ANALYSING THE EFFECTS OF TRAVEL INFORMATION ON PUBLIC TRANSPORT TRAVELLER’S DECISION MAKING AND LEARNING

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Statement of Originality

This is to certify that to the best of my knowledge, the content of this thesis is my own work. This thesis has not being submitted for any degree or other purposes.

I certify that the intellectual content of this thesis is the product of my own work and that all the assistance received in preparing this thesis and sources have been acknowledged.

Joe Fai Poon

ABSTRACT

This thesis examines the longer-term effect of travel information on a traveller's decision making under habitual travel, in which the traveller repeats the same journey multiple times while being exposed to the same travel information source. It investigates whether the effect of information is sustained over time and if the type and reliability reinforces the learning process. It seeks also to understand if the converse applies, i.e., whether the learning process reinforces the acquisition and use of information. Five hypotheses were developed to explore the interplay between learning, the type of information, and the information reliability. It is postulated that the utility-maximising traveller will attain better decision outcomes over time through learning. When given information, his learning process will be reinforced further, and this leads to even better decision outcomes, with dynamic information exhibiting a stronger effect than static information. This reinforcement effect is more pronounced when the dynamic information is reliable. In general, it is postulated that reliable dynamic information would produce the best outcomes, followed by less reliable dynamic information, static information and lastly, no information. To test the hypotheses, a series of computer-based experiments, in which the participants made hypothetical home-based work trips by public bus, were conducted. Participants were presented with several experimental conditions in which the types of bus service information and operating conditions were varied. Tests reveal that such hypothesised relationships are not observed at a statistically significant level across experimental conditions at the aggregate level.

At the disaggregate (individual traveller) level, the analyses show that the day-to-day choice decisions relate significantly to the travel outcome of the previous day, with the participant more likely to seek a more rewarding but riskier departure time choice if the previous day sees no adverse consequence, and vice-versa. Changes in his choices are found to be affected by the type of simulated travel information. When the information is static and non-specific, decision changes are few and incremental, and are made by few participants. When it is dynamic, more frequent occurrences of decision changes of a larger magnitude are observed among greater proportions of participants, whose choices are observed to 'anchor' around the values provided by the information, regardless of its reliability. Nonetheless, there exists a significant proportion of participants who made few, if any, decision changes, regardless of information or operating conditions. The findings reveal a higher propensity for some travellers to use dynamic information over static information. Given that this likelihood is

sustained over time, regardless of the level of information reliability, this suggests that Advanced Traveller Information Systems (ATIS) are highly likely to be used by both ad-hoc and regular users in real life, providing a strong justification for their provision. On the other hand, acquiring information is found not necessarily to maximise the utility of travel decisions, implying that the traveller acquires such information for other less quantifiable factors. The benefits could also be further circumscribed by the heterogeneity of the responses. This set of findings clearly deviates from the assumption of many studies that travellers are a homogeneous group who respond to information in a fully utility-maximising manner. It suggests that such a simplifying assumption may run the risk of over-estimating the effect of travel information. The thesis recommends a more refined approach that recognises such heterogeneity at the disaggregate level.

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My PhD journey is more than an academic one. It is also one in which I learnt valuable lessons on what really counts in my life journey. As any parent and spouse would know, it is not easy holding everything together in the family while thousands of miles apart. For many a time, the anguish of being an absent father to my four lovely children, Charlynn, Charles, Chantz and Channery, can be too much to bear. This pain cannot however, be compared with that faced by my wife. For several years in all, Serene stood by me and held the fort at home in my absence. Without her understanding, patience and encouragement, I could not have completed this journey.

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1 INTRODUCTION

Variability is a well-known and common phenomenon in transport systems. A motorist experiences variable day-to-day travel times on the same route and varying availability of parking spaces at the same destination. Over the entire road network, traffic volumes on each segment at the same time each day will not be exactly identical from day to day. The waiting times of a public transport user at a bus stop for a service will not be the same even if the user arrives at the stop at the same time each day. Even a train service that is considered punctual would depart later than scheduled on a small number of occasions.

Obviously, certain attributes of a journey may be variable but predictable, and decision making with respect to those attributes will be straightforward. For example, road toll rates may vary by time of day and day of week, but they are certainly predictable because they are explicitly made known in advance. However, most attributes of a journey are not. Some, such as waiting time at a signalised junction, may be predicted to be within a certain range with some degree of confidence (especially if the traveller has passed this junction regularly, except on rare occasions in which the traffic signals experience a blackout or a vehicle at the front of the queue breaks down!). However, most of the other trip-associated attributes are much more variable and much less predictable. The traveller has to make travel decisions that take into account such unpredictability. It is this unpredictability, or perceived uncertainty that directly influences decision-making, rather than the inherent variability in the transport system, even though the former phenomenon is clearly related to and a consequence of the latter. This distinction between unpredictability and variability from a behavioural perspective is emphasised by Bonsall (2004).

There are a number of strategies the traveller may adopt to address this uncertainty. Five types of strategies have been identified by Bonsall (2004). One type is to make the best decision in the light of uncertainty through the use of the strategies in which the traveller makes decisions based on the full probability distribution of outcomes (as espoused in the classic Expected Utility Model of Von Neumann and Morgenstern, 1944), or on the most probable, pessimistic or optimistic outcomes. Another group of strategies seeks to reduce the consequences of this uncertainty by building a safety margin into the schedule among several others. The use of this strategy has been modelled in the work of Ettema and Timmermans (2006), among others.

One particular type of strategy identified by Bonsall (2004) involves the access of additional information to reduce the uncertainty. Apart from seeking subjective advice from other travellers, the traveller could either consult maps and timetables, subscribe to a real-time traffic information service, or seek the necessary information from a telephone enquiry line or an internet site. In response to this need for information, Advanced Traveller Information Services or systems (ATIS) have seen significant development over the years and are now widely available. ATIS dynamically collect data on the state of the transport system, process them to generate information or advice relevant to the travellers, and disseminate them through various media (Toledo and Beinhaker, 2006). The ability to capture dynamic and up-to-date information of the state of the transport system and deliver it to the traveller is what distinguishes ATIS from the traditional forms of travel information, such as road and public transport service maps, street directories, and public transport service timetables. The latter sources provide, with little exception, static, or at the best, historic information.

The continuing rollout of ATIS over the years is driven by their purported benefits to the traveller at the individual level, to service providers at the fleet level, and to the transport system at the network level. For the individual traveller, these benefits include travel-time savings; reductions in traffic delays, travel time variability, and fuel consumption; and positive psychological effects. For fleet operators, such as freight companies and public transport service providers, each trip by their fleets gain benefits similar to those accruing to the individual traveller, which translate to better fleet utilisation, more reliable service delivery, lower operating cost, and greater customer satisfaction and retention. Improvements in network efficiency and performance and overall reduction in emissions are also envisaged at the aggregate system level.

The advent of information services, especially ATIS, has resulted in the impetus for research on their effects on and effectiveness for the user. Understanding the potential role of travel information, and its limits, is crucial in informing decisions by the various players in the transport industry on the investment, design, and delivery of ATIS. Indeed, a large body of literature on the effects of travel information, in particular ATIS, on travel behaviour has been built up over the past two decades. Lappin and Bottom (2001) reported more than 180 published papers on the topic of travellers' responses to real-time travel information alone by mid-2001.

1.1 Research on Travel Information

In the literature, discussion of the effects of travel information often involves the examination of behavioural responses to uncertainty. These behavioural responses are driven primarily by the traveller's subjective perceptions of, instead of the actual, state of the travel situation. As Bonsall (2004) puts it succinctly, it is the beliefs, rather than the reality, that matters. The traveller makes a decision by taking into account the perceptions of one or more trip attributes pertinent to his travel. (For ease of writing, only the male pronouns are used in all references to an individual traveller who can be of either gender.) Such decision-making is typically framed as making a choice among two or more travel alternatives. For example, given the uncertain travel times on a regular route from home to work, a driver has to choose a departure time among all other possible times. Likewise, a passenger has to decide on the time to arrive at the bus stop, knowing that the bus service may arrive ahead, on, or behind schedule. The major decision-making phenomena investigated in mainstream research on travel behaviour are the traveller's choice of mode, route, or departure time, which are typically described by discrete choice models based on random utility theory. Strictly speaking, departure time is not on an integer scale, but the traveller's choice of departure time can be expressed in discrete time intervals, which are sufficiently small to approximate a continuous scale (e.g., Ettema and Timmermans, 2006; Avineri and Prashker, 2006; and Ettema *et al.*, 2005).

