a month) after the extensive marketing, there was not enough time for most travelers to adjust their travel behavior, even if they used ShuttleTrac once or more times. For the panel of wave 1 and 3, the adjustment periods are much longer. If we assume a random distribution of first-time ShuttleTrac use, the average adjustment duration for respondents who reported ShuttleTrac use in Wave 3 survey is 3.5 months (or 2 months if excluding summer break). Actually, the distribution of first-time ShuttleTrac use is skewed to the left, with a large portion of ShuttleTrac users used it already before Wave 2 survey. Using the descriptive statistics of the three-waved full panel as reference, we may get the following information: 28% of riders used ShuttleTrac before Wave2 survey point, which gives them 7 months for adjustment before Wave3 survey point (4 if summer break excluded); and another 21% of respondents reported they used ShuttleTrac between wave 2 and 3 survey points (see Table 5.3), which gives them an average of 3.5 months for adjustment (2 if summer break excluded), assuming a random distribution; in sum, for all ShuttleTrac users, their average adjustment period at Wave3 survey point is about 5.5 months (3.14 months if excluding summer break). Thus, the results imply that the exposure to real-time bus arrival information system will induce more shuttle trips for travelers, but this kind of effect will only be in place with an average of five and a half months of adjustment.

The coefficient of ShuttleTrac use dummy in Model 1-3 is also significant and has similar magnitude as in Model 1-2. But interpretation of this result is somewhat tricky. It seems to tell that use of ShuttleTrac will immediately increase monthly shuttle trip-making frequency by 24.5% and this effect will keep constant in the future time. This time path for the effect can be illustrated in Figure 5.1A.

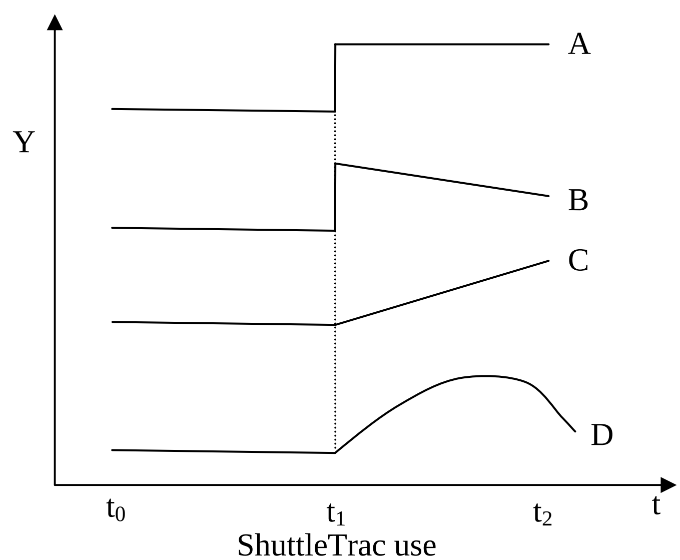


Figure 5.1 Possible time paths for the effect of ShuttleTrac use on monthly trip rate
(Source: adapted from Allison, 1994)

However, from above discussion, we have learned that the use of ShuttleTrac cannot immediately alter travelers' shuttle trip rates. More plausible time paths for the effect shall be like Figure 5.1C or Figure 5.1D, indicating that there is a longer-term effect of ShuttleTrac use. More specifically, when travelers first use real-time passenger information system, they will not immediately modify their transit usage. It takes time for them to gradually increase their transit trip rates. The comparison of model results of Model 1-1 and 1-2 has implied this phenomenon. It is just not clear that which form, linear (as in Figure 5.1C) or curvilinear (as in Figure 5.1B), this longer-term effect takes though.

In addition to Model 1-3, another model specification has been tried to capture this longer-term effect using three-wave panel dataset by including a longer-term variable – a product of ShuttleTrac use dummy with time variable. However, it does successfully depict the form of longer-term effect because of two reasons. One reason is that there are only three waves, thus it is not possible to detect non-linear effect of any kind. A more important reason is that the adjustment durations for so-called "new users" of ShuttleTrac in two waves are systematically different. In other words, a new value of 1 for ShuttleTrac use in wave 2 and 3 means totally different things. In wave 2, the adjustment period is mostly less than 2 weeks (maybe with only a few exceptions because of the test run). In wave 3, travelers who newly reported ShuttleTrac use have an average of 3.5 month of adjustment duration, assuming a random distribution of first use. In this sense, it is not appropriate to treat these 1s as identical, which is actually the case in the models using the three-wave panel dataset such as Model 1-3. Therefore, as a matter of fact, result for this particular variable in Model 1-3 provides no more than a mere repetition of Model 1-2.

Nevertheless, the results in Model 1-1 and 1-2 have given us an adequately clear picture of how a significant longer-term effect of exposure to real-time bus arrival information system on transit trip rate takes place as travelers' adjustment periods grow.

With insignificant coefficients for ShuttleTrac use in Model 2-1, 2-2, and 2-3, the same kind of effect of real-time transit information system use on monthly campus-based shuttle trip rates has not been found.

Another ShuttleTrac-related variable is the perceived inaccuracy of ShuttleTrac prediction (accurate 50% or less). In Model 1-2, this variable is found to be negatively related to number of shuttle trips at a very high significance level (t = -2.90). Other factors being kept unchanged, between wave 1 and 3, the number of monthly shuttle trips is to decrease by about 59% when riders feel ShuttleTrac's prediction accuracy is generally poor. This impact cannot be found between wave 1 and 2, implying that there is also latency in this effect. The magnitude of this effect is about 2.5 times higher than that of ShuttleTrac use. Suppose a rider has used real-time passenger information and somehow obtained the perception that the prediction accuracy is poor, with some period of adjustment, his transit trip rate is to decrease by about 36%. Interestingly, the same effect is found in Model 2-2, indicating that, during the period between wave 1 and 3, the mere use of ShuttleTrac is not to increase campus-based shuttle trip rates, but once passengers perceive that the prediction of ShuttleTrac is problematic, they will reduce their campus-based shuttle trips by about 53%. These findings highlight the issue of mis-information, which shall be a caution to information providers.

For other variables in Model 1 and 2, I will mainly report the results in three-wave models, Model 1-3 and 2-3. In Model 1-3, six variables are significantly related to the number of shuttle trips. The highly significant coefficient for wave 3 dummy shows that, as a general trend, UMD travelers in Fall semester of 2007 tend to reduce their Shuttle-UM trip rates by about 50% as compared to Fall 2006. Three vehicle-related variables all have negative coefficients at various significance levels (all meeting the significance level of 0.1). The results show that, other things being constant, the action of obtaining a driver license, regular access to a private vehicle (e.g., buying a car), or a campus parking permit is to reduce the shuttle trip rate by 54%, 34%, and 55% respectively. The magnitude of these effects is rather large. Suppose a young student takes all of these three actions by getting a license, buying a new car, and applying for a parking permit. All these negative effects on shuttle usage may add up, and as a result this young student is most likely to give up Shuttle as his or her transportation mode entirely.

Moving from an off-campus residence to an on-campus one will also reduce the shuttle trip rates. This finding is somewhat contradictory to our expectation. However, this result should be interpreted together with other findings discussed below. First, the opposite effect was actually found for number of monthly campus-based trips, suggesting that campus-based shuttle trip rate is to increase by about 36% if one moves from off-campus to on-campus (see Model 2-3). Another significant variable in Model 1-3 is "<5 min walk to nearest shuttle stop". Similarly, it suggests that moving from a place where shuttle is not accessible by walk to one where nearest shuttle stop is less than five minutes away increases the overall shuttle riding frequency by 61.5%, another huge effect.

Again let us suppose a scenario, in which one student moves from an off-campus residence where Shuttle-UM is not accessible by foot to an on-campus residence hall with just less-than-five-minute walk to the shuttle lines (which is true for nearly all on-campus residence halls). Other things being equal, the first effect of movement on his or her shuttle-riding behavior is that *campus-based* shuttle trip-making frequency is to increase by 36%. Second, on-campus living is to reduce his/her *overall* shuttle trip rate. However, this negative effect is fully offset by the positive effect caused by higher accessibility to shuttle service (-53% vs. 62%, see Model 1-3). As a result, this student is about to maintain his/her monthly shuttle trip rate, perhaps with a little bit increase, and in the mean time he/she is riding more Shuttle-UM for some non-mandatory activities, such as going to downtown College Park for shopping and/or meals.

5.3 Dominant Commuting Mode

5.3.1 Datasets and Variables

The dataset used for analyzing the dominant commuting mode is limited to the Wave 3 commuter cross-sectional dataset because of several reasons. First, Wave2 is not considered because it is believed that this kind of habitual mode shift cannot take place immediately after first-time use of real-time information. Second, I did not pool Wave1 and Wave3 cases to get a Wave1+3 commuter panel dataset, simply because there is a lack of statistical package that is able to handle multinomial logit model with panel data using FE or RE estimator. I have tried the GLLAMM[6] with the Wave1+3 panel dataset, but the instability of such program could not give successful estimation. Thus only the cross-sectional dataset extracted from the Wave3 survey is used in the model, with a two-stage instrument variable technique to address potential self-selection problem.

Explanatory variables commonly used for mode choice models include travel times and costs for each alternative mode. I have tried to manually generate different types of travel times and costs for alternative modes for each case following steps as follows.

- Each off-campus living respondent was geocoded on Google Maps (http://maps.google.com/) based on address (or intersection) he provided in online survey.
- Taking his location as the origin and Stamp Student Union as the destination, driving time (In-vehicle time (IVT) for car mode) and distance (D) were derived with Google Maps direction function. Egress time from the parking lot to respondent's buildings on campus (EgTime) was set at a constant number of 2 minutes. Out-of vehicle time (OVT) is simply equal to egress time for car mode.
- Travel costs for car mode were computed using the simple equation: Cost = Distance * Gas Price / MPG. Average retail gas prices in Maryland in September 2006 and November 2007 were $2.50 per gallon and $3.05 per gallon respectively according to U.S. Energy Information Administration

[6] A famous Stata program to fit generalized linear latent and mixed models. Random-effects multinomial logit model is said to be able to be fit with GLLAMM. (see www.gllamm.org)

(EIA)[7]. Average Miles per Gallon (MPG) for passenger cars in 2006 and 2007 was 22.5 according to EIA[8].

- Respondent's geocoded address was checked against the nearest Shuttle-UM stop. Access time to the stop (AccTime) was derived with Google Maps with address as origin and the nearest shuttle stop as destination. Shuttle riding time from the stop to Stamp Student Union or Regents Drive Garage (In-vehicle time (IVT) for shuttle mode) was extracted from published Shuttle-UM timetable. Initial waiting time (WaitTime) and egress time from final stop to the destination building (EgTime) were both set as 2 minutes. Out-of vehicle time (OVT) for shuttle mode is a sum of AccTime, WaitTime and Egtime. Travel cost for shuttle mode is set to be 0 because Shuttle-UM is free of use for qualified passengers.
- Travel times and costs for transit mode were entirely relied on the Trip Planner tool provided on Washington Metropolitan Area Transit Authority (WMATA)[9]. The respondent's address was input as origin, and the Stamp Student Union on campus was input as destination. Moreover, 8:00am was input as departure time in order to resemble the morning commute, a weekday during survey periods was set as the travel day. In addition, minimizing traveling time and allowing walking distance up to 0.6 mile were set as two rules for planning trips (see Figure 5.2A for the interface of Trip Planner). The output page is exampled as in Figure 5.2B. Access times (AccTime), in-

[7] http://www.eia.doe.gov/oil_gas/petroleum/data_publications/wrgp/mogas_history.html, accessed in May 2008.
[8] http://www.eia.doe.gov/emeu/mer/pdf/pages/sec1_17.pdf, accessed on May 20 2008.
[9] http://www.wmata.com/rider_tools/tripplanner/tripplanner.cfm accessed in June 2008.

vehicle times (IVT), transfer times (XferTime), number of transfers (Xfer), and transit fares (Fare) were all extracted from the output mostly by hand. Initial waiting times (WaitTime) and egress times (EgTime) were set as 2 minutes. Out-of-vehicle time (OVT) for transit mode is a sum of AccTime, WaitTime, XferTime, and EgTime.

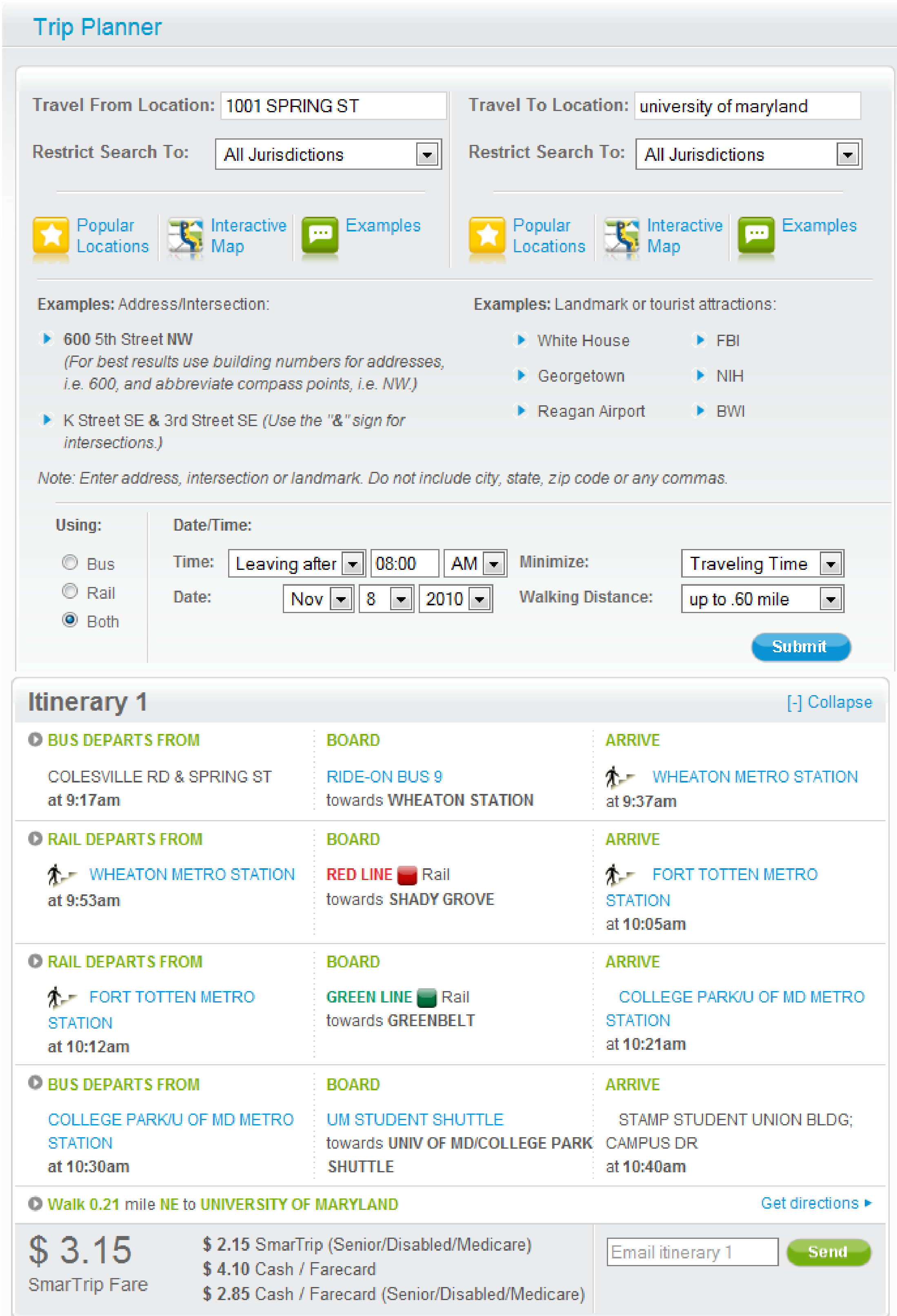


Figure 5.2 Interface of online transit trip-planner at WMATA (Source: Author)

- Respondent's travel time by non-motorized mode is computed simply using the equation of Time = Distance / Speed. The travel speed depends on bike availability. If the respondent reported that he owns a bicycle, average bicycle speed is designated as 20 mph. Otherwise, I use average walking speed of 3 mph. These parameters I used are commonly used. Travel time by bike or walk constitutes out-of-vehicle time (OVT) for non-motorized mode.
- Each respondent may not have all four modes as his available options. I set up some rules to exclude one or more modes that I deem as unavailable for the respondent. Car mode is not available for respondents who reportedly have no regular access to cars. Shuttle mode is not available for respondents whose locations are not within 20 minutes away from the nearest shuttle stop. Transit mode is not available for those whose residences are more than 0.6 miles away from stops. And non-motorized mode is unavailable for respondents whose travel time by this mode is greater than 60 minutes.

Admittedly some of the treatment is somewhat arbitrary. Nevertheless, following above steps, these variables can be generated to measure the travel times and costs for each alternative commuting mode. In addition, sensitivity tests showed that different values of access times and egress times (0, 2, 4 minutes respectively) made no significant difference in modeling results. The descriptive statistics of this dataset is displayed in the following Table 5.6.

Table 5.6 Descriptive Statistics of Wave3 Commuter Dataset

	N	Min	Max	Mean	SD
Car					
In-vehicle time	237	2	95	11.86	9.89
Out-of-vehicle time	237	2	2	2	0
Fuel cost	237	0.08	3.95	0.49	0.41
Campus parking permit	237	0	1	0.56	0.50
Shuttle-UM					
In-vehicle time	258	3	50	19.90	10.30
Out-of-vehicle time	258	6	19	8.85	4.28
Use of ShuttleTrac	258	0	1	0.57	0.50
Perceived inaccuracy	258	0	1	0.11	0.31
Transit					
In-vehicle time	247	3	89	18.39	11.83
Out-of-vehicle time	247	5	50	12.71	7.53
Fare	247	0.75	4.05	1.35	0.47
Non-motor					
Out-of-vehicle time	184	3.56	54.6	17.47	9.06
# respondents = 290 Chosen mode: Car = 150; Shuttle = 63; Transit = 14; Non-motor = 63					

5.3.2 Model Specifications

Conditional Logit Model, an extension to multinomial logit model, is commonly used for modeling transportation mode choice, since it may include explanatory variables that are attributes of choice alternatives (alternative-specific variables). In this part of analysis, conditional logit model is utilized to model traveler's choice of dominant commuting mode.

The utility functions for four alternatives are formulated as follows:

$$U^i_{car} = \beta'_1 IVT_i + \beta'_2 OVT_i + \beta'_3 Cost_i + \beta'_4 Parking_i + \varepsilon^i_{car} \tag{5.11}$$

$$U^i_{shuttle} = \beta'_1 IVT_i + \beta'_2 OVT_i + \beta'_5 TracUse_i + \beta'_6 Accuracy_i + \varepsilon^i_{shuttle} \tag{5.12}$$

$$U^i_{transit} = \beta'_1 IVT_i + \beta'_2 OVT_i + \beta'_3 Cost_i + \varepsilon^i_{transit} \tag{5.13}$$

$$U^i_{nonmotor} = \beta'_2 OVT_i + \varepsilon^i_{nonmotor} \tag{5.14}$$

I can use ShuttelTrac use dummy and perceived inaccuracy dummy, two variables specific to shuttle mode, in the utility function for shuttle mode so as to estimate effects of these two variables on the probability of commuter choosing shuttle as dominant mode of transportation. However, there exists a highly potential self-selection problem, as commuters who use shuttle as their dominant modes sort themselves into the group of ShuttleTrac users. If that is the case, the parameter of Tracuse would be correlated with the error term $\varepsilon_{Shuttle}$, and the estimates for the variable in the equation would be biased and inconsistent. A common solution when independent variables are correlated with the error term is to use instrumental variables. Therefore, in this study, the Two-Stage Instrumental Variable Model, similar to what was used in Khattak and Rodriguez (2005) for addressing self-selection in residential choice, was adopted to address self-selection bias.

In the first stage, I rely on instruments to estimate a binary logit model for choice of ShuttleTrac use, because this choice is dichotomous. The equation of the binary logit model is as follows:

$$Z_i = \beta_0' + \beta' X_i + \varepsilon_i \qquad (5.15)$$

Where *Zi* is the logit for individual *i*, *X* is the vector of instrumental variables, and β is the vector of coefficients to be estimated.

Then for each individual *i*, the probability of choosing to use ShuttleTrac is given as follows:

$$P_i(TracUse) = \frac{1}{1+e^{-(\beta_0'+\beta' X_i)}} \qquad (5.16)$$

In Stage Two, the conditional logit model presented previously is employed, with the replacement of Tracuse dummy variable. Using estimated coefficients, predicted probability of using ShuttleTrac for each individual is used to substitute ShuttleTrac use dummy in utility function for shuttle mode in stage two. Thus, utility equation 5.12 is replaced by the new equation given as follows:

$$U_{shuttle}^{i} = \beta_1' IVT_i + \beta_2' OVT_i + \beta_5' P_i(TracUse) + \beta_6' Accuracy_i + \varepsilon_{shuttle}^{i} \quad (5.17)$$

The key to the two stage approach is to find appropriate instruments. Generally, instrumental variables should satisfy two criteria: they must be correlated with the endogenous variable they are predicting ("relevance"), but not be significantly correlated with the error term of the Stage-Two equation ("exogeneity") (Mokhtarian and Cao, 2008). In this case, the endogenous variable is choice of ShuttleTrac use, and error term of the Stage-Two equation represents unmeasured variables explaining utility associated with choosing shuttle mode as dominant commuting mode. Some of the personal characteristics variables that I think are correlated with ShuttleTrac use choice were incorporated into the Stage-One binary logit model to predict probability of using ShuttleTrac, including age, gender, race, nationality, and campus status. While some other personal characteristics are also considered to be related to ShuttleTrac choice, but conceptually they are very much correlated with the error terms in the utility function in conditional logit model. These variables are ones measuring driver license ownership, regular access to vehicles, campus parking permit ownership, and accessibility to shuttle stops. Although incorporating these variables will enhance the predictive power of Stage-One equation, they were not included in order to ensure "exogeneity" of instruments.

The conditional logit model depends on the independence of irrelevant alternatives (IIA) assumption. That is, the relative probabilities between choices must be independent of other alternatives. An example of IIA violation is the well-known "Blue Bus / Red bus" case. In this study, relative probabilities of choosing between shuttle and transit are likely to be dependent of each other because both may be deemed as public transportation modes and thus IIA assumption is likely to be violated. The Hausman specification tests (Hausman and McFadden, 1984) were performed to check whether the violation of IIA is the case. The tests can be conducted by eliminating a subset of the choices from the choice set and re-estimating the model. If the parameters of the restricted model are not systematically different from the parameters of the full model, then the IIA property holds.

I tried to eliminate four alternative modes from the choice set one by one and perform the Hausman tests. Hausman tests gave χ^2 test statistics of 14.79 (p=.0663), 45.91 (p=.000), 14.96 (p=.0921) and 15.99 (p=.0671), all of which are significant at 10% level. Therefore, in all cases, we cannot reject the hypothesis that the IIA property holds for the choice set. Thus conditional logit model is justified to be the proper specification for Stage-2 model for estimating commuting mode choice.

5.3.3 Modeling Results

The estimated results of stage-1 binary logit model and stage-2 conditional logit model are together presented in Table 5.7, with ShuttleTrac use coded as 1 and non-ShuttleTrac use coded as 0. The result shows the first stage of estimation, using instruments of personal characteristics. The model fit is reasonable (Pseudo R^2=0.113), and two variables of personal characteristics are statistically significant at the 10% level, namely gender and race. The results suggest that male and non-white people are more likely to use ShuttleTrac, other things being equal. The predicted probabilities of using ShuttleTrac are saved as a new variable (for Shuttle mode) for use in Stage Two of the model.

Table 5.7 Results for Dominant Commuting Mode

	Coef.	*Z.*
Stage-1: Binary Logit Model for ShuttleTrac use		
Age	-0.066	-0.80
Age square	0.0003	0.26
Male	**0.532**[c]	**1.84**
Student	0.361	0.82
White	**-0.796**[b]	**-2.32**
Foreign citizenship	0.314	0.83
Constant	2.085	1.26
# obs	249	
Log Likelihood	-150.396	
Pseudo R^2	0.113	
Stage-2: Conditional Logit Model		
In-vehicle time	0.018	0.90
Out-of-vehicle time	**-0.053**[a]	**-2.43**
Monetary cost	**1.31**[a]	**3.43**
Car		
Campus parking permit	**2.566**[a]	**6.94**
Shuttle-UM		
Probability of ShuttleTrac use	0.372	0.47
Perceived inaccuracy	-0.066	-0.13
Constant		
Car	-0.558	-0.82
Transit	**-3.135**[a]	**-3.54**
Non-motor	**1.408**[a]	**2.20**
# obs	906	
Log Likelihood	-189.211	
Pseudo R^2	0.411	

NOTE: Significant values are boldfaced.
a: p<0.01; b: p<0.5; c: p<0.1

The second stage is to estimate the dominant commuting mode choice, with predicted probability of ShuttleTrac use substituted for ShuttleTrac use dummy. The results of the mode choice model are also presented in Table 5.7. As discussed previously, in addition to the predicted probability of ShuttleTrac use and perceived inaccuracy of prediction, the independent variables included are three commonly used alternative-specific variables such as in-vehicle travel time, out-of-vehicle travel time, and out-of-pocket travel cost, as well as two other ones such as parking permit ownership for car mode and less-than-five-minute distance to shuttle lines for shuttle mode.

The stage-two model shows a reasonably good fit (Pseudo R^2=0.415). Two of three dummy variables for alternatives (Transit and Non-motor) are statistically significant at a 0.05 level. The negative sign of coefficient for transit mode indicates that, other things being equal, transit mode is less preferable than shuttle mode. And the positive sign for non-motorized dummy shows that other factors being equal, commuters tend to prefer to walking or cycling to the campus in comparison with shuttle. The insignificant coefficient for car mode suggests that between car and shuttle commuters are likely to be neutral when factors are equal.

Out-of-vehicle travel time is found to be significantly related to commuting mode choice. The variable has a negative coefficient as expected, indicating that the higher the out-of-vehicle travel time for a mode, the lower the possibility of traveler choosing this mode. Travel cost has a statistically significant yet *positive* correlation with mode choice and in-vehicle travel time has not shown a significant relationship with mode choice. Both findings are somewhat inconsistent with prior expectation. I actually have little idea of explanation of these counterintuitive findings. Probably it is because of the less satisfactory data I generated.

As far as two variables of our interest – ShuttleTrac use and perceived inaccuracy – are concerned, the signs are consistent with our expectation, but the effects are not statistically significant, showing that the probability of using real-time information systems will not significantly increase commuter's probability of using shuttle as their dominant commuting mode. Interestingly, if we look at the model with original ShuttleTrac use dummy, this variable has a positive coefficient on at a very high significance level of 0.01 (*coef.* = 2.20, z = 4.43), which seems to suggest a positive effect of use of real-time information system on commuting mode choice. In light of the results of two-stage models, we may conclude that the positive effect found in such model is largely due to self-selection bias. In other words, controlling for the self-selection and other variables, we cannot find significant impact of real-time passenger information system on the commuting mode choice decision, even with a few months of adjustment.

5.4 Psychological Responses

5.4.1 Datasets and Variables

Similar to trip-making frequency, three panel datasets were used in modeling psychological responses to real-time information. But these panel datasets are different in that they exclude respondents whose monthly shuttle trip count is zero for each one of the waves in respective panel dataset (e.g. for Wave1+2 panel, respondents with zero shuttle trip in both wave 1 and 2 are excluded). The underlying rationale is that only riders of Shuttle-UM have perceptions of and attitudes towards Shuttle-UM through their shuttle riding experience. In fact, many non-riders did not answer the questions regarding attitudes toward Shuttle-UM because they think these questions are not applicable to them. See Table 5.8, 5.9 and 5.10 for descriptive statistics for three rider panel datasets.

Table 5.8 Descriptive Statistics of Wave1+2 Rider Panel Dataset

	Wave1 (Pre-test)					Wave2 (Post-test1)				
Variables	N	Min	Max	Mean	SD	N	Min	Max	Mean	SD
feeling of security at day	453	1	5	4.81	0.52	460	1	5	4.75	0.55
feeling of security at night	414	1	5	3.99	1.03	429	1	5	4.06	1.02
perception of on-time performance	422	1	5	3.62	0.79	419	1	5	3.77	0.61
waiting anxiety level	436	1	5	1.86	1.11	448	1	5	2.00	1.1
overall satisfaction level	442	1	5	3.83	0.91	454	1	5	3.92	0. 87
ShuttleTrac use						482	0	1	0.51	0.50
Perceived inaccuracy						482	0	1	0.09	0.29
Age	475	16	72	28.68	10.75	475	17	73	29.68	10.75
Age square	475	256	5184	937.94	797.11	475	289	5329	996.31	818.30
Male	478	0	1	0.42	0.49	time-invariant				
Foreign citizen	479	0	1	0.20	0.40	time-invariant				
White	477	0	1	0.66	0.47	time-invariant				
Student	481	0	1	0.72	0.45	479	0	1	0.72	0.45
Driver license	478	0	1	0.92	0.27	477	0	1	0.94	0.24
Car access	482	0	1	0.69	0.46	480	0	1	0.72	0.45
campus Parking permit	482	0	1	0.48	0.50	480	0	1	0.47	0.50
Live on campus	482	0	1	0.19	0.39	482	0	1	0.19	0.39
<5 min walk to nearest stop	482	0	1	0.44	0.50	482	0	1	0.45	0.50
5-10 min walk to stop	482	0	1	0.12	0.32	482	0	1	0.11	0.31
10-20 min walk to stop	482	0	1	0.08	0.28	482	0	1	0.06	0.25

Table 5.9 Descriptive Statistics of Wave1+3 Rider Panel Dataset

	Wave1 (Pre-test)					Wave3 (Post-test2)				
Variables	N	Min	Max	Mean	SD	N	Min	Max	Mean	SD
feeling of security at day	432	1	5	4.82	0.56	438	1	5	4.80	0.54
feeling of security at night	407	1	5	4.06	0.99	422	1	5	4.05	0.96
perception of on-time performance	416	1	5	3.59	0.86	409	1	5	3.82	0.54
waiting anxiety level	427	1	5	1.76	1.12	421	1	5	1.98	1.07
overall satisfaction level	435	1	5	3.83	0.89	431	1	5	4.00	0.77
ShuttleTrac use	N/A					464	0	1	0.64	0.48
Perceived inaccuracy	N/A					464	0	1	0.10	0.30
Age	452	17	72	28.51	10.56	452	18	73	29.51	10.56
Age square	452	289	5184	924.31	795.89	452	324	5329	982.34	816.67
Male	457	0	1	0.43	0.50	time-invariant				
Foreign citizen	461	0	1	0.25	0.43	time-invariant				
White	458	0	1	0.64	0.48	time-invariant				
Student	463	0	1	0.76	0.42	462	0	1	0.74	0.44
Driver license	460	0	1	0.90	0.30	461	0	1	0.93	0.25
Car access	464	0	1	0.65	0.48	462	0	1	0.74	0.44
campus Parking permit	464	0	1	0.43	0.50	462	0	1	0.47	0.50
Live on campus	464	0	1	0.18	0.38	464	0	1	0.16	0.37
<5 min walk to nearest stop	464	0	1	0.47	0.50	464	0	1	0.44	0.50
5-10 min walk to stop	464	0	1	0.16	0.36	464	0	1	0.13	0.34
10-20 min walk to stop	464	0	1	0.08	0.27	464	0	1	0.07	0.26

Table 5.10 Descriptive Statistics of Wave1+2+3 Rider Panel Dataset

	Wave1 (Pre-test)					Wave2 (Post-test1)					Wave3 (Post-test2)				
Variables	N	Min	Max	Mean	SD	N	Min	Max	Mean	SD	N	Min	Max	Mean	SD
feeling of security at day	245	1	5	4.84	0.51	255	1	5	4.81	0.48	891	1	5	4.74	0.62
feeling of security at night	228	1	5	4.11	0.96	239	1	5	4.16	0.96	850	1	5	3.91	1.02
perception of on-time performance	234	1	5	3.61	0.81	237	1	5	3.81	0.63	735	1	5	3.83	0.53
waiting anxiety level	242	1	5	1.84	1.13	251	1	5	2.08	1.11	773	1	5	2.04	1.07
overall satisfaction level	243	1	5	3.88	0.87	255	1	5	3.98	0.87	808	1	5	3.97	0.79
Use of ShuttleTrac	N/A					262	0	1	0.39	0.49	262	0	1	0.65	0.48
Perceived inaccuracy	N/A					262	0	1	0.08	0.27	262	0	1	0.09	0.29
Age	261	18	72	29.24	11.12	261	19	73	30.24	11.12	261	19	73	30.24	11.12
Age square	261	324	5184	978.31	843.89	261	361	5329	1037.80	865.80	261	361	5329	1037.80	865.80
Male	262	0	1	0.41	0.49	time-invariant					time-invariant				
Foreign citizen	262	0	1	0.23	0.42	time-invariant					time-invariant				
White	261	0	1	0.67	0.47	time-invariant					time-invariant				
Student	262	0	1	0.73	0.44	260	0	1	0.72	0.45	261	0	1	0.70	0.46
Driver license	259	0	1	0.92	0.27	258	0	1	0.93	0.25	260	0	1	0.95	0.23
Car access	262	0	1	0.66	0.48	260	0	1	0.68	0.47	261	0	1	0.73	0.45
campus Parking permit	262	0	1	0.42	0.50	260262	0	1	0.40	0.49	261	0	1	0.47	0.50
Live on campus	262	0	1	0.20	0.40	260	0	1	0.19	0.39	262	0	1	0.15	0.36
<5 min walk to nearest stop	262	0	1	0.48	0.50	262	0	1	0.48	0.50	262	0	1	0.42	0.49
5-10 min walk to stop	262	0	1	0.13	0.33	262	0	1	0.13	0.33	262	0	1	0.12	0.32
10-20 min walk to stop	262	0	1	0.10	0.29	262	0	1	0.07	0.25	262	0	1	0.11	0.31

5.4.2 Model Specifications

The five psychological dependent variables consist of discrete values, and therefore the OLS estimation is not appropriate. Furthermore, because these variables are all ordered responses, a good approach is to estimate ordered probit or logit models. Parallel to above discussion, the fixed effects estimator is preferable to the random effects estimator in our panel dataset. However, fixed-effects ordered logit/probit model is not commonly used because of its estimation difficulty. In psychology and economics literature (e.g., Karni *et al.*, 2008), random effects ordered probit model is commonly utilized to explain categorical dependent variables with natural order in panel data. Hence I used this type of model to examine ShuttleTrac's effect on shuttle riders' perceptions on Shuttle-UM.