Many of the studies that investigate travel information from a behavioural perspective attempt to model its effects on traveller's choices. The consequence of acquiring information can be expressed in the choice models through:

1. the alteration of the (user-perceived) value of an attribute (e.g., highway travel time on a particular route) to resemble more closely the value supplied by the information service for that attribute (travel time estimates on an en-route variable message sign), a change termed as the information effect by Chorus *et al*. (2006a);
2. a change in the weight (or parameters) for that attribute (Bonsall, 2004); or
3. a change in the (error) term that describes the confidence placed in the attribute value, or both.

But more commonly, a probability distribution is used to describe the traveller's perception of the attribute, where the mean and standard deviation represent the traveller's perceived value of the attribute and his confidence in this value respectively (Ettema and Timmermans, 2006 and Chorus *et al.,* 2006a, 2006c), and the effect of information is simply a modification of both the mean and standard deviation. One of the common approaches to describe this modification is through the Bayesian perception updating model, which originates from psychological research, but has since been adopted in travel behaviour research (Jha *et al.*, 1998; Chen and Mahmassani, 2004; and Chorus *et al.*, 2006a). Its mechanism involves the combination of the (prior) distribution describing the pre-existing perceptions with another distribution representing the supplied information to yield an updated (posterior) perceived distribution. Typically, the existing perceived value is not updated to the fullest extent to be identical to that of the information, given such limiting factors as the traveller's expectations of the costs and benefits of information use, his mental processing ability, and his perception of the reliability of the information itself (Chorus *et al.*, 2006b). The probability of each choice of action post-information is then obtained from the (discrete) choice model using the modified distribution that describes the updated perception of the attribute. This may lead to a choice of action that may or may not be the same if based on the pre-information perception. For example, a driver may decide to switch route if he receives a message that his planned route will encounter additional delays, but he may not choose to if the resultant perceived delay is still within his acceptable range.

These studies, which explore the behavioural aspects of the acquisition and use of travel information, constitute one part of the vast literature on the topic. In a recent review of the literature, Chorus *et al.* (2006a) note that there are also studies, primarily empirical in nature, which examine manifest determinants of travel information acquisition and use, such as trip characteristics and socio-demographics. The broad consensus from this large body of literature is that the benefits of travel information are positive. These benefits are well documented, ranging from quantified travel time savings (Toledo and Beinhaker, 2006) to “positive psychological factors” and greater satisfaction with the transport service (Dziekan and Kottenhoff, 2007). With such positive effects reported, it is inevitable that various stakeholders in the transport industry have demonstrated considerable interest and committed significant investment in developing ATIS.

However, less attention has been paid to a logical follow-on question: do these effects persist over time, or are they merely evident during the initial period of use? This is a valid and pertinent concern in the context of habitual travel, in which a traveller makes approximately the same journey multiple times within a period of time, e.g., the home-based work trip for an office worker with a routine work schedule. In addition, when making repeated trips, the traveller may be exposed to the same information format, if not the same contents. Hence, one can ask further: will he continue to use the information that is continuously supplied over time? Several studies reviewed by Chorus *et al*. (2006a) suggest there is a high likelihood of information use in certain types of repeated trips such as commute trips, because commuters are sensitive about when they arrive at their work destinations (not being late obviously!) and tend to travel during peak periods when there is greater variability in the traffic conditions. On the other hand, Taylor and Bonsall (2000) have argued that the value of travel information is limited for travellers making routine trips because they are less likely to reconsider their entrenched travel decisions due to habit or inertia. Before one delves further into this apparent contradiction, it might be useful to examine first the process of learning which is inherent in repetitive travel.

1.2 Repetitive Travel and Learning

Travel typically involves making the same trip repeatedly, e.g., in a home to work commute. In such repeated trips, iterative learning and experience come into play. Chorus *et al.* (2006a) develop an iterative decision scheme that is useful to describe the processes of perception updating, learning and travel information acquisition involved in a repeated trip scenario, described as follows. Every trip involves a decision by the traveller on say, departure time. The traveller makes the decisions based on his perceptions of the travel environment (e.g., likely range of travel time, likelihood of traffic disruptions). For each of these trips, he compares the outcomes of the decision with his prevailing expectations and may decide to modify his existing perceptions regarding the pertinent attribute(s) of the travel environment in light of the outcome of this trip, and perhaps of those preceding it. The updated perceptions then form the basis for decisions on the next trip. Thus, learning brings about the evolution of perceptions over time as the traveller is continually and repetitively exposed to the same travel environment within the same travel context. For example, suppose a traveller departs from home at time t for his commute trip (which could be either a driving or public transport trip) and experiences a travel time T that results in him arriving late for work for that day. In light of this outcome, and perhaps also recalling the travel times and arrival times of previous trips which commenced around the same time, the traveller updates his prevailing perception of travel times associated with time t. This update of perception may then lead to a change in decision for the subsequent day, say, to depart home earlier than time t. On the other hand, if he departs at this time t and experiences a travel time T which is unexpectedly shorter than all of his previous trips such that it results in him arriving exceedingly early at work, he may modify his prior perception drastically to account for this atypical outcome. (On the other hand, he may also discount this anomaly that is unlikely to be repeated and thus make only a small change to his existing perceptions). On the next day, he may delay his departure time as a result of any change in his perception of travel times. If his journey time is very similar to what he has experienced and results in him arriving early (but not so early that another later departure time would be likely to arrive in time), then his prior perception is not likely to be modified substantially. He will then use this departure time as a reference case for the next trip and continue to leave at about the same time, until such time that he arrives late to work. In the event of late arrival, he may adjust his departure time on the following day, if he perceives the likelihood of being late again is high if he continues to choose this departure time. Alternatively, he may deem the occurrence as a rare event and decide to depart at the same time the next day. Hence, the actual outcomes from his choice departure, which are the resultant journey time and arrival time at work, will then form the inputs for subsequent updates to his perception.

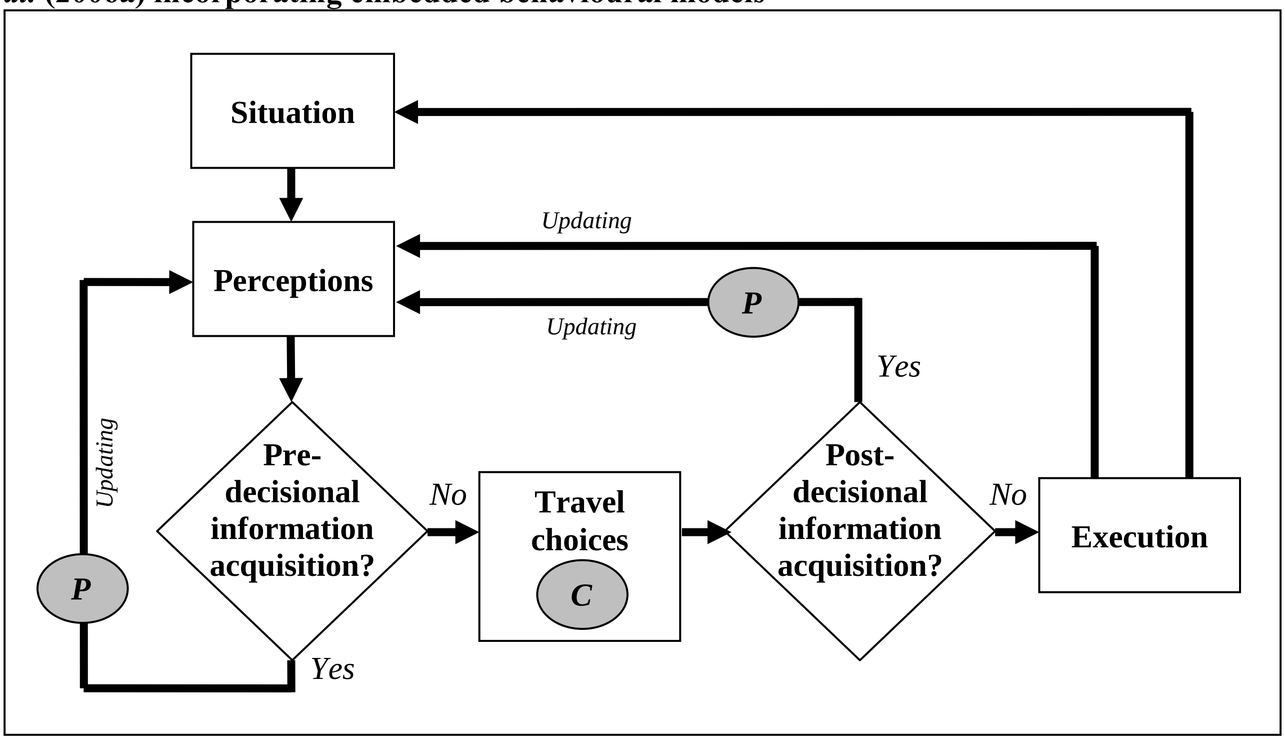
Concurrently, if information pertinent to his habitual travel is present, the traveller will also learn more about the characteristics of the travel information, such as its reliability. If the information service is able to provide consistently accurate estimates of the travel attribute he is concerned about, say travel time along a highway, or departure time of a public transport service, he is likely to perceive it as highly reliable and will be inclined to use it. Conversely, a poorly performing information service will result in a lower propensity of the traveller to use it, or he may even ignore it altogether. Thus, as the traveller gains information and learns from experience about the circumstances of his trip over time, he modifies his perceptions over time, not only of the pertinent travel attribute(s), but also of the reliability of information, and the benefits of its acquisition. The importance of studying the interaction between information acquisition and learning/experience cannot be overestimated. Knowledge of the effects of this interplay between the two phenomena can inform on two important aspects crucial to policy makers and operators of travel information services: what is the upper limit of the effects and what are the longer term benefits of providing information to travellers? To this end, there have been a number of studies that considered the learning effect by incorporating the presence or absence of experience with the travel environment (Abdalla and Adel-Aty, 2006) and/or with the information source (Jou *et al*., 2005) as explanatory factors. However, studies that capture the evolution of decision-making over time, specifically from day to day are much fewer in number. A group of such studies that do so using numerical simulations to model explicitly the iterative updating of traveller's perceptions of trip attributes include those by Jha *et al.* (1998) and Ettema *et al.* (2004, 2005). These studies examine the behavioural mechanisms by which perceptions are updated as a consequence of information acquisition, and contribute to closing of a knowledge gap identified by Chorus *et al.* (2006a), who lamented, at the time of their review, the lack of empirical literature on the behavioural mechanisms of information acquisition.