The random-effects ordered probit model can be described as follows:

$$y_{it}^* = \beta X_{it} + \epsilon_{it}, \qquad i = 1, \ldots, N, \qquad t = 1,2\ (two\ wave)\ or\ 1,2,3 (three\ wave)$$

$$\epsilon_{it} = \alpha_i + \varepsilon_{it},\ \ Var(\epsilon_{it}) = \sigma_\alpha + \sigma_\varepsilon = \sigma_\alpha + 1,\ \ Corr(\epsilon_{it}, \epsilon_{is}) = \rho = \frac{\sigma_\alpha}{1+\sigma_\alpha}$$

$$y_{it} = \begin{cases} 0 & if\ y_{it}^* \leq \mu_1, \\ 1 & if\ \mu_1 < y_{it}^* \leq \mu_2, \\ 2 & if\ \mu_2 < y_{it}^* \leq \mu_3, \\ 3 & if\ \mu_3 < y_{it}^* \leq \mu_4, \\ 4 & if\ \mu_4 < y_{it}^* \end{cases} \qquad (5.18)$$

Where, y_{it}^* is an unobserved latent variable, and y_{it} is the observed ordered categories in the data; μ_i is the *J*-th cut-off point for the categories; X_{it} are observable explanatory variables; ε_{it} is a time-varying error term, normally distributed, uncorrelated with X_{it}; and α_i is the unobserved individual heterogeneity, normally distributed, constant over time and uncorrelated with X_{it} (assumption of random-effects). The cross-period correlation of ϵ_{it} is ρ. If ρ is significantly different from 0, it indicates there is cross-period correlation with respect to ϵ_{it} (Greene, 2002). Readers are referred to Frechette (2001) for details of estimation process. I used "reoprob" command in Stata 9, written by Frechette, to estimate coefficients. Note that the time-invariant variables are not canceled out in this specification.

With a random-effects estimator, unobserved individual heterogeneity α_i will not be eliminated. Thus the assumption of independence between explanatory variables and α_i has to be met. In this regard, the solution to self-selection bias used for modeling trip-making frequency is not available here. However, self-selection is considered to be less likely a problem for psychological models because 1) some of the individual traits that are considered to be determinants of first use of ShuttleTrac, were explicitly incorporated into the models already; and 2) some are not hypothesized to be related to psychological outcomes as to behaviors. Therefore, the unobserved error term can be assumed to be uncorrelated with ShuttleTrac use. In other words, I assume that those who have more positive perceptions of shuttle do not sort themselves into the group of ShuttleTrac users. Admittedly, even though this assumption is reasonable to a certain extent, yet it is a compromise due to a lack of appropriate methods to deal with the potential violation to this assumption.

5.4.3 Modeling Results

1) Feeling of security about riding the shuttle.

Table 5.11 and 5.12 summarize estimation results of models regarding feeling of security about riding the shuttle in daytime and nighttime. The significant, negative coefficients of Wave2 dummy and Wave3 dummy in Model 3-1 and 3-2 respectively show that riders feel less safe at day during riding Shuttle-UM in Wave 2 or Wave 3 than in Wave 1. The Wave3 dummy in Model 4-2 has also significant coefficient, suggesting that riders also tend to feel less safe at night in Wave 3 compared to Wave 1. Presumably, the systematic decrease in feeling of security along time is due to the longer exposure to potential threats and accumulation of, if any, bad experience.

In Model 3-1 and 3-2, the positive coefficients of ShuttleTrac use dummy have significance levels of 0.1 and 0.05 respectively. The similar pattern has been found also in Model 4-1 and 4-2, with both coefficients having a significance level of 0.1. This seems to suggest that the real-time information system has shown somewhat impacts on passenger's general feeling of security both during daytime and nighttime, and that these kinds of effects not only occur immediately after the first use of the system, but last for at least a few months.

Table 5.11 Estimated Results for Feeling of Security at Day

Feeling of security at day	Model 3-1 Wave 1+2		Model 3-2 Wave 1+3		Model 3-3 Wave 1+2+3	
Independent varaibles	*Coef.*	*z*	*Coef.*	*z*	*Coef.*	*z*
Wave 2 dummy	**-0.410[a]**	**-2.66**	N/A		-0.357	-1.92
Wave 3 dummy	N/A		**-0.352[b]**	**-2.51**	-0.327	-1.50
Use of ShuttleTrac	**0.343[c]**	**1.73**	**0.398[b]**	**2.22**	0.283	1.42
Accuracy of ShuttleTrac: 50% or less	**-0.812[a]**	**-2.73**	-0.092	-0.27	-0.303	-0.99
Age	**0.126[b]**	**2.46**	**0.137[a]**	**3.05**	**0.137[b]**	**2.30**
Age square	**-0.001[b]**	**-2.02**	**-0.001[a]**	**-2.76**	**-0.001[c]**	**-1.86**
Male	**0.493[a]**	**2.91**	**0.528[a]**	**3.18**	0.133	0.66
White	-0.018	-0.10	**0.385[b]**	**2.22**	0.180	0.80
Driver license	-0.061	-0.17	0.454	1.32	-0.601	-1.35
Car access	-0.145	-0.66	0.065	0.28	0.166	0.68
Campus Parking permit	-0.082	-0.43	**-0.473[a]**	**-2.57**	-0.155	-0.69
Live on campus	-0.022	-0.09	0.373	1.47	0.186	0.68
Student	0.186	0.77	**0.426[c]**	**1.92**	0.360	1.22
Foreign citizen	0.031	0.13	0.268	1.17	0.204	0.72
<5 min walk to stop	**0.476[a]**	**2.30**	**0.325[c]**	**1.75**	0.225	0.96
5-10 min walk to stop	0.279	1.05	0.180	0.78	0.118	0.40
10-20 min walk to stop	0.452	1.48	**0.697[b]**	**2.34**	0.494	1.46
_cut1	-1.153	-1.15	0.119	0.13	-0.909	-0.76
_cut2	-0.892	-0.90	0.313	0.34	-0.155	-0.13
_cut3	-0.227	-0.23	1.124	1.22	1.206	1.01
_cut4	1.310	1.32	**2.369[b]**	**2.53**		
rho	**0.488[a]**	**5.90**	0.545	7.08	**0.462[a]**	**5.45**
# obs	886		815		734	
# groups	469		431		257	
Log Likelihood	-452.795		-382.856		-326.799	
P-value	0.0001		0.0000		0.185	

NOTE: Significant values are boldfaced.
a: p<0.01; b: p<0.5; c: p<0.1

Table 5.12 Estimated Results for Feeling of Security at Night

Feeling of security at Night	Model 4-1 Wave 1+2		Model 4-2 Wave 1+3		Model 4-3 Wave 1+2+3	
Independent varaibles	*Coef.*	*z*	*Coef.*	*z*	*Coef.*	*z*
Wave 2 dummy	-0.054	-0.44	N/A		-0.077	-0.58
Wave 3 dummy	N/A		**-0.268[c]**	**-1.94**	**-0.302[c]**	**-1.92**
Use of ShuttleTrac	**0.264[c]**	**1.66**	**0.306[c]**	**1.95**	**0.363[b]**	**2.35**
Accuracy of ShuttleTrac: 50% or less	-0.016	-0.06	0.294	1.19	0.111	0.44
Age	**0.083[c]**	**1.74**	**0.078[c]**	**1.86**	**0.093[c]**	**1.80**
Age square	-0.001	-1.40	-0.001	-1.52	-0.001	-1.44
Male	**0.716[a]**	**4.48**	**0.554[a]**	**3.67**	**0.437[b]**	**2.29**
White	**0.361[b]**	**2.02**	-0.057	-0.35	0.206	0.97
Driver license	0.013	0.04	-0.030	-0.11	0.056	0.18
Car access	-0.116	-0.60	-0.165	-1.00	-0.142	-0.75
Campus Parking permit	-0.211	-1.20	0.051	0.35	-0.097	-0.55
Live on campus	0.133	0.60	-0.123	-0.63	0.108	0.47
Student	0.006	0.02	0.001	0.00	0.082	0.31
Foreign citizen	0.092	0.41	-0.207	-1.05	0.023	0.09
<5 min walk to stop	0.281	1.52	0.188	1.18	0.027	0.14
5-10 min walk to stop	-0.211	-0.93	-0.248	-1.25	-0.152	-0.66
10-20 min walk to stop	0.080	0.32	-0.146	-0.64	0.015	0.06
_cut1	-1.344	-1.44	**-1.918[b]**	**-2.25**	-1.377	-1.32
_cut2	-0.115	-0.12	-0.727	-0.87	-0.206	-0.20
_cut3	1.194	1.28	0.502	0.60	0.989	0.96
_cut4	**2.549[a]**	**2.73**	**1.879[b]**	**2.24**	**2.437[b]**	**2.36**
rho	**0.616[a]**	**14.82**	**0.534[a]**	**11.04**	**0.581[a]**	**12.97**
# obs	818		775		692	
# groups	445		414		251	
Log Likelihood	-974.733		-909.052		-767.069	
P-value	0.000		0.005		0.111	

NOTE: Significant values are boldfaced.
a: p<0.01; b: p<0.5; c: p<0.1

It we want to see whether the immediate effect is going to increase or decrease along with time (illustrative examples shown in Figure 5.1), the mere comparison of magnitudes of two coefficients is not appropriate. Instead, we may construct a dummy variable representing the continuation of ShuttleTrac use in wave 3 and incorporate it into two three-wave models (Model 3-3 and 4-3). Any person who uses ShuttleTrac in wave 2 will get a value of 1 for this variable in the Wave 3 record[10], while others, including those newly self-reported

[10] In the random-effects ordered probit models, each person has three records for three waves respectively.

ShuttleTrac users in wave 3 survey, will get a value of 0. The coefficient of this variable actually reflects the slope of the presumed linear function that the potential longer-term effect may take. To save space, I do not present the full estimation results here. Results of the new specifications for two models both give us insignificant coefficients for the newly-incorporated variable[11]. It seems to tell us that the ShuttleTrac's immediate boosting impact on feeling of security is likely to be constant over time as illustrated in Figure 5.1A. However, there is a caveat for adopting this constant form of longer-term effect on feeling of security. As I discussed before, the newly self-reported ShuttleTrac users in wave 2 and 3 have systematically different adjustment periods. Thus the constant form of longer-term effect suggested in models using the three-wave panel dataset stands only if we hold the assumption that the new ShuttleTrac users in wave 3 survey have an average of around 2 weeks of adjustment period.

The perceived inaccuracy of prediction has shown insignificant impacts on feeling of security about riding the shuttle in all models except for Model 3-1. It seems that once passengers have the perception that ShuttleTrac provides inaccurate bus arrival information, they are less likely to feel safe while riding buses.

Other factors that influence passenger feeling of security about riding the shuttle are age and gender. Age is found to be positively correlated with feeling of security in daytime and nighttime. The results indicate that as respondent age grows, they generally feel safer about riding the transit. The dummy variable of gender has a significant coefficient only in Model 4-3, telling that male feels safer about riding transit during night time. These findings are consistent with our expectations.

[11] For Model 3-3, *coef.* = .182 (z = .51); for Model 4-3, *coef.* = -.045 (z = -0.18)

2) Perception of On-time Performance.

Results for models regarding perception of on-time performance are shown in Table 5.13. This time we found significant increase in perception of on-time performance over the time, other things equal, according to the coefficients of two wave dummy variables. This may probably be attributed to either the increased familiarity of the system or the measures that the operator adopted to actually improve the on-time performace. Yet if statistics of missing or delays of Shuttle-UM are available, the causes of such systematic changes in perceived on-timeness can be sorted out.

Table 5.13 Estimated Results for Perception of On-time Performance

Perception of on-tim performance	Model 5-1 Wave 1+2		Model 5-2 Wave 1+3		Model 5-3 Wave 1+2+3	
Independent varaibles	*Coef.*	*z*	*Coef.*	*z*	*Coef.*	*z*
Wave 2 dummy	**0.269**[c]	**1.91**	N/A		**0.647**[a]	**3.81**
Wave 3 dummy	N/A		**0.368**[b]	**2.08**	**0.573**[a]	**2.76**
Use of ShuttleTrac	**0.495**[a]	**2.76**	0.273	1.40	0.224	1.16
Accuracy of ShuttleTrac: 50% or less	**-1.144**[a]	**-4.21**	**-0.984**[a]	**-3.94**	**-1.034**[a]	**-3.78**
Age	-0.053	-1.11	-0.037	-0.80	-0.051	-0.83
Age square	0.001	1.29	0.001	0.88	0.001	0.88
Male	-0.179	-1.18	0.084	0.53	-0.046	-0.22
White	-0.216	-1.24	-0.090	-0.52	0.048	0.20
Driver license	0.101	0.36	0.430	1.60	0.414	1.21
Car access	-0.115	-0.62	-0.034	-0.19	0.159	0.72
Campus Parking permit	0.062	0.36	0.136	0.84	-0.071	-0.35
Live on campus	**-0.381**[c]	**-1.71**	-0.097	-0.46	-0.377	-1.41
Student	**-0.461**[b]	**-1.97**	-0.357	-1.49	**-0.570**[c]	**-1.84**
Foreign citizen	0.108	0.49	0.174	0.81	0.392	1.34
<5 min walk to stop	**-0.421**[b]	**-2.27**	**-0.561**[a]	**-3.08**	**-0.504**[b]	**-2.17**
5-10 min walk to stop	**-0.571**[b]	**-2.42**	**-0.610**[a]	**-2.74**	**-0.549**[b]	**-1.97**
10-20 min walk to stop	-0.158	-0.60	-0.260	-0.97	-0.248	-0.85
_cut1	**-4.917**[a]	**-5.15**	**-3.973**[a]	**-4.18**	**-4.615**[a]	**-3.71**
_cut2	**-3.840**[a]	**-4.10**	**-2.977**[a]	**-3.20**	**-3.431**[a]	**-2.81**
_cut3	**-2.448**[a]	**-2.65**	**-1.619**[c]	**-1.77**	**-2.055**[c]	**-1.70**
_cut4	1.299	1.42	**1.979**[b]	**2.16**	**2.272**[c]	**1.89**
rho	**0.557**[a]	**10.29**	**0.550**[a]	**9.49**	**0.607**[a]	**11.20**
# obs	817		769		690	
# groups	450		418		253	
Log Likelihood	-684.769		-659.353		-488.982	
P-value	0.000		0.000		0.000	

NOTE: Significant values are boldfaced.
a: $p<0.01$; b: $p<0.5$; c: $p<0.1$

Again we first look at the effects of ShuttleTrac use and perceived inaccuracy. Our estimation results show that ShuttleTrac use has a significant effect on perceptions of shuttle on-time performance in Model 5-1, but not in Model 5-2 or 5-3 (see Table 5.13). More specifically, other things being constant, shuttle riders do tend to feel the shuttle on-time performance is better immediately after they use the real-time information system. But this effect seems not to last in a medium or long run. Let us try to give plausible explanations for this phenomenon in two different scenarios. First, suppose that the actual on-time performance of transit service keeps unchanged between before and after periods. The immediate positive effect of real-time information system on the perception of on-time performance is most likely a temporary illusion caused by the provision of real-time arrival times. As time goes, this kind of illusion disappears as riders gradually find out that the on-time performance is not actually being improved. Alternatively, we may suppose that the actual on-time performance does get improved due to better management with real-time tracking system. The immediate effect of real-time information on the perception of on-time performance likely comes directly from this virtual lift of service punctuality. However, because transit riders are well-known to be adaptive yet demanding, they tend to be accustomed to and thus less appreciative of the improvement in a longer run. In this regard, the perception of transit service punctuality may return to a level where room is made by demanding passengers for further improvement. The question of which scenario is more likely the case depends on how measures of on-time performance actually change over time before and after the real-time information system is deployed.

The perceived inaccuracy of ShuttleTrac has shown a very strong negative effect on the on-time performance perceptions in all three models. This is to indicate that whenever a transit rider maintains the perception that real-time arrival time prediction is poorly estimated, he or she will think the transit service itself is poor in terms of punctuality. In practice, the accuracy of bus arrival time estimation and transit on-time performance are not necessarily connected. In fact, when the bus is not on time, accurate bus arrival estimation can be provided to passengers waiting at the stop. Alternatively, when inaccurate prediction is provided, the bus can still arrive on time pursuant to the print timetable. However, our findings seem to suggest that in general passengers perceive that they are correlated. In other words, perception of inaccurate real-time information contributes to perception of unpunctual transit services, and likely vice versa.

Coefficients of wave 2 and wave 3 dummies show that in general riders felt on-time performance of shuttle service is higher in wave 2 or 3 than in wave 1. Findings for other variables shown in Model 5-3 are presented as follows. For shuttle on-time performance, students feel worse than faculty and staff members do, perhaps because students tend to be pickier about shuttle which is one of their major transportation modes. Some interesting findings are about shuttle accessibility variables. People who live within 5 min walk to a nearest shuttle stop feel shuttle service is less punctual. Those who live 5-10 minute walk to a stop have the same negative feeling about shuttle on-time performance.

3) Waiting Anxiety.

Results for models regarding passenger anxiety in waiting are shown in Table 5.14.