If one were to formulate similar models that describe how perceptions are updated iteratively and evolved through learning, how would they integrate with the choice models that describe decision making? The iterative decision scheme by Chorus *et al.* (2006a) offers a useful theoretical framework to integrate these two sets of behavioural models. The scheme is premised on the generally accepted paradigm that the traveller makes decisions based on his perceptions of the actual situation. The perceptions involved may be of the availability of travel alternatives and/or of the characteristics of these alternatives themselves, as well as of those of the information service(s) and of his own existing knowledge, among others. They shape his assessment of the costs of acquiring information, like time, effort, and money and the corresponding benefits before making the trip decision. This assessment may or may not lead to an active search for pertinent information. If the traveller engages in information search, the acquired information may lead to an update of the prevailing perceptions. The resultant information effect may lead to the traveller being aware of previously unknown alternatives that are then added to his choice set, or he may change his perception of the characteristics of existing travel alternatives. This information effect may, in turn, lead to repeated searches for more information until the perceived benefits of an additional search no longer outweigh the costs. This process, labelled by the authors as *active* information acquisition, is distinguished from a passive one, in which the traveller is supplied with the information unasked for, and he merely needs to decide whether to use it.

Once the active acquisition process ceases, the traveller chooses the travel alternative based on his prevailing perceptions. Prior to executing the choice, he may also engage in further acquisition of information that may help him execute the choice. This post-decisional information acquisition may lead to a further change in perceptions, which could trigger a new loop of active information search or even a reconsideration of the earlier choice decision. It is only when no further pre- or post-decisional information acquisition takes place that the traveller executes his decision. After the decision has been executed, changes in the transport system may result in a further alteration of the traveller's perceptions. This may then lead to new iterations of pre-decisional acquisition.

The scheme of Chorus *et al.* (2006a) is reproduced in Figure 1-1. It is clear from the figure that the perception updating and the choice processes are distinct stages in the scheme. This allows the perception updating (*P*) and choice (*C*) models, which describe the respective behavioural processes, to be embedded unambiguously in the scheme as shown. Hence an appropriate modelling framework can be constructed to examine the effect of information from a behavioural perspective.

Figure 1-1: Information Acquisition and Perception Updating Scheme by Chorus *et al.* (2006a) incorporating embedded behavioural models



An alternative approach that does not involve the modelling of perceptions involves the conduct of experimental research to obtain direct empirical data. The importance of such work cannot be overstated, not least to test the behavioural assumptions behind, and to estimate, the behavioural models that are used in numerical simulations (Ettema *et al.*, 2004) and, of course, formulated in theoretical studies. However, studies that replicate day-to-day evolution of decision making and learning in a laboratory experimental setting are few. Two recent studies that do so are by Avineri and Prashker (2006) and Ben-Elia *et al.* (2008). In the work of Avineri and Prashker (2006), participants were asked to choose repeatedly over 100 trials between a pair of alternative routes, whose variable travel times were drawn from two different distributions, under one of two scenarios. In the first scenario, no information about the routes was available; in the second, static information on the mean travel times along each route was supplied prior to the commencement of the experiment. The experimental results reveal that, contrary to the common view that information acquisition leads to better travel decisions in aggregate, the choices of the participants became more heterogeneous over time when exposed to information. The authors argue that learning does take place when information is provided but this does not necessarily lead to utility maximisation behaviour. Instead, there is a “classification effect” in which the information enables faster adoption of various behavioural patterns among the participants.

The experiments conducted by Ben-Elia *et al.* (2008) were very similar to that of Avineri and Prashker (2006) in that participants in each session were also asked to choose between a pair of routes repeatedly over 100 trials when either given a priori information about the routes’ travel times or no information at all. The key exception was that the simulated information was dynamic such that the routes’ estimated travel time ranges (and the actual travel time) changed on each trial-day. A key finding is that (dynamic) information results in a higher proportion of participants choosing the faster route across all scenarios during the initial period. Within the same period, risk-seeking behaviour is also induced by this information, such that more chose the faster route if its travel time has greater variability than if it has lower variability. Over the entire trial period, the choice behaviour of the participants with information is more heterogeneous than that of those without.

The above framework is developed on the premise that the traveller does respond to actual outcomes of information acquisition and travel decisions, which in turn influence subsequent decisions related to further information acquisition. However, an earlier study by Verplanken *et al*. (1997) suggests that conscious and reasoned decision making in response to stimuli, either from actual outcomes or from travel information, does not necessarily take place, because those with strong habits tend towards lesser information acquisition and choice strategising. Even though interventions through requiring decision makers to account for their decisions and drawing their attention to selected and unselected information can help attenuate the effects of habit initially, such effects re-emerge subsequently. It should be noted that the findings are in the context of travel mode choice, whose attributes presented are much less variable on a daily basis (e.g., physical effort, expected personal convenience). In contrast, contemporary travel information services tend towards informing travellers about such highly variable attributes as travel times along a route or waiting times for transport services.

1.3 Types and Formats of Travel Information

The information simulated respectively by Avineri and Prashker (2006) and Ben-Elia *et al.* (2008) represent the broad types of travel information. Using the classification of Toledo and Beinhaker (2006), travel information can be considered *static, historic, instantaneous (real-time)* or *predictive*, in increasing order of technological sophistication and demand on data and computational resources. The work of Avineri and Prashker (2006) involves non-variant estimates of travel time along routes, which can be classified as either static, or historic if the estimates are updated based on the historical travel times actually encountered. In contrast, Ben-Elia *et al.* (2008) provided route travel times which simulate those on variable message signs (VMS), which typically supply real-time and predictive information that are in response to changes in the transport network or system. Alternatively, travel information can be classified by the way in which its content is presented, i.e., the information format. For illustration, advice on public transport service waiting time can be presented in terms of arrival time, headway, and waiting time (Avineri, 2004). It may also be differentiated by the stages at which it is delivered, such as pre-trip, wayside or in-vehicle (Grotenhuis *et al.*, 2005) or pre-trip or en-route (Toledo and Beinhaker, 2006), or whether it is qualitative or quantitative, descriptive or predictive (Ettema and Timmermans, 2006), or whether it is descriptive (values of attributes of travel choices) or prescriptive (suggestions on travel choice) (Ben-Elia *et al.*, 2013). The route travel time information in the work of Avineri and Prashker (2006) and Ben-Elia *et al.* (2008) is clearly quantitative but may be either pre-trip or en-route, depending on when the information is received by the traveller before the point he has to makes his choice of route.