Table 5.14 Estimated results for Waiting Anxiety

Waiting anxiety	Model 6-1 Wave 1+2		Model 6-2 Wave 1+3		Model 6-3 Wave 1+2+3	
Independent varaibles	*Coef.*	*z*	*Coef.*	*z*	*Coef.*	*z*
Wave 2 dummy	**0.224**[a]	**2.13**	N/A		**0.300**[b]	**2.52**
Wave 3 dummy	N/A		0.197	1.48	**0.247**[c]	**1.70**
Use of ShuttleTrac	0.002	0.01	0.188	1.27	0.073	0.52
Accuracy of ShuttleTrac: 50% or less	-0.353	-1.52	**-0.599**[a]	**-2.81**	**-0.387**[c]	**-1.72**
Age	0.014	0.37	0.016	0.43	0.031	0.67
Age square	0.000	0.18	0.000	0.08	-0.000	-0.21
Male	0.143	1.16	0.140	1.10	0.205	1.20
White	**0.379**[a]	**2.65**	0.147	1.07	**0.530**[a]	**2.74**
Driver license	0.095	0.39	-0.012	-0.05	-0.060	-0.21
Car access	-0.168	-1.08	0.004	0.03	0.068	0.40
Campus Parking permit	0.117	0.84	-0.043	-0.34	-0.078	-0.50
Live on campus	-0.161	-0.88	-0.025	-0.14	-0.151	-0.73
Student	-0.277	-1.51	-0.159	-0.83	-0.292	-1.19
Foreign citizen	0.147	0.82	-0.206	-1.22	0.326	1.41
<5 min walk to stop	0.103	0.68	0.159	1.14	0.117	0.67
5-10 min walk to stop	-0.174	-0.93	0.163	0.93	0.018	0.09
10-20 min walk to stop	**0.368**[c]	**1.78**	0.217	1.05	0.288	1.31
_cut1	-1.162	-1.57	-0.964	-1.32	-0.690	-0.74
_cut2	0.252	0.34	0.114	0.16	0.553	0.59
_cut3	**1.465**[b]	**1.98**	**1.482**[b]	**2.03**	**1.940**[b]	**2.08**
_cut4	**2.787**[a]	**3.73**	**2.713**[c]	**3.69**	**3.482**[a]	**3.71**
rho	**0.493**[a]	**11.51**	**0.461**[a]	**9.76**	**0.544**[a]	**13.27**
# obs	860		802		714	
# groups	461		431		256	
Log Likelihood	-1198.548		-1126.167		-945.930	
P-value	0.000		0.001		0.000	

NOTE: Significant values are boldfaced.
a: $p<0.01$; b: $p<0.5$; c: $p<0.1$

The coefficients for use of ShuttleTrac in three models have positive signs as expected. But this effect is found to be insignificant in either Model 6-1 or 6-2 in Table 5.14, indicating that the use of ShuttleTrac has no significant impact on how anxious passengers feel while waiting for shuttles, no matter how much time is given to them for adjustment. For perceived inaccuracy of ShuttleTrac dummy, the significantly negative coefficient in Model 6-2 tells that if passengers think the bus arrival time prediction is 50% or less accurate, they will tend to increase their general waiting anxiety level. Combining above findings, we may say that provision of real-time passenger information system may not reduce passenger's anxiety in waiting. However once they have a perception that these estimated bus arrival times are inaccurate in general, chances are that they will feel more anxious when waiting for buses. Another variable that is found to be significantly related to waiting anxiety is white dummy, suggesting that white people generally feel more anxious in waiting for shuttles.

4) Overall Satisfaction with Shuttle-UM Service.

Estimation results for models with overall satisfaction as the dependent variables are shown in Table 5.15. The wave dummy variables are insignificant in all models, showing that in general travelers do not have difference in satisfaction about Shuttle-UM over the year (Fall 2006-Fall 2007), if nothing is changed.

Table 5.15 Estimated Results for Overall Satisfaction

Overall satisfaction	Wave 1+2		Wave 1+3		Wave 1+2+3	
	Model 7-1 w/o oth	Model 7-2 w oth	Model 7-3 w/o oth	Model 7-4 w oth	Model 7-5 w/o oth	Model 7-6 w oth
Independent varaibles	*Coef.* *(z)*	*Coef.* *(z)*	*Coef.* *(z)*	*Coef.* *(z)*	*Coef.* *(z)*	*Coef.* *(z)*
Wave 2 dummy	-0.003 (-0.03)	-0.103 (-0.74)	N/A		0.043 (0.33)	-0.081 (-0.55)
Wave 3 dummy	N/A		0.026 (0.18)	0.005 (0.03)	-0.026 (-0.17)	-0.107 (-0.61)
Use of ShuttleTrac	**0.524**[a] **(3.31)**	0.272 (1.59)	**0.384**[b] **(2.41)**	0.151 (0.92)	**0.508**[a] **(3.31)**	**0.336**[b] **(2.07)**
Accuracy of ShuttleTrac: 50% or less	**-0.859**[a] **(-3.31)**	**-0.467**[b] **(-1.74)**	**-0.620**[a] **(-2.68)**	-0.257 (-1.11)	**-0.633**[a] **(-2.67)**	-0.317 (-1.30)
Age	-0.066 (-1.44)	**-0.121**[a] **(-2.75)**	0.028 (0.68)	0.016 (0.43)	0.025 (0.51)	0.008 (0.17)
Age square	**0.001**[c] **(1.85)**	**0.002**[a] **(3.11)**	-0.000 (-0.02)	0.000 (0.38)	-0.000 (-0.01)	0.001 (0.46)
Male	0.028 (0.19)	0.028 (0.20)	0.159 (1.13)	0.077 (0.63)	-0.155 (-0.86)	-0.097 (-0.62)
White	**-0.484**[a] **(-2.75)**	**-0.560**[a] **(-3.42)**	-0.151 (-0.98)	-0.153 (-1.15)	-0.034 (-0.17)	-0.165 (-0.92)
Driver license	0.018 (0.06)	-0.042 (-0.16)	0.019 (0.08)	-0.124 (-0.57)	-0.174 (-0.57)	-0.244 (-0.87)
Car access	-0.252 (-1.36)	-0.068 (-0.39)	-0.147 (-0.93)	-0.194 (-1.34)	-0.091 (-0.50)	-0.175 (-1.01)
Campus Parking permit	0.235 (1.41)	0.151 (0.93)	**0.257**[c] **(1.83)**	**0.357**[a] **(2.68)**	**0.307**[c] **(1.82)**	**0.442**[a] **(2.68)**
Live on campus	-0.119 (-0.54)	-0.145 (-0.71)	0.120 (0.63)	0.055 (0.31)	0.120 (0.53)	0.182 (0.86)
Student	**-0.485**[b] **(-2.17)**	-0.305 (-1.40)	0.096 (0.47)	0.204 (1.08)	-0.030 (-0.12)	0.162 (0.69)
Foreign citizen	0.141 (0.64)	0.035 (0.18)	0.003 (0.01)	-0.128 (-0.79)	0.402 (1.64)	0.269 (1.26)
<5 min walk to stop	0.114 (0.63)	0.157 (0.91)	0.050 (0.32)	0.133 (0.92)	-0.043 (-0.23)	-0.048 (-0.26)
5-10 min walk to stop	-0.161 (-0.74)	-0.040 (-0.18)	**-0.326**[c] **(-1.70)**	-0.170 (-0.94)	-0.060 (-0.26)	-0.010 (-0.05)
10-20 min walk to stop	-0.372 (-1.55)	-0.374 (-1.52)	**-0.423**[c] **(-1.92)**	**-0.408**[c] **(-1.85)**	**-0.421**[c] **(-1.81)**	**-0.496**[b] **(-2.08)**

(Table continues in the next page)

Table 5.15 (continue)

Overall satisfaction	Wave 1+2	Wave 1+3	Wave 1+2+3			
	Model 7-1 w/o oth	Model 7-2 w oth	Model 7-3 w/o oth	Model 7-4 w oth	Model 7-5 w/o oth	Model 7-6 w oth
Independent varaibles	*Coef.* *(z)*	*Coef.* *(z)*	*Coef.* *(z)*	*Coef.* *(z)*	*Coef.* *(z)*	*Coef.* *(z)*
Feeling of security at day	NA	**0.475[a] (3.81)**	NA	**0.475[a] (4.17)**	NA	**0.513[a] (3.42)**
Feeling of security at night	NA	0.084 (1.16)	NA	**0.115[c] (1.76)**	NA	0.013 (0.17)
Perception of on-time performance	NA	**0.827[a] (8.35)**	NA	**0.888[a] (9.56)**	NA	**0.816[a] (7.60)**
Waiting anxiety	NA	**0.363[a] (5.84)**	NA	**0.213[a] (3.84)**	NA	**0.285[a] (4.42)**
_cut1	**-4.977[a] (-5.32)**	-1.330 (-1.40)	**-2.278[a] (-2.78)**	**2.005[b] (2.45)**	**-2.760[a] (-2.72)**	0.609 (0.61)
_cut2	**-3.875[a] (-4.23)**	-0.058 (-0.06)	**-1.406[c] (-1.75)**	**3.045[a] (3.71)**	**-1.767[c] (-1.77)**	**1.950[b] (1.97)**
_cut3	**-2.703[a] (-2.99)**	1.216 (1.31)	-0.237 (-0.30)	**4.429[a] (5.28)**	-0.621 (-0.63)	**3.225[a] (3.25)**
_cut4	-0.192 (-0.21)	**3.926[a] (4.12)**	**2.121[a] (2.62)**	**6.794[a] (7.70)**	**1.856[c] (1.86)**	**5.775[a] (5.64)**
rho	**0.614[a] (15.15)**	**0.479[a] (7.56)**	**0.519[a] (10.73)**	**0.291[a] (4.12)**	**0.561[a] (12.62)**	**0.400[a] (6.53)**
# obs	870	734	820	705	729	628
# groups	461	402	454	399	259	243
Log Likelihood	-945.435	-689.393	-871.523	-649.029	-722.252	-559.392
P-value	0.000	0.000	0.000	0.000	0.001	0.000

NOTE: Significant values are boldfaced.
a: p<0.01; b: p<0.5; c: p<0.1

Results of Model 7-1 in Table 5.15 show that ShuttleTrac use has significantly positive effects on riders' overall satisfaction with shuttle service at the 0.01 level. In ordinal models, magnitude of coefficients only has meaning for the latent variable. To interpret the coefficient of ShuttleTrac use, I predict probabilities for different situations[12]. Other variables being kept fixed at mean values, ShuttleTrac use decreases the probability of one rating satisfaction level 4 by 0.008 (from 0.562 to 0.554), while increases the probability of rating 5

[12] Postestimation commands (mfx or predict) are not useable for "reoprob". Therefore, I used "predict" for "regoprob2" to compute the possibilities for two hypothetical records with mean values of all variables but Use of ShuttleTrac.

by about 0.1 (from 0.186 to 0.285). In terms of time frame, this positive effect arises almost immediately after the deployment of ShuttleTrac.

Results of Model 7-3 in Table 5.15 also give a positive coefficient of ShuttleTrac use dummy variable at a significance level of 0.05, suggesting that passenger satisfaction rating tends to rise due to ShuttleTrac use, even after a few months. To interpret the coefficient, other variables kept fixed at mean values, ShuttleTrac use decreases the probability of one rating satisfaction level 4 by 0.004 (from 0.584 to 0.580), while increases the probability of rating 5 by about 0.078 (from 0.179 to 0.257). Comparing the effects of ShuttleTrac use on overall satisfaction in above two models, it is to imply that the use of real-time passenger information system may immediately lift passengers' satisfaction with transit service and this boost will continue after a number of months, but the magnitude of this positive impact seems to decrease with a considerable period of adaption.

Similar to what has been tried previously, I incorporated a new dummy variable representing ShuttleTrac usage in wave 2 in Model 7-5, aiming at capturing the slope of linear function the longer-term effect takes. The estimation results of new specification give us an insignificant coefficient[13], showing that the slope is not significantly different from zero. However, as we have discussed, this finding is also strongly binding to the assumption that new ShuttleTrac users in wave 3 made their first use within a couple of weeks prior to wave 3 survey time points.

The dummy variable of perceived inaccuracy of ShuttleTrac shows negative impact on overall satisfaction rating in both Model 7-1 and 7-3 in Table 5.15 at a high significance level of 0.01. This tells that, everything else being equal, if passengers have the impression that ShuttleTrac estimates bus arrival times only 50% or less accurately, they tend to rate

[13] For Model 7-5, *coef.* = -.047 (z=-0.25).

their overall satisfaction lower. The absolute values of the variable are greater than those of ShuttleTrac use dummy in respective models, which imply that passengers are very much more concerned about accuracy of real-time information. We suppose that a passenger has used ShuttleTrac and felt that it is generally inaccurate (both ShuttleTrac use dummy and perceived inaccuracy dummy take value of 1). Other variables being fixed at means, compared with those who have never used ShuttleTrac and no adverse impression of ShuttleTrac accuracy, the probability of this passenger rating satisfaction at 5 decreases by 0.052 (from 0.193 to 0.141), and the probability of rating satisfaction at 4 decreases by 0.019 (from 0.563 to 0.544). These results are applicable in Model 7-1 in Table 5.15. In Model 7-3, the decrease in probability of rating satisfaction at 5 is 0.063 (from 0.198 to 0.135), and decrease in the probability of rating satisfaction at 4 is 0.019 (from 0.583 to 0.564), other variables kept at their means. This case has clearly shown how perceived inaccuracy of real-time information lower passengers' overall satisfaction ratings in both short and medium runs, even with positive impact of real-time information system per se.

As discussed in Chapter 3, there exist both direct and indirect paths linking real-time transit information to overall satisfaction. The results from three models (Model 7-1, 7-3, and 7-5) in Table 5.15 show the satisfaction effect of real-time information as a combination of impacts from both paths. To distinguish the direct and indirect effects, I further estimated three models, explicitly incorporating ratings of lower-level psychological outcomes as independent variables, including feeling of security at day and night, perception of on-time performance, and waiting anxiety. Note that it is generally not recommended to directly use the ordinal ratings of these variables in the models. A more preferable way is to convert the ratings into dummy variables. However, in doing so a lot of degree of freedom will be lost because in total 16 new dummy variables are to be included for these four psychological outcomes. In view of that, I did not take this approach.

The coefficients of these four variables in three models (Model 7-2, 7-4, and 7-6 in Table 5.15) are highly significant in general, showing that they are highly correlated with overall satisfaction, which is consistent with our expectations. When these intermediate psychological variables are controlled for, the ShuttleTrac use variable does not show significant effect in Model 7-2 or 7-4. It seems to imply that the direct path linking real-time transit information use and overall satisfaction may not be as prominent as the indirect path. The perceived inaccuracy is found to be significant in Model 7-2, suggesting that, even if other psychological outcomes were controlled for, the inaccurate prediction per se makes passengers lower their satisfaction with the transit service. The insignificant coefficient of the same variable in Model 7-4 can be explained this way: given a period of adjustment, perceived inaccuracy of information will not continue to directly affect passenger's overall satisfaction level, because they have already learned to adjust their expectation of the new real-time information system. Referring back to the (dis)satisfaction model shown in Figure 3.7, even if the perceived service quality is still poor, the lowered expectation makes the negative disconfirmation is less likely the case. And in turn, in a longer run the overall satisfaction is not going to be significantly decreased solely due to poor quality of the real-time transit information system.

5.5 Findings and Discussions

5.5.1 Summary of Findings

Modeling findings regarding relationships between real-time passenger information systems and traveler's general responses can be summarized in the Table 5.16. This table entails three dimensions. The first dimension is the two variables regarding real-time information system, namely, use of ShuttleTrac and perceived inaccuracy of prediction. The second dimension includes three behavioral variables and five psychological variables measuring traveler's general behavioral and psychological responses to real-time information systems. Using panel datasets derived from online surveys for one pre-system wave and two post-system waves, we can furthur distinguish the effect of each of the two variables in the first dimension on each one of variables in the second dimension into immediate and longer-term effect in terms of the third dimension – adaption period.

Table 5.16 Summary of General Responses to Real-time Transit Information

	ShuttleTrac use		Perceived inaccuracy of ShuttleTrac	
	Immediate effect	Longer-term effect	Immediate effect	Longer-term effect
Shuttle trip rates	No	Yes	No	Yes
Campus-based trip rates	No	No	Yes	Yes
Commuting mode choice	N/A	No	N/A	No
Feeling of security at day	Yes	Yes	Yes	No
Feeling of security at night	Yes	Yes	No	No
Perception of on-time performance	Yes	No	Yes	Yes
Waiting anxiety	No	No	No	Yes
Overall satisfaction	Yes	Yes	Yes	Yes

Use of ShuttleTrac has shown none immediate effect on traveler's general behaviors, which is understandable because travelers do need time to adapt and adjust according to real-time information systems. Interestingly, providing a few months for adjustment, those who used real-time information system are likely to increase their transit trip-making frequency. That means a longer-term effect of real-time transit information use on transit trip rate has been found with our panel dataset. Although the magnitude of effect may not be large (about 23% increase), still it is a very encouraging message to advocates of such systems.

Dominant commuting mode has not been found to change because of ShuttleTrac use, even with a few months of adjustment, suggesting that real-time transit information system itself is not sufficient to shift commuter's dominant mode of transportation. This is not surprising because as Gärling *et al.* (2002) pointed out, a change of travel mode is perceived by a traveler as a relatively costly adaption, when compared to changes in departure times or routes. Also this finding echoes what was suggested using a numerical simulation in the study by Chorus *et al.* (2006c).

The perception of information accuracy also plays a role in influencing traveler's transit trip-making frequency, especially when more adjustment time is given. Negative longer-term effect of perceived inaccuracy of information was found to be significant on both the total number of monthly shuttle trips and the number of campus-based shuttle trips. The findings show that if somehow travelers got the impression that real-time information has very poor accuracy, they will decrease their transit trip-making frequency. Again the perception of information accuracy has no significant relationship with commuter's choice of dominant commuting mode.

Unlike for behavior, immediate effects are actually found to be significant for some of psychological outcomes, including feeling of security about riding buses at day and at night, perception of on-time performance, and overall satisfaction with transit service. Results tell that immediately after using the real-time information systems, passengers tend to feel safer about riding buses at day or night, feel transit service more on-time, and feel more satisfied with the transit service. These immediate effects tend to persist for at least several months, except for perception of on-time performance. However, because of the limitation of our datasets, it remains unclear whether the magnitude of these effects are decreasing or holding constant.

As for perception of information accuracy, some immediate and longer-term effects were also found for a few psychological outcomes. Immediately after use of real-time transit information system, with perception of inaccurate prediction of such information, passengers are likely to feel less safe about riding the shuttle at day, feel the service less on-time, and feel less satisfied with the service. Given a few months, if passengers still have this perception of information inaccuracy, they will continue to feel the service less on-time and less satisfied with the service, and will generally feel more anxious while waiting for buses. In terms of effect magnitude, the general finding is that the negative effects caused by inaccurate prediction on rider's general psychology are higher than the positive effects of using real-time information. That is, no matter how much positive psychological effect the real-time information systems can generate, these effects may be offset or surpassed by the negative impacts caused by poor information.

5.5.2 Discussions

This chapter is concerned about traveler's behavioral and psychological responses to the real-time transit passenger information system. The design of ShuttleTrac system provides us with the opportunity to differentiate two groups of people, ShuttleTrac users (treatment group) and non-users (control group), and explore changes in their travel behavior and perceptions of and attitudes toward shuttle service. It is noted that behavioral and psychological outcomes we examined in this chapter are not about specific trips or system use. Instead they are general in nature in that travelers are given time to adapt and adjust after their first use of such system.