The provision of real-time and predictive route travel time information as that represented in Ben-Elia *et al.* (2008) is one of many applications of Advanced Traveller Information Systems (ATIS), which has motivated much of the work in the literature. In fact, the existing literature is arguably ATIS-centric or at the minimum, ATIS-motivated. As a result, there is little or no reference to or comparison with other non-ATIS types of information, which are either static or historical. This may suggest a settled, and somewhat implicit, consensus of the superiority of ATIS over its traditional counterparts. Indeed, its purported advantages over the static types are apparent. For example, it can be argued easily that only real-time information from ATIS can be responsive to variable travel conditions, whilst static information is ill suited to address such conditions, and thus should induce greater acquisition than the latter. Indeed, this perspective is supported by the study of Toledo and Beinhaker (2006), who find that ATIS based routing information does outperform such other types as static and historic information in travel-time savings and variability in general.

To this apparent consensus, one may again pose a question analogous to the one raised previously: is the assumed superior performance of ATIS information over its non-ATIS counterpart sustainable over time? As the development of ATIS continues apace, this is a crucial question to address, in order to avoid the less than ideal state of affairs described by Taylor and Bonsall (2000): that initiatives for such systems are formulated to drive the development of technological ‘gadgets’ rather than for sound economic reasons. However, it is noted that, studies that are similar to Toledo and Beinhaker (2006) in comparing directly the performance of ATIS relative to other different types of information in the same context and setting are very rare, and those examining the relative advantages of different information types over the longer term have not been conducted, to the best of this researcher's knowledge.

The above discussion assumes that the various types of information have different effects on the traveller because the contents they deliver are different. For example, the travel time estimates from an ATIS differ from the timetable on a daily basis, and even by the minute. However, the traveller may respond differently to information from an interactive, user-friendly website delivered through his personal mobile device from that printed on a sheet, even if the contents are identical. This is the argument put forth by Waygood *et al*. (2012) who suggest that the traveller is also influenced by how travel information is presented in the form of images, symbols and context. Such contextual information might influence the extent of learning and information acquisition by the traveller, even if he is largely not aware of their effects, and therefore cannot be under-estimated. This idea postulates that the presentation of facts is as relevant and important as the facts themselves, to decision making. Nonetheless, this study focuses on information content rather than contextual information.

1.4 Travel Information Reliability

It is earlier mentioned that through the learning process, the traveller learns not only about attributes of his trip, but also the characteristics of the travel information source, one of which is its reliability. The examination of the effect of travel information is often associated with the discussion of this attribute. Information reliability, or more generally the quality of information, is recognised in the literature as an important attribute in information acquisition. In the transport context, reliability commonly describes the relationship between the estimate by the information service of a travel attribute and its actual value. This attribute is particularly pertinent to the study of ATIS. Where estimates are dynamic and vary from day-to-day, this relationship can be defined as a stochastic variable which is the difference between the estimated and the actual values, and follows a certain distribution, usually the normal. For example, Ettema and Timmermans (2006) represent the difference between the travel time predicted by the information service T^i and the true travel time T^* by an error term ε^i, whose values are distributed normally.

Earlier it is postulated that a traveller is likely to be more inclined to acquire information if the information service is consistently accurate in its predictions than if it performs poorly, i.e., the propensity of a traveller to acquire information is positively (negatively) affected by its perceived reliability (unreliability). This is intuitive and is indeed consistent with the literature. The results of numerical simulations by Chorus *et al.* (2009) show that the probability of a hypothetical traveller complying with non-personalised information increases with its reliability. It is also congruent with the results of an Expected Regret model by Chorus *et al.* (2006c) that indicates a decline in utility of acquiring information as its perceived reliability decreases. Similarly, Toledo and Beinhaker (2006) find that inaccuracy in the information leads to reduced travel-time savings and higher disbenefits relative to fully accurate information. Such an intuition is certainly sufficiently uncontentious enough for Chorus *et al.* (2007) to use it as one of several criteria against which the internal validity of data from a multimodal travel simulator is assessed.

A more recent study by Ben-Elia *et al*. (2013) offers a different perspective on information reliability[1] by examining its effect on travel choice, among others. The findings suggest lower information reliability induces more to choose travel options with less variability (routes with more reliable journey times), including that with lower expected utility (longest mean journey time).

[1] The term ‘accuracy’ is used by Ben-Elia *et al*. (2013) to describe the discrepancy between estimated travel times and actual ones experienced by the traveller. This shares the same definition used in other earlier studies cited in this section. The term ‘reliability’ is therefore used for consistency of use of term in this thesis.

1.5 Travel Choice Making after Information Acquisition

After acquiring information and updating his perceptions, the traveller makes his travel choices, as described by the iterative decision scheme of Chorus *et al.* (2006a). The choice model to describe his choice making ((*C* model) in Figure 1-1) is determined by the choice paradigm. A common and early paradigm is the classical Expected Utility (EU) theory that assumes a rational traveller who is motivated to maximise his perceived expected utility. Its inadequacy in explaining choice behaviour under uncertainty has led to more recent travel behaviour studies to consider such deviations from the EU paradigm as Prospect Theory (Jou *et al*., 2008, Ben-Elia and Shiftan, 2010), the payoff variability effect (Avineri and Prashker, 2005, Erev and Barron, 2005) and loss aversion (Erev and Barron, 2005).

The main postulation of Prospect Theory (Kahneman and Tversky, 1979) is that, in a static setting, the decision maker's choice is framed in accordance with his reference points, and that he responds asymmetrically to perceived gains and losses relative to those points. However, in a dynamic setting with repeated route choices, Ben-Elia and Shiftan (2010) did not find travellers exhibit behaviour in line with Prospect Theory. Instead, they found initial risk seeking behaviour in the short term, but with learning and risk aversion in the longer term. This is in line with the findings of Erev and Barron (2005) that indicate decision makers in iterated tasks trend towards choices that minimise losses rather than those that maximise expected payoffs, or loss aversion.

Another finding of note by Erev and Barron (2005) is the payoff variability effect in which the decision maker appears to shift towards random choices as the variability of payoffs (or outcomes) becomes highly variable. The payoff variability effect is supported by empirical results of Avineri and Prashker (2005), who examined travellers' sensitivity to travel time variability in iterative route choices with immediate feedback of choice outcomes.

Nonetheless, the EU framework still provides a simple but useful starting point to analyse how travellers respond to travel uncertainty and information for many studies, e.g., Ettema and Timmermans (2006).

1.6 Potential for Research

This short review has highlighted three phenomena of research interest, namely, the learning process, information type, and information reliability. A review of the literature suggests that the effects of one or two of these phenomena on information acquisition are typically investigated. However, to the best of the author's knowledge, there is yet to be a study that includes all three phenomena and also investigates the interaction between them. Also, the studies reviewed assume ATIS-based information and omit the traditional, usually static, type of information generally, with a few exceptions (such as Toledo and Beinhaker, 2006, Avineri and Prashker, 2006, Ettema and Timmermans, 2006). Given the current paucity of empirical literature, research into the concurrent interplay between these three phenomena should be fruitful. The study of these interactions between the three is pertinent because their effects occur concurrently and cannot be isolated in real life.

This research program seeks to address a number of pertinent research questions. First, one may question whether information effects, if present, can be sustained over time and reinforce the learning process if the traveller is exposed repetitively to the same information. If so, one needs to understand whether the type and quality (reliability) of information are significant influences on this reinforcement. Given that the learning of the traveller also pertains to attributes of the information service itself, one may also ask if the converse applies, i.e., whether the learning process reinforces information acquisition. As the traveller gains experience on the characteristics of his regular trips, one may ask if he may encounter diminishing returns from the information and be less inclined to acquire the information. Similarly, one may again ask about the impact of type and reliability of information on the propensity to acquire information over time.

Specifically, the research should also shed light on whether ATIS exhibits significant advantages over the traditional (static) forms of information in terms of the likelihood of being acquired, enhancing the learning process, and maximising the utility of the traveller's decisions over time. In particular, one may want to confirm the intuition that the greater variability in the transport system, the more significant this advantage will be, because of the purported responsiveness of ATIS to changes in the system. A similar question may be asked of the sustainability over time of such an advantage, if present. Research towards this question will provide indications of the value, and its limits, of investing in substantially more costly and more technologically challenging ATIS, as opposed to providing traditional types of information.

This research program emulates the research approach of Avineri and Prashker (2006) and Ben-Elia *et al.* (2008), in investigating the day-to-day effects of information on decisions under an experimental setting. It builds upon their work by including the simulation and comparison of *both* static and dynamic information in the same scenarios, of which several are introduced to investigate traveller's responses under different operating environments. Although this research program draws its initial inspiration and research idea from the studies by Avineri and Prashker (2006) and Ben-Elia *et al.* (2008), it differs from them substantially in several aspects. The key difference is that a *public transport* travel setting is used instead of a typical highway travel scenario because it presents aspects of decision making that are different from those involved in the oft-researched phenomena of route and/or departure time choice under the driver-traveller scenarios. This deliberate choice is made considering that comparatively few studies investigate the effects of providing public transport schedule information on users of public transport. Zhang *et al.* (2009) find that there have been few studies on real-time public transport information among the more than 180 studies reviewed by Lappin and Bottom (2001). It is believed that the examination of the decisions of travellers making repeated trips on public transport is a relatively new direction in experimental research in which few, if any, studies have been attempted. It offers an opportunity to examine if the behavioural patterns similar to those from Avineri and Prashker (2006) and Ben-Elia *et al.* (2008) are manifested in a very different context and thus provides additional insights to the effects of travel information. The public transport context also provides the opportunity to explore the traveller's responses to multiple sources of variability that are inherent in a public transport journey. In contrast, many travel information studies examine the simplified car trip with only the journey time and travel information as the primary sources of variability.

An empirical approach has been adopted. Data needed to study the phenomena of interest can be obtained through either real-life observations or experiments. It is suggested that it is difficult, if not impossible, to sample travellers who are exposed to the various types, formats, and reliability levels of travel information to be examined within the timeframe of this study. The requirement to isolate both information and learning effects in real life environments from other nuisance factors may also be overly onerous. Hence, this study draws from a series of experiments that is based on a hypothetical travel scenario. Details of the scenario are discussed in the next Chapter.

This thesis is set out as follows: the hypotheses and experimental scenario are formally set out in the next Chapter. This is followed by a description of the experimental design and programme in Chapter 3. Chapter 4 covers such implementation issues as the conduct of pilot experiments, sampling, recruitment and administration of experimental participants and assessment of the face validity of the data collected. Chapters 5 and 6 present the results of the experiments, outcomes of the tests of the hypotheses and detailed follow-on analyses before the last Chapter summarises the main lessons learnt and discusses future research directions.

2 EXPERIMENTAL SCENARIO AND HYPOTHESES

In Chapter 1, several research questions concerning the nexus between information acquisition, learning, and travel information type and reliability are posed. In order to frame these questions in a coherent and interrelated fashion within a common context, they are embedded in a descriptive scheme under a hypothetical public transport scenario. From this scheme, a number of hypotheses are derived on the likely relationships between the various phenomena of interest.

2.1 Experiment Scenario

The public transport scenario is first constructed. In such habitual travel as home-based work trips, a typical driver-commuter can adjust his departure time from home or switch between highway routes or both, which are choices commonly modelled in travel behaviour studies. However, his public transport counterpart has a far more limited choice set in routes on the public transport network. Unless both his trip origin and destination are located within a dense public transport network, he is unlikely to have a competitive alternative to the route he takes on a regular basis (short of a major service disruption on that route). There is, therefore, much less chance for an equivalent route-choice decision for the public transport traveller. The choice he can make meaningfully is therefore his departure time from home.

To simplify the scenario, it is assumed, not too unreasonably, that the traveller commutes from his home to the workplace by public bus every day. Each day, he walks to the bus stop near home and catches a bus that brings him directly to the work place, which is only a short walk from the alighting stop. The traveller has to reach the work place by the work start time, which is assumed to coincide with his preferred arrival time (PAT) at the workplace, again for the sake of simplicity. The services of that route depart from his stop based on a timetable, but for a start, it is supposed that he has no knowledge of its schedule at all. However, one can assume safely that he is aware that the services depart at certain intervals. The departure time of the service he actually catches (t_s) and the in-vehicle trip time he spends on it (T_v) vary daily due to congestion and other operating circumstances. The traveller is never fully certain of these respective times given their day-to-day variability, although from experience, he does have some perceptions of what they will likely be. (In all subsequent discussion, clock times are designated by lower case letters with an appropriate subscript. Elapsed times are indicated by uppercase letters with an appropriate subscript.)

Like most commuters, this traveller considers the access time to the boarding bus stop (T_a) and egress time from the alighting bus stop (T_e), the waiting time for the service (T_w) and the in-vehicle time on the bus (T_v) when planning when he leaves home each day. Suppose during this planning, he seeks not to be late for work, but is also mindful not to arrive too early. This is because being late may incur penalties, both tangible (financial for certain shift workers) or intangible (missing an important meeting) at the actual workplace. Conversely, some desire not to spend more time than is necessary at the office without commensurate compensation and hence do not wish to be too early for work. To achieve these dual objectives, the traveller selects a time to depart home (t_h) each day that will bring him to the boarding bus stop at t_b, such that, given the uncertainty involved, it gives him a reasonable chance to catch the one service he believes will bring him to the work place at time t_l that is as close to but not later than the start work time (*PAT*), as well as to minimize the waiting time ($T_w = t_s - t_b$, $t_s \geq t_b$) for that service. Each day, he learns from the outcome of his trip decision how late or early he is, and how long the wait for the service is. From this outcome, and likely from those from previous days as well, the traveller may adjust his departure time for the following day. In this study, he is assumed to be motivated solely to maximise his utility by not being late for work, and minimising both the waiting time for the bus service T_w and the gap between his early arrival time and *PAT*.

The home to work commute scenario is selected because the home to work commute trip provides a suitable setting to observe repetitive trip decisions that are subject to time constraints imposed by a typically fixed start work time. Other trip purposes are arguably less repetitively in comparison. The work to home commute is omitted because it may be less repetitive (many may travel to other destinations after work, instead of home), and are less constrained generally by a specific time needed to reach home.

It is also argued that a home-to-work commuter scenario is a typical one, especially where the public bus is a common mode of transport for commuters. For example, in the researcher's city of residence, the average daily public bus trips per person in the resident population is around 0.6. (Land Transport Authority, Singapore, 2014).

Obviously, the real-life travel experience for many public bus commuters is more complex. The bus commuter may make chained journeys involving two or more bus trips, or another mode of transport such as the train (again common in the researcher's city) or the car (e.g., park and ride). His decision to take the bus to work may also be influenced by his after-work activities that will result in trips either back to home or to other destinations. Nonetheless, this study has kept to a single-purpose, single-mode scenario for simplicity and to focus on the trips that are repetitive.

2.1.1 Public Transport Information

The above scenario takes place in the *absence* of travel information. Suppose now travel information is provided to the traveller. What would be the information that he will use in his decision-making? In real-life, the contents of public transport travel information services vary. Some provide travellers with pre-trip advice on alternative services or combinations of services to intended destinations, and such associated costs as journey times and fares, which helps the traveller plan his journey. Others supply en-route information, which is often dynamic and real-time, that is related to the waiting time for service, current location of the vehicle or the next stop.

This study omits pre-trip information on public transport alternatives for the traveller. This is because the inclusion of the learning effect in the scope of study requires the examination of a traveller's behaviour over time as he makes the same trip repeatedly in his commute trips. For such trips, information related to alternative services can be assumed to be largely irrelevant. Instead, trip attributes that are likely to be factored in the decision making process by the traveller repeatedly, together with their associated travel information, are considered.

Two trip attributes are selected for this scenario, namely the departure time of, and the travel time on, the bus service. The reasons are, first, these attributes are identified by Grotenhuis *et al*. (2005) as among those ranked highest in terms of importance by surveyed respondents; second, they are typically subject to considerable variability; third, the traveller typically has little information on them for the current trip, although he usually has an idea of the range of likely values they will take on; and fourth, information on this attribute may be supplied in the various types and formats that are to be studied.