Travel behaviors that were examined are monthly shuttle trip-making frequency, monthly campus-based trip-making frequency, and dominant commuting mode choice. Our hypothesis is that, with real-time transit information system, travelers will increase their trip-making frequency and shift their commuting mode to transit more, especially with a longer period of adjustment. The empirical results generally do not support our hypotheses, except that the longer-term effect of ShuttleTrac on monthly trip rate was found with an average of five and a half months of adjustment.

This significant longer-term effect on trip-making frequency is a surprisingly encouraging finding for advocates and providers of real-time passenger information systems, because it validates their anticipation of ridership increase as a result of deployment of such advanced systems. However, we need to emphasize several precautions before one becomes too excited about such good news. First, the effect size may not be as large as one expects. 23% increase in transit trip-making frequency seems to be somewhat large if it can be directly translated into the increase in ridership. However, it is not that easy. For one thing, this increase at an individual level may vary to a great extent among different user groups (e.g. frequent riders have smaller increase, infrequent riders have higher increase) thus make such figure (23%) difficult to be directly interpreted as the aggregate ridership increase rate. For another thing, as we will further discuss in Chapter 7, the special characteristics of Shuttle-UM prevents us from generalizing such effect to the typical urban public transport systems without special considerations. Early estimates (more like guesses) for ridership increases, as a result the deployment of advanced traveler information systems, range from 1% to 3% (Goeddel, 2000). It is safe to say that our empirical findings confirm the existence of ridership effect of real-time information in a longer run, but there is no definitive answer of how much.

Second, one cannot expect this increase to occur immediately after the deployment of a new system. At least a few months is needed to allow this effect to surface as travelers gradually adjust their transit riding behavior. Third, the question of whether this positive effect will hold constant or drawback in a longer future is not clear because of a lack of evidence. Fourth, the perception of real-time transit information accuracy also shows a longer-term effect on trip-making frequency. And the effect size is about 2.5 times higher than mere exposure to the system. The implication for system providers is that if you want to deploy such system, please try to provide accurate information, because inaccurate information might very well ruin all of your efforts and actually generate decrease in ridership.

A stated-preference survey in Chicago shows that about 67% of all respondents said that they would increase transit usage when provided with real-time transit information, 60% for current users and 70% for non-current users (Tang and Thakuriah, 2006). In light of our results, such stated preference may need to be considered with reservation and patience.

Psychological outcomes, on the other hand, are found to be generally influenced by real-time information system. Not only some immediate impacts are found, but also latent psychological effects are prominent, suggesting that the positive effects are able to persist for a while. These findings are consistent with what most evaluation studies have reported. Therefore, even if transit agencies and scholars might not be too optimistic about achieving ridership increase or shifting commuter's mode by providing real-time information to travelers, they can expect immediate and lasting positive psychological benefits to transit riders. However, again, the perception of information accuracy has shown greater effect on traveler's general attitude towards transit service than mere use of system does. What is reinforced by these findings is the following message to transit agencies: if you want to do it, please do it right.

In this semi-natural experimental environment, the treatment is the use of ShuttleTrac system. From the day travelers first use such system, they are being classified into the treatment group, no matter how many times they use thereafter. It is realized that such treatment is not likely to be randomly assigned among travelers because they may deliberately select whether they start to use it or not. Therefore, endogeneity caused by self-selection is a potential problem when causal relationships are being examined between treatment and outcome. It is noted that the frequency of system use was deliberately excluded from models as it is conceived to be a more problematic endogenous variable. Different approaches were utilized to address this possible endogeneity issue for our key variable.

First, for trip-making frequency models, panel datasets were used for estimating the models with fixed-effects (FE) estimator. A nice thing about FE estimator is that unobserved individual differences as a part of unobserved disturbance are canceled out. In other words, FE models allow for endogeneity of all the regressors and the unobserved individual effects. If we assume that the endogenous variable is only correlated with the unobserved individual heterogeneity which is likely the case, the self-selection is no longer a problem. Second, for commuting mode choice model, because cross-sectional dataset was being used, I adopted a two-stage modeling approach with instruments as substitute for the endogenous variable. Third, for psychological outcomes, panel datasets were used for modeling the relationships with random-effects (RE) estimators. It is true that with RE estimator unobserved individual heterogeneity is not eliminated and hence non-correlation shall be assumed between it and explanatory variables. However, the use of real-time passenger information system is considered to be less likely correlated with unobserved disturbance for psychological models as discussed above. Therefore, self-selection bias is less of a problem for models of psychological outcomes.

Our results also suggest that other approaches (e.g. building more on-campus student housing, rerouting lines or rearranging stops to make shuttle within walking distance for more students, or increasing the price of a campus parking permit) would increase shuttle usage significantly. This is consistent with previous studies (e.g., Toor and Havlick, 2004). Universities may consider such approaches, along with other proven policies (e.g. unlimited access (Brown *et al.*, 2003) and promoting non-motorized mode (Toor and Havlick, 2004)), if they want to achieve goals such as increased transit ridership and promote sustainability in campus community.

5.6 Chapter Summary

The good timing of ShuttleTrac deployment offers me a good opportunity to make a quasi-experimental design and undertake a empirical study in order for genuine understanding of causal effects of real-time bus arrival information on traveler's general/cumulative behavior and psychology. This chapter presents the empirical analyses that, using panel datasets derived from three online surveys, examine the relationships between real-time information and three behavioral and five psychological variables measuring traveler general behavior and psychology. Several interesting findings were reported and discussed. This part of analysis has shown that real-time transit information systems do make a difference in transit trip-making frequency and passenger's perceptions of and attitudes toward transit.

Chapter 6: Trip-specific Psychological Responses to Real-time Transit Information

6.1 Introduction

Suppose a passenger is going to take a specific journey to the destination, which involves a transit mode. When real-time transit information is provided and acquired by the passenger, she may or may not change her travel behaviors accordingly. However, in spite of non-change in behavioral responses, chances are that the real-time information will induce some psychological responses as the passenger is experiencing the journey. This kind of trip-specific psychological response to real-time information is different from the general attitudes toward transit service in terms of their time frames. But cumulatively trip-specific psychological response may build up to some general attitudes, as we discussed in Chapter 3.

Chapter 5 has examined the short-term and medium-term changes in general attitudes toward Shuttle-UM service caused by real-time information. Now the focus is turned to trip-specific psychological responses. The objective of Chapter 6 is to empirically investigate whether real-time bus arrival information would change passengers' psychological conditions during specific transit trips, and how these trip-specific psychological effects of real-time information vary among user groups and under different conditions. Using data collected from a shuttle on-board survey conducted immediately after the extensive advertising of ShuttleTrac, a series of models can be estimated to try to capture the correlations between provision and accuracy of real-time information and four psychological outcome variables, i.e. perceived waiting time, feeling of security, waiting anxiety, and satisfaction with at-stop transit service.

The structure of Chapter 6 is as follows. Section 2 describes the methodology used in analysis in details, followed by Section 3, which is the report of modeling results. Section 4 further discusses the results and conclusions are drawn in Section 5.

6.2 Modeling Methodology

6.2.1 Datasets and Variables

The dataset employed in this part of research is the cross-sectional dataset derived from the onboard survey conducted after the deployment of ShuttleTrac. I further divide the respondents into two groups: waiters (who have been waiting for the coming bus) and non-waiters (who boarded buses without waiting). It is conceivable that some of the psychological effects are only concerning waiting experience, such as feeling of security and anxiety while waiting. Therefore, actually two datasets were used in different models for these four dependent variables. The descriptive statistics are shown in Table 6.1.

The four dependent variables to be modeled are: 1) perceived waiting time. The average perceived waiting time is 6.21 minutes for waiters, and 4.58 minutes for all riders; 2) feeling of security while waiting; 3) waiting anxiety level; and 4) satisfaction with at-stop service. It is hypothesized that use of real-time bus arrival information will make a difference in these four variables. The derivation of these dependent variables was introduced in Chapter 3 in details.

Table 6.1 Descriptive Statistics of Wave2 Onboard Survey Dataset

	Waiter dataset					Full dataset				
	N	Min	Max	Mean	SD	N	Min	Max	Mean	SD
Perceived waiting time	502	1.5	30	6.21	5.33	680	0	30	4.58	5.33
Feeling of security	495	1	5	4.23	1.04	N/A				
Waiting anxiety	490	1	5	3.76	1.27	N/A				
Satisfaction	492	1	5	4.10	0.29	668	1	5	4.16	0.87
Pre-trip ShuttleTrac use	499	0	1	0.08	0.27	670	0	1	0.09	0.28
At-stop ShuttleTrac use	499	0	1	0.23	0.42	670	0	1	0.19	0.39
Perceived bus earliness against real-time info	508	0	1	0.05	0.21	686	0	1	0.05	0.22
Perceived bus lateness against real-time info	508	0	1	0.06	0.25	686	0	1	0.05	0.21
Pre-trip timetable awareness	504	0	1	0.63	0.48	681	0	1	0.64	0.48
At-stop timetable awareness	504	0	1	0.19	0.39	681	0	1	0.17	0.37
High frequency	508	0	1	0.35	0.48	686	0	1	0.34	0.48
Night	508	0	1	0.23	0.42	686	0	1	0.20	0.40
On campus stop	507	0	1	0.54	0.50	684	0	1	0.55	0.50
Status: student	475	0	1	0.86	0.35	647	0	1	0.85	0.36
Gender: male	471	0	1	0.44	0.50	642	0	1	0.44	0.50
Race: white	468	0	1	0.44	0.50	637	0	1	0.43	0.49
Age	457	16	75	24.19	7.72	622	16	75	24.24	7.77
Age square	457	256	5625	644.84	549.93	622	256	5625	648.00	550.51
On-time perception: always on-time	487	0	1	0.15	0.36	662	0	1	0.17	0.38
On-time perception: mostly on-time	487	0	1	0.62	0.49	662	0	1	0.62	0.49
How important to arrive on time: 2	503	0	1	0.09	0.29	N/A				
How important: 3	503	0	1	0.18	0.39	N/A				
How important: 4	503	0	1	0.25	0.43	N/A				
How important: 5	503	0	1	0.40	0.49	N/A				

Timetable is the static information that passengers can acquire. Two variables about timetable knowledge are “pre-trip timetable knowledge” and “at-stop timetable knowledge”. In hypothesis, knowledge of scheduled bus arrival time will be positively influences on passenger’s behavior and psychology.

The perceived lateness of the bus is a representation of the difference between actual and scheduled arrival times. If the passenger thinks a bus is late in comparison to the published timetable, he will generally have negative perceptions on the transit service.

It is a general understanding that campus is a safer place than places outside of the campus. Especially some of the neighborhoods (e.g. College Park, Springhill Lake, etc.) nearby the university are known for their unsafely. Therefore, waiting at an on-campus stop is hypothesized to be positively related with feeling of security.

Three activity engagement variables are derived from the question about what activities the passenger is engaged in while waiting for the bus. “Reading” and “Listening to music” are classified as self engagement, while “talking with people” is classified as communicative engagement. If a passenger spends some of the waiting time in nearby place, he is engaged in a diversionary activity.

A number of individual characteristics were incorporated into regression models as independent variables, including gender (male=1), race (white=1), status (student=1), and age. Age square was also included in psychological models to capture possible non-linear effect of age on psychological dependent variables.

Bus service frequency is a key factor that will substantially influence passenger perception on service quality. The headway of the boarding stop was extracted from the timetable. The headway variable was coded into a dummy variable named “High-frequency” (1 if headway <= 20 minutes; 0 otherwise). The breaking point (20 minutes) is identified according to literature and actual situation of Shuttle-UM. In general, within-campus and nearby-community shuttle lines enjoy higher frequency with headway is no greater than 20 minutes. Also the shuttle line to the Greenbelt Metro Station has a high frequency. Other distant-community shuttle lines suffer a much lower frequency, some even with headway of 90 minutes.

Passenger psychology, especially feeling of security, may change dramatically from day to night. A dummy variable named “night” is generated showing whether the boarding time is after 8pm. It is hypothesized that at night feeling of security decreases and waiting anxiety increases.

The previous perception on bus service may well influence passenger’s trip-specific psychological responses. In the onboard survey a question was asked about respondent’s perception on the usual on-time performance of the particular line he or she intended to ride. The answers were re-coded into three dummy variables: “Always on time”, “Mostly on time”, and “no more than 50% on time”. The first two were incorporated in the models to represent the general perception on on-time performance.

6.2.2 Model Specifications

Perceived waiting time was transformed from categorical to continuous. Therefore, a multivariate linear regression specification (OLS) is used to model effects of real-time information and other explanatory variables on perceived waiting time.

$$PWT = \alpha + \beta X + \varepsilon \qquad (6.1)$$

Where, PWT denotes perceived waiting time, X the vector of independent variables, α coefficient of constant to be estimated, β coefficients of vector X to be estimated, and ε the error term.

When the dependent variable takes more than two values, but these values have a natural ordering, the ordered probit model would be appropriate. It would be inappropriate to use the multinomial logit because this model does not account for the ordering of the dependent variable. Further, a regression model would not be appropriate because it assumes differences between categories of the dependent variable to be equal, whereas, the data are only ordinal. The results would be substantially different if ordered dependent variables are analyzed using regression instead of using the ordered probit.

Consider a latent variable model of the following form, where y^* is the unobserved dependent variable, X a vector of explanatory variables, β vector of an unknown parameter to be estimated and ε the error term.

$$y^* = \beta' X + \varepsilon \qquad (6.2)$$

Instead of y*, the following is observed:

$$\begin{aligned}
&y = 0 \text{ if } y^* \leq 0 \\
&y = 1 \text{ if } 0 < y^* \leq \mu_1 \\
&y = 2 \text{ if } \mu_1 < y^* \leq \mu_2 \qquad (6.3) \\
&\ldots\ldots \\
&y = J \text{ if } \mu_{J-1} < y^*
\end{aligned}$$

Where y is the ordered dependent variable and μ the vector of unknown threshold parameters that is estimated with coefficients β vector. ε is assumed to have a standard logistic distribution. The threshold between the lowest and the next lowest categories is always set to 0. Moreover the threshold values must be ordered from lowest to highest. Resulting from the standard logistic distribution, the probability that y_i falls into the jth category is given by:

$$\Pr[y_i = j] = \Phi[\mu_j - \beta' X_i] - \Phi[\mu_{j-1} - \beta' X_i] \qquad (6.4)$$

Where μ_j and μ_{j-1} denote the upper and lower threshold values for category J, and Φ is the cumulative standard normal.

The likelihood function for the model is given by:

$$L = \prod_{i=1}^{n} \prod_{j=1}^{n} \left[\Phi\left(\mu_j - \beta' X_i\right) - \Phi\left(\mu_{j-1} - \beta' X_i\right)\right]^{y_{ij}} \qquad (6.5)$$

Since three dependent variables about feeling of security, anxiety and satisfaction are all ordinal, ordered logit models are adopted to estimate the coefficients of explanatory variables. Ologit command in Stata was used to execute the estimations.

6.3 Modeling Results

6.3.1 Perceived Waiting Time

According to previous review, passengers who are aware and unaware of timetables will show fundamentally different arrival patterns and thus generate different patterns of actual waiting time. Two models for unaware and aware passengers were estimated to model how real-time transit information influence passenger perceived waiting time. The passengers who boarded without waiting (i.e. waiting time is 0) are also included.

Table 6.2 Modeling results for perceived waiting time (Full)

	Unaware Model (full)		Aware Model (full)	
Variables	*Coef.*	*t*	*Coef.*	*t*
Headway	**0.101[a]**	**3.33**	0.009	0.74
Pre-trip ShuttleTrac use	-2.382	-0.73	-1.050	-1.32
At-stop ShuttleTrac use	1.207	1.32	0.815	1.12
Perceived bus earliness against real-time info	2.410	0.98	-0.228	-0.21
Perceived bus lateness against real-time info	2.501	1.17	**2.363[c]**	**1.87**
Perceived bus lateness against timetable	**2.848[b]**	**2.19**	**2.812[a]**	**3.75**
Night	0.300	0.34	**1.846[b]**	**2.52**
Access mode: walking	0.918	0.88	0.611	0.90
At campus origin stop	0.269	0.32	0.053	0.10
Status: student	-0.291	-0.23	-0.374	-0.43
Gender: male	-0.248	-0.31	-0.496	-1.06
Race: white	-0.015	-0.02	**0.857[c]**	**1.78**
Age	-0.319	-1.22	-0.172	-1.20
Age square	0.0039	1.02	0.0022	1.18
On-time perception: always on-time	-2.119	-1.50	**-1.403[c]**	**-1.68**
On-time perception: mostly on-time	-0.078	-0.09	-0.836	-1.19
Anxiety	-0.136	-0.43	0.031	0.16
Constant	7.318	1.59	**6.149[b]**	**2.17**
Number of obs	195		370	
R^2	0.1826		0.1445	
NOTE: Significant values are boldfaced. a: p<0.01; b: p<0.5; c: p<0.1				

Table 6.3 Modeling results for perceived waiting time (stepwise)

	Unaware Model (stepwise)		Aware Model (stepwise)	
Variables	*Coef.*	*t*	*Coef.*	*t*
Headway	**0.100[a]**	**3.72**	--	--
Pre-trip ShuttleTrac use	--	--	**-1.320[c]**	**-1.92**
At-stop ShuttleTrac use	**1.677[b]**	**2.10**	--	--
Perceived bus earliness against real-time info	--	--	--	--
Perceived bus lateness against real-time info	--	--	**2.921[b]**	**2.46**
Perceived bus lateness against timetable	**2.837[b]**	**2.50**	**3.185[a]**	**4.65**
Night	--	--	**2.023[a]**	**2.86**
Access mode: walking	--	--	--	--
At campus origin stop	--	--	--	--
Status: student	--	--	--	--
Gender: male	--	--	--	--
Race: white	--	--	0.744	1.64
Age	**-0.441[c]**	**-1.94**	--	--
Age square	**0.0059[c]**	**1.74**	--	--
On-time perception: always on-time	**-2.628[b]**	**-2.22**	--	--
On-time perception: mostly on-time	--	--	--	--
Anxiety	--	--	--	--
Constant	**9.341[a]**	**2.71**	**3.061[a]**	**9.34**
Number of obs	195		370	
R^2	0.1611		0.1276	
NOTE: Significant values are boldfaced. a: p<0.01; b: p<0.5; c: p<0.1				

In traditional models, headway plays a vital role in determining passenger's waiting time. Here the effect of headway in different scenarios can be clearly found in the Unaware Model and Aware Model. In Unaware Model, headway has positive impact at a high significance level 0f 0.01. The coefficient indicates that 10-minute increase in headway will generate 1-minute increase in passenger perceived waiting time. In Aware Model, this significant effect was not found, showing that aware passengers do plan their arrivals according to timetable, thus waiting times are not influenced by bus headways. This finding confirms validity of differentiation of aware passengers and unaware passengers in terms of their timetable knowledge and arrival patterns, as suggested by literature.