As discussed in Chapter 1, there are four main types of information, according to the classification of Toledo and Beinhaker (2006), namely, static, historic, instantaneous, and predictive. For the purpose of this thesis, they are grouped into two broad types. The first is labelled *static* information that encompasses both static and historic information. (It is noted that historic information can be updated periodically, but within the timeframe of decision making by the traveller in this context, it can reasonably be treated as invariant.) So for the current scenario, the static information the traveller receives may be in the form of an information sheet providing the service headways, a printed timetable listing the service departure times and/or the estimated travel time between two locations using the service. Alternatively, it could be from a travel information service that provides regular updated estimates of service departure times or wait time, and delivers them via, say personal communication devices, to the traveller prior to the commencement of his trip. It may even provide *predictive* information on estimated travel times for later travel. The instantaneous and predictive information are grouped together under the family of *dynamic* information to reflect a typical characteristic of ATIS-supplied information. Under this scenario, the traveller bases the decision on the time to depart home on not only his experience but also the information to which he is exposed.

With the broad scenario established, one can now present the research questions posed in Chapter 1 in their context. They are introduced in the following descriptive scheme.

2.2 Descriptive Scheme on Decision-Making over Time

Suppose the traveller in the scenario makes his first work trip on day 1. He knows of the bus route that he will have to take daily to the workplace but is not familiar with it. This is because his previous trips to the workplace were to attend interviews that took place at times different from the work start time, and were made on a different mode (say, taxi). Suppose also there is no information on the bus route, except for advice from a colleague, that its services are scheduled to depart at regular intervals and about the range of in-vehicle times, T_v, he can expect for his ride on the bus route from home.

Based on this partial information, the first task he sets herself is to identify the appropriate service to catch. As stated in the scenario, he does not want to be late for work, but he also prefers not to be excessively early. So in the first few days, he attempts to try out different services and learn about their respective departure times (t_s) by choosing different times to leave home (t_h) (and equivalently different times to arrive at the bus stop, t_b). Based on the range of estimated T_v, he knows his t_h should not be later than a certain time. Still, his first few t_h in this exploratory period are likely to be fairly random. He may endure a long wait if he inadvertently chooses to arrive just after a service departs. He may also catch a service without waiting, but he still ends up late. Soon, he learns that if t_h is after a certain time, he is likely to catch a service which will not bring him to the work place on time. On the other hand, a t_h that is much earlier will result in him catching another service that results in him arriving much too early for work, which he does not prefer. Over time, the traveller would identify one or more services by the departure time t_s and, if there is more than one service, deduce, albeit imperfectly, which of them is most likely to enable him to reach the destination closest to, but not later than, the work start time. For example, he could work out that there is a service departing between 7:55 and 8:05, and another between 8:10 and 8:20. If the start work time is 9.00 and the bus ride takes about 40 minutes, he may reason that the second service is the better choice.

Now, among the services available to the traveller, there is one that does allow him to arrive closest to start work time each day, and catching it will maximise his utility on that day. For ease of discussion, this service is termed the "best" service. His actual choice of service may or may not be this best service and he cannot be fully certain if he has chosen the best service on a particular day. This is because he may not have caught it at all during his initial exploration and so it is within his choice set in subsequent days. Even if he believes he has identified and caught the best service on a particular day, he cannot be sure catching it again the following day is the best option, due to variability in t_s and T_v. For example, the traveller could have arrived exactly on time at his work place on the previous day taking the 8:00 service (or the service he believes departs at 8:00, to be precise). On the following day, even if he catches this service again, he may arrive late because its travel time may be longer than scheduled due to on-route congestion or because of a delayed departure (say, at 8:05). In either case, the service preceding this service is the best for that day. In the absence of further information and not being prescient, clearly he cannot hope to catch the best service of the day on every trip. He thus settles on his choice of service that he believes has the greatest likelihood to be the best service most of the days. He is not likely to change it, unless he experiences frequent late arrivals when using it subsequently, or if he suspects it is one too early because there is a substantial and persistent time gap between his arrival time at the work place and the start work time. His settled choice marks the end of his efforts to explore the services in the first several days. For ease of reference in subsequent discussion, this activity is henceforth known as "*service search*". Apart from deciding on his regular choice of service, this process may also have resulted in him incurring several trips with long wait times or late arrivals that reduce his utility.

With the cessation of the service search process, the traveller turns his focus in the subsequent days to adjusting his t_h so as to ensure he can catch the above service of choice regularly. He knows from experience that the departure time of his target service, t_s (and of all other services of the same route) varies from day to day. On some days, the service is late to arrive at the stop, causing him to experience a wait at the stop that is longer than what he has expected or desired. On other days, it departs earlier than he has expected, causing him to wait for the next service, and perhaps to be late for work as well. So what would be his response to the variability of t_s? It is assumed that he uses one of the strategies described by Bonsall (2004): to build in a 'safety margin' between the choice of t_h and his best guess of t_s. Here, it is assumed that this margin is influenced by the traveller's perception of t_s variability such that the larger the perceived uncertainty, the larger is the safety margin. The initial margin should be quite large, because the traveller has made only a small number of trips on the service and is highly uncertain of how t_s might vary. However, as he makes more repeated trips on the service and gains experience, he becomes increasingly confident of his own perception of the t_s distribution. He may realise that the initial margin has resulted in his wait time $T_w = t_s - t_b$ to be unacceptably long. So, he reduces this safety margin (and thus the wait time) progressively by moving t_h to a later time. Obviously, the safety margin cannot be eliminated fully because below a certain threshold, he will perceive the likelihood of missing the service to be unacceptably high. This threshold cannot fall to zero even as he gains more experience of the service because there is an inherent variability and hence unpredictability in t_s. Conversely, perhaps after a series of events of missed services, he may realise that the likely t_s of his service is earlier than his prevailing best guess of it, or may become less confident of his perception of t_s variability. As a response, he may move t_h backward to maintain the same margin with the updated best guess of t_s, or to increase the safety margin to account for the increased uncertainty. This process is labelled "*safety margin adjustment*".

The above describes how the traveller in the scenario learns about the characteristics of the bus route over the repeated instances of travel and adjusts his decision-making in response to this learning to achieve the travel objectives outlined in Section 2.1. Inherent in these objectives is the assumption that he seeks to maximise his utility from his work trip over time. In his pursuit of maximum utility each day, he engages in a decision-making process that can be framed as one that can be decomposed into two distinct phases. The first phase is the identification and selection of the service that he intends to catch, and the second is associated with his actual attempt to catch that targeted service. In the first phase, he attempts to maximise his utility by choosing what he believes is, or has the highest likelihood to be, the best service of the day. In the second, he does so by reducing the wait time to the minimum while ensuring the risk of missing the service remains acceptable to him. Therefore, these two phases of decision-making are related respectively to the two consecutive processes of service search and safety margin adjustment that are described earlier in this section. As is explained in subsequent Chapters, the decomposition into these two decision-making aspects defines how the traveller's behaviour is analysed.

At this juncture, it is also useful to compare and contrast this scenario with those by Avineri and Prashker (2006) and Ben-Elia *et al.* (2008), and other similar studies with a typical highway route choice scenario. In these studies, and also in others examining departure-time choice in similar highway settings, the travel time is often the predominant, and sometimes the only, attribute pertinent to the decision-making. In this bus service scenario, the decision-making is more complex. Although departure time from home appears to be the choice phenomenon, the decision-making is two-fold: which of the services plying the route to choose, and once this particular service is identified, when to arrive at the bus stop to catch this service. Each of these aspects is associated with the service search and safety margin reduction processes described previously. Furthermore, the public transport traveller has to contend with variability in two attributes: the in-vehicle time (T_v) and the departure time of the services (t_s). (He would also have to consider such other attributes as the access and egress times to the bus stops, T_a and T_e, but one may assume their variability does not factor in his decision-making because they are much less variable relative to T_v and t_s and because he largely determines the walking time to and from the stops.) The present scenario is closer to that of Ben-Elia *et al*. (2013) in which the traveller, who is also required to arrive on time at a destination, is also presented with an apparent choice situation involving a bundle of routes and departure times. The choice of service is analogous to the route choice, and that of the arrival time at the bus stop to catch the service, the departure time choice of the latter. However, Ben-Elia *et al*. (2013) argue that, in their context, the dominant strategy is route switching, with departure time choice playing a very small role.