Results of two real-time information acquisition variables show interesting patterns. Pre-trip ShuttleTrac use has shown significantly negative effect only in Aware Model, suggesting that if passengers knew the scheduled bus arrival time and also acquired real-time arrival information before trip, the passenger perceived waiting time will decrease by 1.32 minutes, other things being constant. This effect is perhaps mainly due to the passenger's better planning of the departure time to coordinate with predicted bus arrival time. In this sense, actual waiting time, as the intermediate variable, was reduced by acquiring real-time information and thus making more efficient pre-trip travel decisions.

At-stop ShuttleTrac use has shown significant effect on perceived waiting time in Unaware Model, but the sign is positive. This seems to imply that when passengers are unaware of scheduled timetable and arrive at stop at random, acquisition of real-time bus arrival time at stop will increase perceived waiting time by 1.68 minutes, other variables being kept constant. This may indicate the reverse causal link, that is, while not knowing the timetable, the longer the passenger has being waiting for the buses, the more likely he or she is going to inquiry the real-time arrival information. This effect was only found in Unaware Model.

The perceived accuracy of real-time prediction in general shows insignificant relation with perceived waiting time, except for the perceived lateness against real-time information in Aware Model. The results seem to say, in the scenario of passenger knowing the timetable, if passengers think the buses arrive later than predicted arrival time, their perceived waiting times will increase by 2.92 minutes. Let's suppose one passenger used pre-trip real-time information and thinks the bus is late in comparison with the prediction. Other factors being kept fixed, the perceived waiting time of this passenger will increase by 1.6 minutes (2.92-

1.32). This magnitude difference shows that accuracy of information plays a relatively greater role in determining passenger perceived waiting time than mere presence of pre-trip information.

In Aware Model, perceived bus lateness against timetable shows greater effect on waiting time than perceived lateness against real-time information. The results also show that, perceived waiting time is increased by 2.02 minutes at night for aware passengers, everything else being constant. Two age variables are found to be significant, showing that as the age increase, passenger perceived waiting time will decrease, but the decreasing rate is being smaller. For unaware passengers, if they perceive on-time performance of the bus service as always on-time, their perceived waiting time will decrease by 2.63 minutes. This means that when passengers have confidence on the reliability of bus service, even they randomly arrive at the stops without knowing the timetable, they feel less waiting duration.

6.3.2 Feeling of Security

Three models are estimated to capture the relationship between real-time information acquisition and accuracy and feeling of security at the stop. Those passengers who boarded bus without waiting are excluded. The results of three models (Overall, Night, and Day models) are shown in Table 6.4.

Table 6.4 Modeling Results for Feeling of Security

	Overall Model		Night Model		Day Model	
Variables	*Coef.*	*z*	*Coef.*	*z*	*Coef.*	*z*
Pre-trip ShuttleTrac use	0.135	0.34	-1.069	-0.91	0.277	0.63
At-stop ShuttleTrac use	**0.538**[c]	**1.93**	**0.975**[c]	**1.74**	0.330	1.01
Perceived bus earliness against real-time info	**-1.877**[a]	**-3.79**	**-2.711**[c]	**-1.93**	**-1.991**[a]	**-3.64**
Perceived bus lateness against real-time info	-0.625	-1.46	-0.324	-0.36	-0.664	-1.30
Perceived waiting time	-0.005	-0.21	0.005	0.10	-0.007	-0.25
Pre-trip timetable awareness	-0.250	-0.81	-0.919	-1.41	-0.185	-0.49
At-stop timetable awareness	-0.464	-1.36	-0.723	-1.34	-0.388	-0.85
On campus stop	**0.359**[c]	**1.77**	-0.408	-0.83	**0.585**[b]	**2.41**
High frequency	0.171	0.65	0.309	0.52	0.022	0.07
Status: student	0.347	1.05	0.022	0.03	0.587	1.52
Gender: male	0.314	1.53	0.190	0.41	0.236	0.98
Race: white	**0.415**[b]	**2.02**	**-1.098**[b]	**-2.46**	**0.850**[a]	**3.38**
Age	0.062	1.15	0.046	0.44	0.090	1.07
Age square	-0.0007	-0.98	-0.0005	-0.40	-0.001	-0.78
On-time perception: always on-time	**1.719**[a]	**4.69**	**2.732**[a]	**2.76**	**1.750**[a]	**4.18**
On-time perception: mostly on-time	**0.826**[a]	**3.42**	**0.910**[b]	**1.67**	**0.892**[a]	**3.12**
Night	**-0.964**[a]	**-3.74**	n/a	n/a	n/a	n/a
/cut1	-1.572		-3.105		-0.513	
/cut2	-0.611		-1.692		0.235	
/cut3	0.523		-0.644		1.472	
/cut4	2.081		1.231		3.031	
Number of obs	432		99		333	
Log likelihood	-470.41731		-119.4827			
Pseudo R^2	0.0676		0.1056		0.0704	

NOTE: Significant values are boldfaced.
a: p<0.01; b: p<0.5; c: p<0.1

First of all, the dummy variable “Night” in Overall Model has a highly significant coefficient, whose sign is negative. This result suggests that waiting for bus in nighttime will make passengers feel less safe than in daytime, other things being equal. This is consistent with expectation and to a certain extent justifies the differentiation of Night Model and Day Model.

Four explanatory variables regarding real-time passenger information show interesting relations with passenger feeling of security in waits. In Overall Model, coefficients of both pre-trip and at-stop real-time information acquisition variables have positive signs. But only at-stop acquisition variable shows positive effect on feeling of security at a significance level of 0.1, other factors being fixed. This suggests that passengers may enhance their feeling of security in waits by querying the real-time bus arrival times at the transit stops. The odds for those who acquired at-stop real-time arrival information to have rated their feeling of security at 5 (very safe) instead of at 1-4 are about 1.713 times[14] as high as those who did not acquire at-stop real-time information, other things being equal. In Night Model, at-stop information acquisition also has a significantly positive impact on feeling of security in waits at night. The odds ratio in this case is 2.651, showing that magnitude of the positive effect of at-stop information acquisition is relatively higher at night. However, in Day Model, the corresponding coefficient is insignificant. It seems to suggest that, at night when passengers feel less safe, querying at-stop real-time bus arrival information could assure passengers and boost their feeling of safety by informing them how long they are going to wait. While in the daytime, this kind of impact is not the case, because in general safety is less a problem and there is little room for improvement.

In terms of perceived accuracy of ShuttleTrac, two variables regarding perceived earliness and lateness of buses show negative effects, with perceived earliness being highly significant at a significance level of 0.01. The result implies that if passengers thought buses arrive early in comparison to the real-time arrival information they acquired (either pre-trip or at-stop), they are likely to rate their feeling of security lower. This shows that, as far as safety is concerned, passengers are truly concerned about accuracy of prediction of bus

[14] Odd ratio is exponentiation of the coefficient.

arrivals. This finding holds unchanged for all three models, except that the absolute value of the coefficient in Night Model is larger than in other two, which implies that accuracy of bus arrival time prediction is more of a concern to passengers regarding their safety in nighttime than in daytime.

The perceived waiting time has negative signs in three models, but the results are insignificant. On-campus stop have significant and positive coefficients in Overall Model and Day Model, suggesting that passengers who are waiting at on-campus stops fell safer in waits in general and in daytime. Two variables for attitudes toward on-time performance show highly significant effects in all three models. The results demonstrates that if passengers think the bus line they are waiting for is always or mostly on time, they tend to rate their feeling of security in waits higher, other things being equal.

6.3.3 Waiting Anxiety

Three models are also estimated to capture the relationship between real-time information acquisition and accuracy and waiting anxiety at the stop (passengers who boarded bus without waiting are excluded). The results of three models (Overall, High-frequency, and Low-frequency models) are shown in Table 6.5.

Table 6.5 Modeling Results for Waiting Anxiety

	Overall Model		High-frequency Model		Low-frequency Model	
Variables	*Coef.*	*z*	*Coef.*	*z*	*Coef.*	*z*
Pre-trip ShuttleTrac use	-0.402	-1.03	-0.956	-0.75	-0.627	-1.45
At-stop ShuttleTrac use	0.197	0.74	**1.191[a]**	**2.65**	-0.269	-0.77
Perceived bus earliness against real-time info	-0.286	-0.60	-0.907	-0.96	-0.167	-0.29
Perceived bus lateness against real-time info	**-0.983[b]**	**-2.21**	**-1.667[b]**	**-2.27**	-0.796	-1.38
Perceived waiting time	-0.007	-0.34	0.047	1.03	-0.030	-1.16
Pre-trip timetable awareness	0.049	0.16	-0.175	-0.39	0.534	1.11
At-stop timetable awareness	-0.234	-0.70	**-1.204[a]**	**-2.72**	0.795	1.37
On campus stop	**0.364[c]**	**1.87**	0.067	0.19	**0.525[b]**	**2.07**
Night	**-0.787[a]**	**-3.04**	**-0.725[b]**	**-2.07**	**-0.946[b]**	**-2.16**
Status: student	-0.140	-0.43	-0.219	-0.39	-0.020	-0.05
Gender: male	0.055	0.28	-0.052	-0.14	0.073	0.30
Race: white	**0.764[a]**	**3.87**	0.438	1.27	**0.920[a]**	**3.64**
Age	-0.031	-0.53	-0.062	-0.72	-0.147	-1.42
Age square	0.0004	0.54	0.0004	0.37	0.0025	1.56
On-time perception: always on-time	**1.734[a]**	**4.99**	**1.749[b]**	**2.42**	**1.738[a]**	**4.04**
On-time perception: mostly on-time	**0.638[a]**	**2.80**	0.198	0.52	**0.868[a]**	**2.87**
How important to arrive on time: 2	**-0.862[c]**	**-1.82**	**-1.617[b]**	**-2.18**	-0.747	-1.14
How important to arrive on time: 3	-0.557	-1.30	**-1.149[c]**	**-1.76**	-0.315	-0.53
How important to arrive on time: 4	**-0.785[c]**	**-1.87**	**-1.643[b]**	**-2.38**	-0.501	-0.89
How important to arrive on time: 5	**-1.294[a]**	**-3.11**	**-1.425[b]**	**-2.17**	**-1.212[b]**	**-2.15**
High frequency	**0.498[c]**	**1.92**	n/a	n/a	n/a	n/a
/cut1	-3.365		-5.757		-4.127	
/cut2	-2.162		-4.607		-2.855	
/cut3	-0.910		-3.197		-1.575	
/cut4	-0.077		-2.155		-0.542	
Number of obs	428		154		274	
Log likelihood	-570.86648		-190.98234		-366.09143	
Pseudo R^2	0.0698		0.1056		0.0878	

NOTE: Significant values are boldfaced.
a: p<0.01; b: p<0.5; c: p<0.1

The dummy variable "High frequency" does show a positive impact on waiting anxiety at a significance level of 0.1. This indicates that when waiting for high frequency bus service, passengers are more likely to fell less anxious.

Significantly positive effect was found for at-stop ShuttleTrac use on anxiety level in High-frequency Model, seemingly suggesting that for high frequency shuttle service, acquiring real-time bus arrival time at stop may reduce passenger waiting anxiety, other factors being fixed. The insignificant coefficient of corresponding variable in Low-frequency Model seems to indicate that the same effect cannot be found in low-frequency service. It is perhaps because passengers are mostly aware of scheduled arrival time from timetable for low-frequency lines, thus they would not be worried much about bus arrivals. Providing the real-time information will not make a difference to their anxiety level. While in waiting for high-frequency service, passengers more likely arrive at random and expect short waiting duration. Therefore, knowing how long exactly they are going to wait for next bus will effectively assure passengers' wait and reduce their waiting anxiety.

Another interesting related finding is that at-stop timetable knowledge shows a negative effect on waiting anxiety level, indicating that knowing the scheduled arrival time of next bus will actually increase passengers' anxiety in waits. It is perhaps due to the fact that high-frequency bus service tends to have poorer on-time performance in perceptions of passengers15. Therefore, the bus timetables at stops for high-frequency service may generate adverse effect on waiting anxiety.

In both Overall and High-frequency Models, perceived bus lateness against real-time information show significant effects on anxiety level. The results seem to suggest that, if the

[15] On-time performance perception: High-frequency service mean=2.113; Low-frequency service mean=2.009 (the lower, the better perceived on-time performance). T-test shows that the difference between two means is significant.

bus was considered late (not within +/- 1 minute) against predicted real-time bus arrival time acquired initially, passengers tend to feel more anxious. Therefore, the accuracy of prediction of real-time arrival time will influence passenger anxiety level while waiting, especially when the service is frequent.

Four dummy variables indicating level of perceived importance to arrive at destination on time have significantly negative coefficients in general (except for firs three in Low-frequency Model), suggesting that the higher the requirement of arriving at destinations on time, the more anxious passengers feel while waiting. This result is consistent with previous studies (e.g. Hall, 2001). Perceptions on on-time performance show significant effect as well in all three models, the positive signs indicate that passengers who think the shuttle lines are always or mostly on time are likely to feel less anxious in waits, as opposed to those who think the lines are 50% or less on time, everything else being unchanged.

Other findings include: a) Passengers who wait at on-campus stops are likely to feel less anxious in waits for shuttles. This effect is of high significance for low-frequency service; b) Passengers have higher waiting anxiety level in nighttime than in daytime, other factors being equal, for both high- and low-frequency services.

6.3.4 Satisfaction

Two models are estimated to model the relationships between real-time information and customer satisfaction with service at stop. The Overall Model includes those who boarded without waiting (i.e. perceived waiting time is 0). And in Waiter Model, those respondents are excluded. The modeling results are shown in Table 6.6.

Table 6.6 Modeling Results for Satisfaction

	Overall Model		Waiter Model	
Variables	*Coef.*	*z*	*Coef.*	*z*
Pre-trip ShuttleTrac use	-0.071	-0.20	-0.049	-0.12
At-stop ShuttleTrac use	-0.005	-0.02	-0.166	-0.62
Perceived bus earliness against real-time info	**-0.876[b]**	**-2.12**	**-1.052[b]**	**-2.04**
Perceived bus lateness against real-time info	**-0.847[b]**	**-2.01**	**-0.787[c]**	**-1.84**
Perceived waiting time	**-0.035[c]**	**-1.88**	**-0.045[b]**	**-2.05**
Pre-trip timetable awareness	0.082	0.32	-0.226	-0.73
At-stop timetable awareness	0.135	0.46	-0.169	-0.05
On campus stop	**-0.359[b]**	**-2.05**	-0.316	-1.55
Night	0.268	1.09	0.218	0.81
High frequency	0.247	1.06	0.126	0.47
Status: student	0.077	0.25	0.071	0.20
Gender: male	0.198	1.14	**0.396[c]**	**1.96**
Race: white	0.012	0.07	-0.007	-0.03
Age	**0.106[c]**	**1.94**	**0.121[b]**	**1.96**
Age square	-0.0010	-1.37	-0.0014	-1.58
On-time perception: always on-time	**2.547[a]**	**7.66**	**2.458[a]**	**6.20**
On-time perception: mostly on-time	**1.056[a]**	**4.75**	**1.080[a]**	**4.30**
Feeling of security at stop	**0.438[a]**	**4.25**	**0.439[a]**	**3.83**
Anxiety at stop	**0.278[a]**	**3.81**	**0.260[a]**	**2.96**
/cut1	-0.177		-0.209	
/cut2	1.529		1.439	
/cut3	4.098		3.878	
/cut4	6.235		6.004	
Number of obs	577		429	
Log likelihood	-562.47096		-427.63286	
Pseudo R^2	0.1437		0.1472	

NOTE: Significant values are boldfaced.
a: p<0.01; b: p<0.5; c: p<0.1

Results for two models are mostly consistent, with coefficients of similar signs, significance levels, and magnitudes, for all variables. It indicates that there is no systematic difference between waiting passengers and the general population. In reporting the results, the Overall Model will be focused on.

Two ShuttleTrac usage variables are not found to be significantly related to passenger satisfaction with at-stop shuttle service. However, the two variables indicating accuracy of real-time bus arrival time prediction show negative impacts on satisfaction level at significance levels of 0.05. The results seem to suggest that, presence of real-time bus arrival times does not matter to passenger satisfaction, but inaccurate prediction of this kind of information (either underestimation or overestimation) will actually lower passengers' satisfaction with transit service.

As expected, for the first time, waiting time perceived by a passenger shows a significant (p<0.1) and negative effect on satisfaction level. For one minute increase in perceived waiting time, the odds of passenger rating his satisfaction level as 1 versus 2-5 are 1.036 times greater, given the other variables are held constant in the model.

Age is found to be positively related to satisfaction, indicating that the satisfaction level goes up as passenger age increases. Passengers waiting at on-campus stop tend to rate their satisfaction level lower. This is somewhat intriguing, because on-campus stops were found to have positive effects on feeling of security and waiting anxiety in previous models. Statistical tests did not find any multicollinearity between this variable and any one of others. This phenomenon can be explained as follows drawing on the (dis)satisfaction model illustrated in Figure 3.7. As previous model results have shown, on-campus stops are more desirable places for passengers as people waiting at those stops tend to have higher safety feeling and lower anxiety level. However, at the undesirable off-campus stops, passengers are less critical about the service and have relatively lower expectation. In this regard, the discrepancy between the expectation and service quality at off-campus stops tends to lead to a relatively positive disconfirmation. Thus, the same level of transit service will generate higher satisfaction level in these undesirable environments than in desirable environments. In other words, to achieve the same level of customer satisfaction, better level of service has to be provided in desirable environments, in this case, on-campus stops.

6.3.4 Summary of Findings

The model findings regarding interactions between real-time information variables and psychological variables can be summarized in the following Table 6.7.

Table 6.7 Summary of modeling results

	Perceived waiting time	Feeling of security	Waiting anxiety	Satisfaction
Pre-trip acquisition	**Positive effect** in Aware Model	No effect	No effect	No effect
At-stop acquisition	**Negative effect** in Unaware Model	**Positive effect** in Night Model	**Positive effect** in High-freq model	No effect
Perceived earliness against real-time info	No Effect	**Negative effect**	No effect	**Negative effect**
Perceived lateness against real-time info	**Negative effect** in Aware Model	No effect	**Negative effect** in High-freq model	**Negative effect**

NOTE: Positive and negative are not signs of coefficients. Rather they mean whether it generates psychological benefits to passengers.

In addition, the conceptual model shown in Figure 3.6 can be modified based on the empirical findings. The links verified by empirical results are kept, and unverified links are removed. The resulting framework is shown in Figure 6.1. Basically all the causal links in the conceptual framework were found to be significantly present, except for the links between perceived waiting time and anxiety and link from perceived waiting time to feeling of security. The direct influences of real-time information on all four psychological variables were also found. But these effects may be only for specific dimensions of real-time information or only exist under certain conditions.

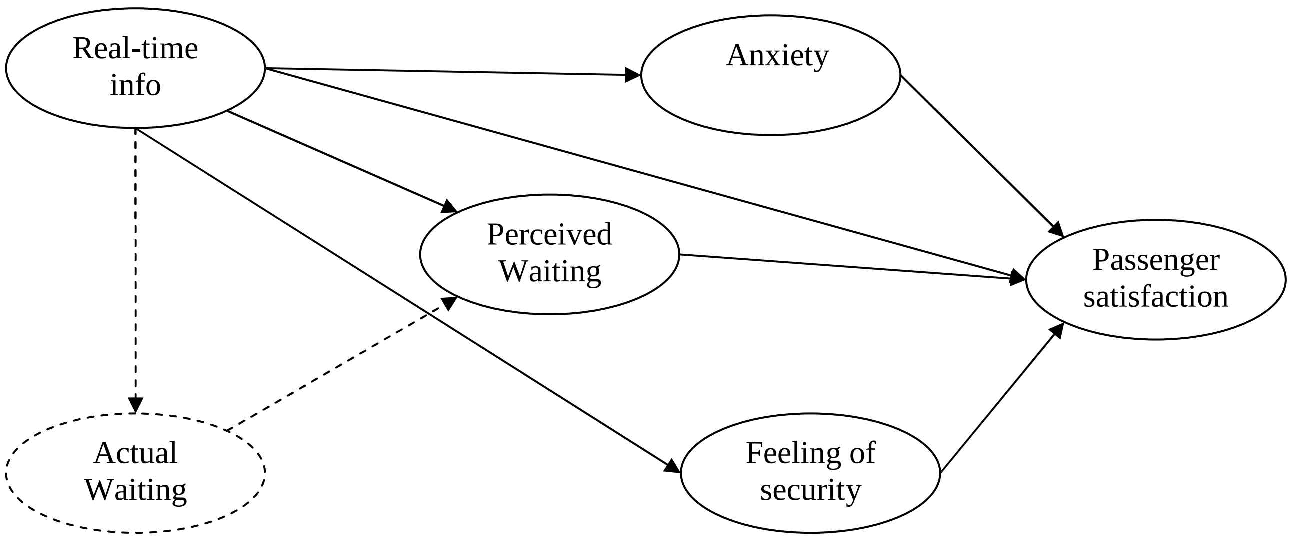


Figure 6.1 Framework with links verified by empirical results

6.4 Discussion

As discussed in Chapter 3, real-time passenger information has many dimensions, such as the information types, place of information, cost of information, and information accuracy and reliability. This dissertation is focused on one type of advanced transit information, i.e. real-time bus arrival information. In terms of place of information, this study considers both pre-trip and at-stop information acquisition. Not only does the information acquisition or presence is considered to be important to transit users, but information accuracy perceived by users is incorporated in models to investigate its effect.

The outcome variables are all psychological responses. It has been conceptually stated that the effects of real-time transit information are more of psychological natures (Dziekan and Vermeulen, 2006). Empirical investigations also seem to support this claim to a great extent. Many project evaluation studies found positive psychological effects of providing real-time information, such as reduced perceived waiting time, increased feeling of security, and so on (see Chapter 3).

Findings from our models have shown that real-time bus arrival information acquisition and accuracy both have direct, significant effects on four psychological outcome variables during a transit trip. The general trend is that pre-trip and at-stop real-time bus arrival information tends to generate positive effects, but these positive effects may easily be offset by poor accuracy of the prediction. For instance, findings from satisfaction models imply that presence of information will not directly increase passengers' satisfaction level (indirect paths still exist), but once this kind of information is inaccurate, passengers are likely to lower their satisfaction with transit service. Also in other models, in terms of magnitude of effects, perceived earliness or lateness of buses against predictions has relatively greater effects than information acquisition does. This implies that even if presence of real-time arrival information could create somewhat positive influence on passenger's psychology, the inaccurate prediction of bus arrival time can easily outweigh this kind of positive influence. Therefore, transit agencies need to be cautious about the deployment of such real-time passenger information systems before they are sure about accuracy and reliability of predicted real-time arrival information they are going to provide. Poor prediction accuracy might easily ruin their effort in providing these systems after all.

In this study, accuracy was defined as within +/-1 minute on-time, which is sort of arbitrary. The margin of errors considered acceptable for transit riders may vary among different groups and under different conditions. A hypothesis would be that the closer to bus arrival, the smaller error margin is acceptable to passengers. This question of grade of accuracy is an open question for further research.

In three sets of models for three outcome variables (perceived waiting time, feeling of security, waiting anxiety), respondents were segmented in terms of crucial criterions (i.e. aware vs. unaware, night vs. day, high frequency vs. low frequency). The model results presented above find that these psychological effects of real-time transit information do vary among user groups and in different scenarios. And these variations of effects give us important policy implications regarding how such real-time information could be effectively supplied to right transits under right situations. At-stop real-time information can be supplied through different media, such as kiosks, displays. Modeling results show that at-stop information is most effective in increasing passenger's feeling of security in nighttime and decreasing their waiting anxiety for highly-frequent bus service. Thus, in line of these findings, bus lines of high frequency and in service at night should have higher priority in deploying real-time transit information systems, in order to gain maxim psychological benefits from transit users. It is also possible to further explore the differentiation of effect size among specific (non-)user groups (e.g. age, frequency of transit use) and under specific scenarios (e.g. commute vs. non-commute).

Because of the nature of on-board survey, the psychological conditions this chapter has examined are mainly regarding passengers' waiting experience. Note that the satisfaction level here is actually not the global satisfaction with the service of particular trips. Nevertheless, waiting experience is no doubt a crucial fraction of the overall transit journey experience. It is worth mentioning that real-time transit information may also influence rider experience en-route and post-trip. An obvious example is that if a transit trip entails transfers, the real-time information of connecting transit service will be much useful. Psychological responses to such information are worth exploration so as to generate a more complete picture regarding psychological impacts of real-time information during the entire journey.

Customers need time to adjust to new services. The Shuttle-UM on-board survey was conducted immediately after the deployment of the ShuttleTrac system. Therefore, the trip-specific psychological effects of ShuttleTrac detected from this survey are very short-term ones in nature and may change over time. It is well-known that customers are very adaptive yet demanding when it comes to service. After a while, when passengers grow accustomed to the system, it becomes a question whether they feel the same way. In general it would become more and more difficult to continually meet their expectations. The battle between public transport and other modes is always a difficult one. However, as Dziekan has said, it is better fought than not.

Finally, psychological responses are intangible and difficult to be quantified. Thus it is seldom included in the benefit-cost analysis for such kind of projects. Report by Cham *et al.* (2006) proposed a return-on-investment evaluation framework for real-time bus arrival information system, in which only reduction in waiting time and in waiting time uncertainty are considered the quantifiable benefits. However, nobody can deny that the intangible psychological impacts of real-time transit information are critical considerations of deployment of such systems, and potentially generate tangible benefits in a longer run.

6.5 Chapter Summary

An on-board survey was conducted immediately after the extensive campaign of ShuttleTrac. The objective of this chapter is to empirically investigate whether real-time bus arrival information would change passengers' psychological conditions during specific transit trips. Four outcome variables of different levels are selected to reflect most important psychological response to real-time information, including perceived waiting time, feeling of security, waiting anxiety, and satisfaction with service at stop. They are regarded as dependent variables. Variables representing pre-trip and at-stop real-time information acquisition and passenger perceived information accuracy were incorporated as independent variables. A series of OLS (for perceived waiting time) and ordered logit models (for other three dependent variables) were estimated to capture a fraction of the complex interactions between real-time information and passengers' trip-specific psychological responses. Nevertheless, several conclusions can be made with varying degrees of generalizability:

- Acquiring pre-trip real-time bus arrival information may reduce passenger's perceived waiting time when they are already aware of the timetable, mainly due to better coordination of passenger arrivals with bus arrivals. This effect can be offset by lateness of bus arrivals against the predictions of real-time bus arrival times.
- In the nighttime, passengers are sensitive to the at-stop real-time information in terms of feeling of security. Acquiring such information may increase their feeling of security. But once the accuracy of prediction is a problem, this effect can also be easily suppressed.
- In the bus service of high frequency, passengers may alleviate their waiting anxiety by acquiring at-stop real-time bus arrival information. Again, in terms of magnitude, this positive effect is smaller than the negative effect caused by inaccurate information.
- Provision of real-time information does not make a difference in influencing passenger's satisfaction with at-stop service. But mis-information caused by inaccurate prediction could significantly lower their satisfaction level.

- The accuracy of real-time transit information plays a greater role in influencing passengers' psychology than the mere provision of information does during a specific transit trip.
- Passenger psychological responses of lower levels generally contribute to the ultimate variable – satisfaction, which implies indirect links between real-time information and passenger satisfaction level.

Chapter 7: Conclusions

7.1 Introduction

This research sets out to provide insights that transportation academics and policy makers appreciate the potentials of real-time transit information systems as a means to induce changes in traveler choices and psychology in favor of public transportation. It does so by providing a framework conceptualizing the behavioral and psychological effects of real-time transit information and empirically examining these effects using revealed-preference data collected from a real-world case. This chapter is to conclude the research with a structure as follows: Section 2 summarizes the major empirical findings from two parts of analysis and discusses their implications to policy-making concerning deploying and managing these systems. Section 3 points out the major contributions and limitations of this research, followed by recommendations for future research in Section 4.

7.2 Major Findings and Policy Implications

This research utilized revealed-preference data to empirically explore the causal relationships between use of real-time bus arrival information system and changes in traveler's behavior and psychology under different response time frames. A Real-time Transit Passenger Information System for Shuttle-UM service, ShuttleTrac, was deployed in University of Maryland, College Park and was used as the case for this research. Three online surveys were administered for one pre- and two post-deployment periods, in order to ascertain the impact of ShuttleTrac use on traveler's general behavioral and psychological responses. Also, an onboard survey was conducted after the deployment in order to find out the trip-specific psychological responses to real-time information. Chapter 5 presents the empirical examination of relationship between real-time transit information and two behavioral variables as well as five psychological variables, using the panel datasets extracted from three online surveys. Chapter 6 presents the empirical examination of impact of real-time information on four riders' trip-specific psychological variables. The detailed empirical findings can be found in the summary sections of two chapters. Here I would like to summarize the major findings of this research as follows:

- Use of real-time transit information will not immediately increase one's transit trip-making frequency or shift one's dominant commuting mode from others to transit. With a few months of adjustment, travelers who used real-time transit information will tend to increase transit trip-making frequency. However, the real-time transit information is not sufficient to shift traveler's habitual mode, even with a few months of adjustment.
- The perception of information accuracy plays a greater role in influencing traveler's transit trip-making frequency, when some adjustment period is given. If somehow the travelers formed the impression that the prediction of real-time information is generally inaccurate, they will decrease their transit trip-making frequency. This negative effect is about 2.5 times higher than the positive longer-term effect of information use.
- Immediately after real-time information use, transit riders will increase their feeling of security about riding buses at day and at night, enhance their perception of transit on-time performance, and increase their overall satisfaction with transit services.

These immediate effects of real-time information use tend to last for at least a few months, except of perception of on-time performance.

- If travelers perceive that the real-time information is generally inaccurate, in no time they will fell less safe about riding bus at day, fell the service less on-time, and feel less satisfied with service. With a few months of adjustment, travelers who hold perception of poor information accuracy tend to fell the service less on-time, feel more anxious while waiting, and feel less satisfied with transit service. In general, the sizes of these negative effects are larger than those of positive effects of real-time transit information use.
- Acquiring pre-trip real-time bus arrival information may reduce riders' perceived waiting time for particular trips, when they are aware of the scheduled arrival times. Acquiring at-stop real-time information may increase rider's feeling of security for particular trips in the nighttime. And, for the bus service of high frequency, passengers may alleviate their trip-specific waiting anxiety by acquiring at-stop real-time bus arrival information. If somehow the prediction of real-time bus arrival times is perceived inaccurate by passengers, these effects of real-time information acquisition will be suppressed by the negative effects caused by such "mis-information". Also, the perceived inaccuracy of real-time information will lower rider's trip-specific satisfaction with transit service.

Empirical findings of this research have also provided some of the implications to the policies regarding provision of such real-time transit passenger information systems to the traveling public. One clear message to the transit agencies as well as scholars is that real-time transit information is undoubtedly found to be effective in influencing traveler's behavior and psychology in ways that transit, as a mode of transportation, is being favored. Specifically, the positive longer-term effect on traveler's transit trip-making frequency of real-time transit information is found. In view of that, the transit agencies, who are going to deploy real-time transit information systems, are entitled to anticipate the ridership and revenue increase as a result of the new real-time transit information systems after a few months of deployment. But they also should be conservative about the magnitude because the magnitude of increase in ridership remains unclear in our research.

The positive psychological outcomes were found both for specific trips and for cumulative experience. Even the most conservative people have to admit that, even if the real-time transit information provision cannot alter traveler behaviors and generate some tangible, economically assessable benefits (e.g. time savings, increase in ridership), agencies can foresee positive psychological effects of real-time information and consequent intangible social benefits (e.g. addressing safety concerns, ease of general anxiety, better image of public transport and public agency). In addition, these positive psychological effects, many of which appear immediately after the deployment, will positively and constantly update the historical perceptions on travel choices involving transit and then potentially change travelers' travel choices in a longer run in ways that transit is in favor. As a matter of fact, the longer-term effect on trip-making frequency may very well be due to such process of updating perceptions on transit. Thus, when agencies are considering deployment of similar systems, they shall not neglect the psychological aspects of traveler's responses to such systems.

How to make the most use of real-time transit information in generating positive psychological outcomes for specific trips? Our findings for trip-specific psychological responses provide some insights into it, i.e., bus lines of high frequency and/or in service at night should have higher priority in deploying at-stop real-time information devices, in order to gain maxim psychological benefits, such as more safety feeling and less waiting anxiety.

Before the agencies are ready to embrace the real-time transit information systems, they need to bear one point in mind: if you ever want to do it, please do it right. Here the accuracy of the real-time information is the key to the success of such systems in influencing travelers in expected ways. Our findings show very a consistent pattern: the negative effects of perceived inaccuracy of information are generally about 1.5-3 times higher than the positive effects of real-time information use (if any). The definition of "inaccuracy" differs here in two parts of research: for general responses, "inaccuracy" means that predication is accurate only 50% times or less (how to tell each time the prediction is accurate or not is up to respondents); for trip-specific situations, the accuracy is defined as within +/-1 minute on-time against predictions in travelers' mind. The objective accuracy of prediction can be measured by comparing the deviations of bus arrivals from predicted arrival times. The information accuracy perceived by travelers is no doubt highly dependent on the objective accuracy. In order to achieve high accuracy, two key components of real-time transit information systems, models/algorithms and historical/current input data, are demanded to be lift to a very high level in terms of quality. And monitoring of operation of such systems and updating of models and data should be conducted on a regular basis so as to ensure the consistency of high quality of real-time information.

7.3 Main Contributions and Limitations of this Research

The main contributions of this research lie in two aspects.

- An integrative, comprehensive and systematic conceptual framework of traveler responses to real-time transit information was developed, taking into account both behavioral and psychological responses under trip-specific and cumulative situations. This conceptual framework is built upon previous theories and research, and provides a solid basis for future studies that will further explore such topic, empirically or theoretically.
- This research utilized revealed-preference empirical data collected in a real-world case of real-time transit information system, a quasi-experimental research design, and sophisticated modeling techniques. Thus useful insights were obtained into the understanding of the real causal relationships between real-time information and traveler behavioral and psychological responses.

It should be noted that this research has its limitations too, some of which are not small. I would like to discuss some of the major limitations.