2.2.1 Effects of Information

With more than one attribute to consider, the public transport traveller should benefit from the provision of travel information as much as, if not more than, the highway traveller. Suppose further there is now travel information relating to one of the attributes in which the traveller is interested, the service departure time t_s, and that the information service provides estimates of it, t_s^i. The in-vehicle time T_v is already assumed to be given in the form of a range of possible values. One expects that the traveller is able to know more about the characteristics of the bus route and make better decisions regarding the departure time from home, t_h, if he acquires information on t_s than if he relies solely on his experience. In other words, information acquisition enables him to attain a better outcome from his t_h choice than if the information is absent, which is congruent with the conventional paradigm on the benefit of travel information.

In the current context, a better outcome means a higher level of utility attained. This is achieved through the choice of service (i.e., by increasing the number of days on which the best service is selected), or by reducing the average wait time when catching this service, or both. It is postulated that the provision of information brings about such outcomes by influencing the two earlier described processes of service search and safety margin adjustment. The various types of information described in Section 2.1.1 affect these processes differently and hence result in differences in how the traveller learns about and responds to the travel environment.

2.2.1.1 Effects of Static Information

First, the effects of providing static information are discussed. In the context of the experimental scenario, this type of information is assumed to take two forms: headway information, i.e., the scheduled time intervals between successive service departures, and a timetable listing the departure times of individual services. Effectively, headway information is no different from the case of no information in the initial trip because it contains no specific estimates of t_s^i. The traveller, despite knowing the headway, still has to engage in the initial service search process to identify the departure times of individual services. The difference is that he can now work out easily the approximate ranges of departure time of all other services for subsequent trips, using the departure time of the service he actually catches on the first day (t_s) and the headway (H). For example, he can work out that the service preceding the service he takes should depart at times around $t_s - H$, and the succeeding service, $t_s + H$. He still may make a few more attempts to be more certain of these times if he does not perceive the t_s from the first day to be representative, but the search process may be shorter. As in the case in which he has no information, he may incur instances of long waits and late arrivals during the initial period, and still end up with a longer-term choice of service that may or may not be the maximising service, and one that is not the best service every day certainly. He still proceeds with the second process of adjusting the safety margin in his t_h choices.

In contrast, the timetable supplies specific t_s^i of individual services. These estimates are their scheduled departure times, $t_s^i = t_s^{sch}$. The estimates are specific to each service and are invariant. With these estimates, the traveller can identify easily each of the services by their respective t_s^{sch} even before he commences the trip on the first day, without needing to engage in the service search process as in the case when no information or only headway information is provided. For example, he knows for certain there is a service scheduled to depart at 8:00, another at 8:10 and so forth. Coupled with information on T_v obtained earlier, he can immediately assess which of the services is the most likely to bring him to the destination on time. In other words, the better outcome associated with timetable information is the elimination of the service search process and the late arrivals and long wait times that are associated with it. Even before he makes his first trip, he can narrow down his potential choices of service to two or at most, three, among which the best service is most likely to be found. Which of the services he eventually chooses on a particular day depends on his prevailing perception of the variability of t_s and T_v.

Without the service search process, the traveller commences on choosing t_h that is perceived to give him a reasonable chance of catching his choice of service right from the first day. The process of the safety margin adjustment process is, therefore, brought forward. Although t_s^i values provide an indication of the likely locations around which the t_s distribution of each service is centred, it does not inform on the variability of t_s itself. So, after selecting the service he wishes to catch, the traveller still has to base his t_h decisions solely on his perceptions of the t_s distribution. The safety margin reduction process is no different from what he would have gone through when no information or only headway information is provided, except that the margin can be expressed explicitly as the deviation of t_h from t_s^i (or equivalently, t_s^{sch}).

The traveller can also make use of the timetable information on occasions when he intends to change his choice of service on the next trip. With the t_s^i of the newly targeted service, he skips the need to do a service search on it to find out about its likely t_s, a process that is earlier described to entail likely misses and long waits. To decide on t_h to catch this service in the next trip, he refers to its t_s^i, draws on his prior perception of t_s variability formed through his experience with his current service (and any other service previously selected) and applies the same safety margin. This assumes that he perceives the current and the newly targeted service to share identical operating characteristics. This assumption is not unreasonable because travellers are likely to form perceptions pertaining to the bus route (e.g., “the buses on this route are often not on time”) rather than individual services (e.g., “the 8:10 service is more reliable than the 8:00 service”). Of course, they will make distinctions in say, the reliability or the level of crowdedness, between a service operating during the peak period and another during the off-peak, or between a weekday service and a weekend service. However, in the context of the current scenario in which the traveller has to choose between consecutive services within a short period, he is very unlikely to assume one is more reliable than the other. Besides, if this is his first attempt to catch the alternative service, he has no prior perception of the t_s variability specific to it, and will have to rely on perceptions formed from the trip experience on other services.

2.2.1.2 Effects of Dynamic Information

When dynamic information is supplied, the traveller is given estimates of t_s^i that are variable, and $t_s^i \neq t_s^{sch}$. The t_s^i of a particular service follows a distribution centred at the actual departure time of that service, t_s. As is commonly depicted in the literature, the spread of the distribution describes the reliability of the estimates; the larger the variance, the less reliable the estimates are deemed to be. The provision of such information affects both the service search and safety margin adjustment processes. In the former process, its effect, as well as the beneficial outcomes accrued, is similar to that of the timetable information – the process is eliminated by allowing the traveller to identify his choice of service prior to the first trip and on subsequent days when he attempts a change in service.

The effects on the latter require some description. Suppose the dynamic information source is fully reliable such that $t_s^i = t_s$ for every service every day. Any traveller fortunate enough to receive such information before departing his home (through say, a website or an application on his mobile device) will surely set his t_h such that the arrival time at the bus stop, t_b coincides with t_s^i of his targeted service without exception. Obviously, this cannot be the case either in real-life or in this scenario because dynamic information is rarely fully accurate. Just as he is uncertain about the variability of t_s initially, the traveller is also uncertain about the reliability of the t_s^i estimates when he is first exposed to the dynamic information source. Therefore, to account for its likely unreliability, he also maintains a gap between t_h and the t_s^i estimate of the service he is targeting. It is intuitive that $t_h < t_s^i$. The state $t_h > t_s^i$ is highly unlikely, but not impossible, especially if the traveller believes the information service estimates to be persistently later than actual. To account for either possibility, this gap, termed the "*information margin*", is defined as $T_i = | t_s^i – t_h |$. It is analogous to the safety margin in response to the uncertainty over t_s in the cases of no information, headway information, and timetable information, but in this case, it is specifically in response to uncertainty over t_s^i. As he learns about the characteristics of the information service over repeated trips, his perception of its reliability evolves and he may adjust T^i consequently to reduce the wait time. How he does so is a topic to which the discussion returns in the next section.

The responsiveness of dynamic information to changes in t_s in this scenario (and, in general, to variable travel conditions in other applications of such information) can bring a benefit to the traveller in a way static information does not. When he is provided with no or static information, he relies only on his perceived t_s distribution to make a guess of the likely t_s of his targeted service for the next trip. This distribution is formed from his recollection of historical service arrival times, t_s, which are likely to be incomplete or inaccurate due to cognitive limitations. Despite his best attempt at guessing, the actual t_s of the pending trip may be out of range of his experience. In contrast, dynamic information can provide him an indication of what the t_s is likely to be for a particular day, and such a prediction is especially helpful in ad hoc occurrences of exceptionally early or late departures. Although there is an element of unreliability with the estimate (and he therefore addresses it by his safety margin with respect to t_s^i), it should reduce his chances of avoiding the consequences of missing his targeted service departing at an out-of-norm t_s. For example, if, on a particular day, the t_s^i value indicates that his targeted service is departing at a time much earlier than he has previously experienced, he can increase his chance of catching that service by also setting a much earlier t_h. Over time, the average likelihood of a missed service or excessively long wait is minimised.

By virtue of its predictive function, the dynamic information has an additional role to play in the traveller's choice of service. Although it has been argued that, with dynamic information, he does not need to explore services other than the service he intends to use, he may need to consider them occasionally. Recall that the traveller's choice of service may not be the best every day and is subject to departures that are exceptionally late or early, as mentioned earlier. Suppose on another day, the t_s^i value indicates that his service is running so late that catching it may result in him arriving at the work place late. He can mitigate this risk by taking an earlier service. Perhaps on the next day, he again notices that the t_s^i of his regular service is running so far ahead of schedule that he will end up too early at work, and that of the next service is such that it is likely to bring him to the workplace on time. He can then choose the second service. Hence, the frequency of errors in choosing the best service can then be lower than if he does not have such dynamic estimates.