- A big pity of this research is that trip-specific traveler behaviors under real-time information cannot be empirically examined simply due to the limitations of the case and data collection. It occurs to me that even if the case is a perfect one (i.e. with all kinds of features, such as common lines, various stops, various user groups), traditional data collection methods (i.e. travel trip-diary/activity log, or onboard survey) cannot capture those behaviors we identified in the conceptual framework. For instance, those travelers who quit the trip or turn to other modes because of real-time information are simply not able to be interviewed with an onboard survey. Therefore, even if the Shuttle-UM case were better and/or a good deal of riders used

ShuttleTrac, little could be done to comprehensively study the trip-specific behavioral responses with the data collection method I proposed and conducted. More innovative data collection methodology shall be adopted.

- An inevitable challenge to this research is the generalizability of the empirical findings to the typical urban public transportation environments. Some special characteristics of Shuttle-UM shall be taken into account if we want to discuss how generalizble of the results in this research: 1) Shuttle-UM is free to riders; and 2) Riders of Shuttle-UM tend to be young, well-educated and pro-high-tech, compared to riders of other urban transit systems. Conceivably, these characteristics tend to make riders of Shuttle-UM more inclined to use real-time transit information and adjust their behavior accordingly. For instance, zero fare gives travelers more flexibility of shifting from other modes to Shuttle-UM without thinking about extra expenditures. For these reasons, I believe that the size of found effect of Shuttle-UM trip-making frequency is likely to be an overestimation in the context of a urban transit system. In terms of psychological effects, the magnitude of effects we found is also likely to be an overestimation, because passengers of normal transit tend feel that they have paid the fare and take additional real-time information service for granted. In sum, when putting our findings in the context of a typical urban public transportation system, these empirically-detected effects of real-time transit information might still be there, but one should not be too optimistic about the size of effects.
- Some other methodological limitations also exist. First, because of a lack of software, multinomial logit models with fixed-effects or random-effects estimators could not be

used on the panel commuter dataset. Therefore, it is the wave3 cross-sectional commuter dataset that was employed to find out the possible link between real-time transit information and commuting mode choice. The instrument variables used in Stage-one model are not quite good ones as the predictive power of such model was mediocre. It would be enhanced if more powerful explanatory variables were incorporated, such as the attitudes toward transportation service. Second, as we discussed, the random-effects ordered probit models does not account for the self-selection problem explicitly.

7.4 Recommendations for Future Work

Some possible extensions of this research are suggested here for future work. Such extensions may include:

- Yet more empirical research on this kind of new strategy for public transportation improvement is desperately needed to really ascertain the effects at individual and aggregate levels. Preferably, a full-fledged, state-of-art Real-time Transit Passenger Information System newly deployed for a typical urban public transportation system with a large amount of passengers and variations in services shall be picked as the research case. Carefully designed and administered surveys before and after the deployment can provide a complete bundle of empirical evidences regarding the existence and effects of real-time transit information as conceptualized in our framework here. These kind of empirical evidences are of greatest significance to fully understand the real and realistic effects of RTPISs on individuals and networks as well as providing sufficient, definitive support to policy making concerning such systems.

- To fully capture the trip-specific travel behavior under real-time information, as I discussed above, innovative revealed-preference data collection methodology beyond conventional simplistic dairy/activity survey and onboard survey shall be designed and adopted. One possible approach is to intensively record trip-makers' travel behavior and decision-making process. For instance, travelers who quite the trip or change to other modes due to real-time information could be interviewed at the end of day with questions concerning their intended choices, actual choices, and information acquisition as well as decision-making process.
- The interrelated questions concerning traveler behavior under real-time transit information popped up in the beginning of this dissertation are all worth serious research and it is preferable that research could take them into account as a whole. For example, the use of real-time information and traveler choices under the information can be explicitly examined as two stages of decision-making process.
- Recently rapid technological developments in ICTs have provided a vision of technological revolution in ATIS towards to what can be called by some people the next-generation ATIS (Adler and Blue, 1998; Kenyon and Lyons, 2003; Chorus et al., 2006a). Such ATIS is expected to be able at any time to provide a traveler with all the travel information, solicited and unsolicited, that is relevant given her time and place in the *multimodal* transport network and her personal characteristics. Complexity of understanding the effects of such next-generation ATIS rises exponentially as so many dimensions and considerations are to be taken into account. Yet transportation academics and professionals shall not be afraid to confront this challenge placed

before us and strive to undertake better study on such promising application in order to provide better transportation to the traveling public.

Appendices

Appendix 1: Campus Transport Survey Round 3 Questionnaire

Campus Transportation Survey Round 3

Introduction

Welcome to the University of Maryland Campus Transportation Survey Round 3. Thank you for your interest.

This survey is a part of a larger research project, which is also an essential part of my doctoral dissertation. Questions in this survey are designed to understand how you commute to campus and your use of and attitude toward Shuttle-UM.

If you currently are a student, staff member or faculty member affiliated with University of Maryland, College Park, you are invited to participate in this survey. Your participation is completely voluntary. You may exit the survey anytime. All information you provide will be kept confidential. Please try to answer all questions to the best of your knowledge.

This online survey website will be open from November 6th to November 21st. Please complete the survey at your earliest convenience. If you have any question, please contact:

Feng Zhang, 301.405.8858, fzhang@umd.edu.

Thank you!

*** 1. To match your input with your previous record, please enter your participant ID (provided in Email), name and email. Thanks!**

Participant ID: ________

Name of Participant: ________

Email: ________

Live on campus

1. Which one of the following two previous online Campus Transportation Surveys have you completed: Round 1 (September 2006) and Round 2 (April 2007).

○ Round 1 only
○ Round 2 only
○ Round 1 and Round 2
○ None
○ Do not remember

*** 2. Where do you live this semester?**

○ On campus
○ Off campus

Part I: Commuting

Page 1

*** 1. In the PAST WEEK, how many days did you travel from from where you live to the College Park campus?**

- 0
- 1
- 2
- 3
- 4
- 5
- 6
- 7

2. In the PAST WEEK, how did you travel from where you live to campus? If you used more than one mode of transportation during a commuting trip, your PRIMARY MODE for this day was the one used for most of the distance. Each commuting day you used only ONE primary mode. Please count the commuting days for each primary mode. Note the sum of answers below should be EQUAL to the answer to above question.

	Did not use as primary mode	1 day	2 days	3 days	4 days	5 days	6 days	7 days
Drive alone								
Carpool								
Shuttle-UM								
Metrobus or other bus system								
Metro, MARC or other rail system								
Walk								
Bicycle								
Other								

Other (please specify)

Part II: Shuttle-UM

*** 1. How far do you currently live from the closest Shuttle-UM stop?**

- Less than 5 minute walk
- 5-10 minute walk
- 11-20 minute walk
- More than 20 minute walk
- Do not know

*** 2. In the past month, how frequently do you ride Shuttle-UM to conduct following activities?**

	Never	Once a month	Less than once a week	1-2 days a week	3-4 days a week	5 or more days a week
Go to class	◯	◯	◯	◯	◯	◯
Go to work	◯	◯	◯	◯	◯	◯
Shopping	◯	◯	◯	◯	◯	◯
Personal business (bank, post office, haircut, etc.)	◯	◯	◯	◯	◯	◯
Have meals/coffee/snacks	◯	◯	◯	◯	◯	◯
Social/Recreational activities	◯	◯	◯	◯	◯	◯
Connect to Metro/MARC	◯	◯	◯	◯	◯	◯
Return to home	◯	◯	◯	◯	◯	◯
Other	◯	◯	◯	◯	◯	◯

*** 3. Are you familiar with ShuttleTrac system – the Real-time Passenger Information System (including Busfinder boxes at stops, online ShuttleTrac website, monitor at Stamp Stuent Union, and PDA/Cellphone or telephone calls)?**

◯ Never heard of it

◯ Knew about it but never used it before

◯ Knew about it and used it for riding Shuttle-UM before

*** 4. How many times have you used each tool of the ShuttleTrac system before?**

	Never	1-3 times	4-9 times	10 times and more
Busfinders at stops	◯	◯	◯	◯
Online via website	◯	◯	◯	◯
Hand held device (PDA or Cellphone)	◯	◯	◯	◯
Telephone (4-2255+option 1)	◯	◯	◯	◯
Monitor at Stamp Student Union	◯	◯	◯	◯

*** 5. How often is the ShuttlTrac's estimated arrival time accurate?**

- Almost always accurate
- Mostly accurate
- About 50% of the time accurate
- Rarely accurate
- Almost never accurate
- N/A

*** 6. How useful do you think the ShuttleTrac system is (on a scale of 1 to 5)? Even if you have not used it, please rate its usefulness imaging you are provided real-time estimated time of bus arrival for your shuttle trip.**

	1. Not useful at all	2	3	4	5. Very useful
Usefulness	◯	◯	◯	◯	◯

*** 7. During the day time, how safe do you feel about riding Shuttle-UM (on a scale of 1 to 5)?**

	1. Very unsafe	2	3	4	5. Very safe	N/A
Feeling of security	◯	◯	◯	◯	◯	◯

*** 8. After dark, how safe do you feel about riding Shuttle-UM (on a scale of 1 to 5)?**

	1. Very unsafe	2	3	4	5. Very safe	N/A
Feeling of security	◯	◯	◯	◯	◯	◯

*** 9. In general, how do you feel about Shuttle-UM's on-time performance?**

- Always on time
- Mostly on time
- 50% on time
- Rarely on time
- Almost never on time
- Does not apply

*** 10. While waiting for Shuttle-UM, how anxious do you generally feel about missing the shuttle, missing the connection, or getting late to your destination (on a scale of 1 to 5)?**

	1. Not anxious at all	2	3	4	5. Extremely anxious	N/A
Anxiety	◯	◯	◯	◯	◯	◯

*** 11. On a scale of 1 to 10, please rate your overall satisfaction level with the service of Shuttle-UM.**

	1. Lowest	2	3	4	5	6	7	8	9	10. Highest	N/A
Overall Satisfaction Level	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯

Part III: Personal Characteristics

You are almost finished with this survey. We just have a few more questions about your personal characteristics. Information you provide will be confidential.

*** 1. What of the following describes best your current status in the University of Maryland, College Park?**

◯ Undergraduate Student
◯ Graduate Student
◯ Faculty Member
◯ Staff Member
◯ Other (please specify)

2. Are you licensed to drive in the U.S.?

◯ Yes ◯ No

*** 3. Do you have regular access to a vehicle during this semester?**

◯ Yes ◯ No

4. Do you participate in a car sharing program such as ZipCar or FlexCar?

◯ Yes ◯ No

*** 5. Do you have a campus parking permit for Fall 2007?**

◯ No
◯ Yes (please specify parking lot number)

Appendix 2: On-board Survey Form

Shuttle-UM ONBOARD SURVEY QUESTIONNAIRE

Department of Transportation Services. Regents Drive Garage. University of Maryland

Dear Member of the University of Maryland community:
In an effort to better understand and analyze your needs, the Department of Transportation Services is conducting a series of surveys. Please take a few minutes to complete all sections (front and back) of this quick survey. You will be entered into a drawing to win an iPOD SHUFFLE.

ABOUT YOUR CURRENT SHUTTLE RIDE

1. At which stop did you get on this Shuttle?

Corner of ____________________

and ____________________

Or, nearest campus building name

____

Or, Stop # ____________________

2. Where did you start this one-way trip before coming to the stop? (Where was your trip ORIGIN?)

____
Street address (or intersection or place name)

____
City, ZIP code

Or, ____________________
Campus building name

3. The origin of this one-way trip is your:

O Home O School
O Work O Other: ____________________

4. When did you leave your trip origin to come to this Shuttle stop?

_____:_____a.m./p.m.

5. When did you arrive at this Shuttle stop?

_____:_____ a.m./p.m.

6. How long (in minutes) do you think you waited for this Shuttle?

O Boarded the bus without waiting O 3-4 O 11-15
O 5-6 O 16-20
O 7-8 O 21-30
O 1-2 O 9-10 O more than 30

7. How did you get to this Shuttle stop? Check only one.

O Walk
O Bike
O Drive
O Have someone drive me

Transfer from
O Bus
O Metro
O Shuttle
O Other: __________

8. At which stop will you get off this Shuttle?

Corner of ____________________

and ____________________

Or, nearest campus building name

____

Or, Stop # ____________________

9. Where is your DESTINATION of this one-way trip?

____
Street address (or intersection or place name)

____
City, ZIP code
Or,

____
Campus building name

10. How will you get there after getting off this Shuttle? Check only one.

O Walk
O Bike
O Drive
O Have someone drive me

Transfer to
O Bus
O Metro
O Shuttle
O Other: __________

11. What are you going to do at your DESTINATION?

O Return home O Office visit
O Go to work O School/Class
O Go shopping O Social/Recreational activities
O Meals O Other: __________

12. How important is it for you to arrive at your destination on time (on a scale of 1 to 5)?

Not important at all — Extremely important

O1 O2 O3 O4 O5

13. What did you do while waiting for this Shuttle? Mark ALL that apply.

O Waited, thinking or daydreaming
O Read books, newspapers, magazines, etc.
O Listened to music
O Talked with people at the stop
O Talked with people on cell phone
O Spent some of the waiting time in nearby places (Stamp Student Union, coffee shop, fast food, etc.)
O Other: __________

14. For this one-way trip, when did you first learn about this Shuttle's SCHEDULED time on timetable? Mark only one.

O Before leaving trip origin
O After leaving origin and before arriving at the stop
O At the stop
O Did not know the SCHEDULED time

15. a) For this one-way trip, how did you find out the REAL-TIME estimated arrival time of this Shuttle via ShuttleTrac? And what was (were) the arrival time(s) when you checked using the following tools? Mark ALL that apply.

O ShuttleTrac online via Web site _______min
O Hand-held device (PDA/Cell) _______min
O Telephone _______min
O Stamp Student Union monitor _______min
O Busfinder box at the stop _______min
O Did not know the REAL-TIME arrival time

b) When did you acquire this Shuttle's REAL-TIME estimated arrival time? Mark ALL that apply.

O Before leaving trip origin
O After leaving origin and before arriving at the stop
O At the stop
O Did not know the REAL-TIME arrival time

c) In comparison to the REAL-TIME arrival time you initially acquired, do you think that this Shuttle arrived:

O 5+ min early O 2-4 min late
O 2-4 min early O 5+ min late
O within +/- 1 min O Do not know

16. a) In comparison to published timetable, do you think this Shuttle was:

O early O on time O late O do not know

b) If it was early or late, for how long (in minutes)?

O less than 1 O 5-6 O 11-15 O more than 30
O 1-2 O 7-8 O 16-20
O 3-4 O 9-10 O 21-30

17. While waiting for this Shuttle at the boarding stop, how safe did you feel (on a scale of 1 to 5)?

Very unsafe — Very safe

O1 O2 O3 O4 O5

18. While waiting for this Shuttle at the boarding stop, how anxious did you feel about missing this Shuttle, missing the connection, being late, or getting on the wrong Shuttle (on a scale of 1 to 5)?

Not anxious at all — Extremely anxious

O1 O2 O3 O4 O5

19. How satisfied were you with Shuttle service at your boarding stop (on a scale of 1 to 5)?

Extremely dissatisfied — Extremely satisfied

O1 O2 O3 O4 O5

Don't forget to register to win an iPOD SHUFFLE on back

turn page

Shuttle-UM ONBOARD SURVEY QUESTIONNAIRE

Department of Transportation Services. Regents Drive Garage. University of Maryland

ABOUT YOUR SHUTTLE EXPIRENCE

20. What is the usual on-time performance of this Shuttle line?

- ○ Always on time
- ● Mostly on time
- ○ 50% on time
- ○ Rarely on time
- ○ Never on time
- ○ Do not know

21. How many times have you used the ShuttleTrac system (not including this trip)?

- ○ Knew it, but never used it before
- ● 1-3 times
- ● 4-9 times
- ○ 10 times or more
- ○ Did not know

22. How useful do you think the ShuttleTrac system is (on a scale of 1 to 5)?

Not useful at all — Very useful

○ 1 ○ 2 ○ 3 ○ 4 ● 5

23. How often is the ShuttleTrac estimated arrival information accurate?

- ○ Almost never
- ○ Rarely
- ○ Sometimes
- ● Mostly
- ○ Almost always
- ○ N/A

24. How often do you ride Shuttle-UM ?

- ○ This is my first time
- ○ 1-3 days a month
- ○ 1-2 days a week
- ○ 3-4 days a week
- ● 5 or more days a week

25. What is the ZIP code of your residence this semester?

20782

ABOUT YOU

The personal information you provide will be kept confidential.

26. What is your primary campus status?

- ○ Undergraduate student
- ○ Graduate student
- ● Faculty
- ● Staff
- ○ Visitor
- ○ Other: ________

27. What is your gender?

● Male ○ Female

28. What is your age?

58 years

29. What is your race/ethnicity?

- ○ White
- ○ African American
- ● Asian
- ○ Hispanic
- ○ Other: ________

30. Do you have a valid driver's license?

● Yes ○ No

31. Do you currently have a campus parking permit?

○ Yes ● No

32. Did you have a motor vehicle available to you for this trip?

● Yes ○ No

33. If this Shuttle was not available, how would you have made this trip today? (Check one only)

- ● Drive myself
- ○ Get a ride with someone
- ○ Bus
- ○ Metro
- ○ Walk
- ○ Bike
- ○ Would not make the trip
- ○ Other: ________

REGISTER TO WIN AN IPOD SHUFFLE

Your name: W. A. Chiou

Home address: ________

Phone number: (301)-405-0541

Email: wachiou@umd.edu

INCREASE YOUR CHANCES OF WINNING AN iPOD SHUFFLE AND PARKING COUPONS BY COMPLETING OUR ONLINE SURVEY AT WWW.TRANSPORTATION.UMD.EDU

Thank you for taking the time to complete this survey.
We certainly appreciate the feedback as it will help us better cater to your needs.

Please turn this survey in the surveyor on board the bus, or to the Shuttle-UM driver.
You may also drop it off at the Department of Transportation office at Regents Drive Garage.

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