This above description of the effect of dynamic information on the traveller's choice of service assumes he trusts the information fully and relies on it to select the service. This may not be true. If he is uncertain about the reliability of the information source, he may perceive a t_s^i estimate to be inaccurate and out-of-range when it indicates his intended service to be exceptionally early or late, and thus decides not to switch service. However, if he learns over time that the reliability of the information has been acceptable, he will take more heed of its estimates when deciding in future which service is the best of the day. It then follows that the traveller increases his likelihood of choosing the best service over time when given dynamic information, provided the information is perceived to be sufficiently reliable. Conversely, if the estimates are inaccurate and lead to numerous errors in selecting the correct service, he may decide he is no better off using this information than relying on his own guess, in which case the likelihood of him choosing the best service is no different from that if he is given no or static information. However, for this discussion, one assumes the information to be deemed sufficiently reliable and used by the traveller such that the benefits are realised.

In summary, the traveller engages in the two processes of service search and safety margin adjustment when choosing departure time t_h from home every day, when he has no information or headway information. When he receives timetable information, he omits the first process but has a head start on the second process. By acquiring dynamic information, and provided this information is assessed to be sufficiently reliable, he not only has the outcomes of timetable information, but also additional benefits of increased likelihoods of choosing the best service of the day, and of catching that service because of the information's responsiveness to the daily variations of t_s. Table 2-1 summarises the processes and outcomes involved with the various types of information. It is apparent that dynamic information is deemed to have better outcomes than static (timetable) information that, in turn, has advantages over no information or only headway information. It is acknowledged that this description of a two-stage decision-making process may turn out to be behaviourally invalid, drawing from the findings of Ben-Elia *et al*. (2013) discussed earlier in Section 2.2, but it is adopted as a plausible starting point for investigation.

Table 2-1 Summary of Processes and Outcomes of Acquiring Various Types of Information

Information on t_s	Processes involved	Outcome
No Information / Headway	Service search in initial period	• May incur long waits, excessively early or late arrivals from exploration. • May not choose best service on most days
	Adjustment of safety margin in later period	• Late start to reduction of wait time.
Timetable	Immediate identification of service (no service search)	• Avoidance of long waits, excessively early or late arrivals from exploration.
	Adjustment of safety margin from day one	• Early start to reduction of wait time.
Dynamic Estimates	Immediate identification of service (no service search)	• Avoidance of long waits, excessively early or late arrivals from exploration. • Higher probability of selecting best service of the day.
	Adjustment of information margin from day one	• Early start to reduction of wait time.
	Responding to unexpected early or late departures.	• Reduce likelihood of long waits due to missed services. • Higher probability of selecting best service of the day.

2.2.2 Learning/Experience and the Information Effect

In Chapter 1, the concept of the information effect introduced by Chorus *et al*. (2006a) is described. When applied to the current context, it is said to be present when the traveller's prevailing *perception* (or 'best guess') of the departure time of his targeted service t_s resembles more closely the t_s^i estimate supplied by the (dynamic) information service. Note that in the last section on dynamic information, the traveller is described as responding to the prevailing t_s^i and relating his t_h choices to it. Since he bases his decision of t_h on his perception of t_s, the descriptive scheme has implicitly assumed that the information effect is present. It follows also that the information margin, $T_i = t_h - t_s^i$ is simply a proxy for the information effect. The smaller the margin, the larger the effect is deemed to be.

Returning to the discussion of the traveller's responses to dynamic information, it is described that he sets an initial information margin between his choice of t_h and t_s^i because he is unsure of the accuracy of t_s^i. As he makes repeated trips, he may observe from these trips that the t_s^i have been consistently very close to the actual t_s and thus perceives the information to be reliable. He then reduces this margin T^i in order to reduce the gap between t_h and the actual t_s for a better decision outcome. This is so that he can reduce the wait time ($T_w = t_s - t_h$) for the service and thus increase his utility. Conversely, he may increase, retain or not decrease the margin as much if the information is perceived to be less reliable. Just as in the safety margin employed in response to the unpredictability of t_s in the absence of information, there is a limit to which T^i can be reduced, given that the information is not fully accurate.

So, if the traveller perceives the dynamic information service to be reliable, the information effect, as measured by T^i, gets stronger over time. This appears logical because as the traveller benefits from reliable information and improves his outcomes, he is more likely to use this information in future and set his t_h choices closer to its estimates. The degree to which the information effect increases is affected by its reliability. In line with intuition and with the literature, the more reliable the dynamic information is, the greater is its effect on the traveller's decisions.

2.3 Hypotheses

The validity of the descriptive scheme of Section 2.2 can be tested by distilling it into hypotheses exploring the nexus between the information type and reliability, learning/experience, and the information effect, when travellers engage in repetitive travel. Two broad families of relationships are investigated. The first family explores the learning process and how it is influenced by the presence of different types of travel information, and the second studies whether the information effect is affected by learning/experience and the level of reliability of (dynamic) information.

In the first family, four hypotheses are formulated based on the predictions contained in Section 2.2.1 that describe how the quality of decision-making evolves over time and across types of information. Hypothesis 1 concerns the learning effect only and is derived from the general postulate that travellers improve the quality of their decision-making over time as they learn and gain experience in the *absence* of information. It defines the baseline against which the effects of different types of information are compared. Under the descriptive scheme, it is suggested that the outcome generally improves as one moves from a situation in which no information is provided, to one with static information, unreliable dynamic information, and finally, reliable dynamic information. This postulate is captured by Hypotheses 2 to 4. Hypothesis 5 concerns how the information effect evolves with learning, as described in Section 2.2.2. The five hypotheses (H_1), with the corresponding null hypotheses (H_0), are shown as follows:

> $H_1(1)$: In the absence of information, the traveller attains better outcomes of decision-making over time through learning and experience.
> $H_0(1)$: In the absence of information, the traveller does not attain better outcomes of decision-making over time through learning and experience.
>
> $H_1(2)$: The traveller attains better outcomes of decision-making and learning when provided with <u>static</u> information than when provided with <u>no</u> information.

$H_0(2)$: The traveller does not attain better outcomes of decision-making and learning when provided with static information than when provided with no information.

$H_1(3)$: The traveller attains better outcomes of decision-making and learning when provided with <u>dynamic</u> information than when provided with <u>static</u> information.
$H_0(3)$: The traveller does not attain better outcomes of decision-making and learning when provided with dynamic information than when provided with static information.

$H_1(4)$: The traveller attains better outcomes of decision-making and learning when provided with <u>reliable</u> dynamic information than when provided with <u>less reliable</u> dynamic information.
$H_0(4)$: The traveller does not attain better outcomes of decision-making and learning when provided with reliable dynamic information than when provided with less reliable dynamic information.

$H_1(5)$: The traveller experiences a stronger information effect and this effect strengthens at a faster rate when provided with reliable dynamic information than when provided with less reliable information.
$H_1(5)$: The traveller does not experience a stronger information effect or this effect does not strengthen at a faster rate when provided with reliable dynamic information than when provided with less reliable information.

Note that the first four hypotheses concern the "outcomes of decision-making and learning". Referring to Table 2-1, one can easily see that these outcomes relate to either the likelihood of choosing the best service or the wait time. A better outcome is therefore manifested as (a) a higher overall probability of choosing the best service, or a shorter wait, or both, and (b) an increase in probability of choosing the best service, or a decrease in waiting time, or both, over time. Chapter 3 describes in greater detail how each of these outcomes is captured and measured in the experiment.

In developing the descriptive scheme and hypotheses, several behavioural processes, such as the exploratory search among services, and the adoption and subsequent reduction in the safety and information margins, are assumed. It is recognised that while they simplify the predictions of how a traveller is likely to respond in both the presence and absence of information, they are likely to be somewhat simplistic and even unrealistic behaviourally. Nonetheless, the descriptive scheme can serve as a useful baseline against which the actual results can be presented and analysed, and the hypotheses tested.

Fundamentally, it is assumed that travellers seek to maximise their utility. It is recognised that, as has been asserted extensively in the literature over the years, such maximising behaviour may not be valid. Certainly, as both the studies of Avineri and Prashker (2006) and Ben-Elia *et al.* (2008) show, the provision of information does not lead to behaviours consistent with utility maximisation. Nonetheless, such behaviour is assumed to serve as a starting point to develop the hypotheses. After comparing these differences, one can then follow up to examine if the non-maximising behaviour can indeed be observed. This is discussed in the following Chapters.

3 EXPERIMENT

Chapter 1 has argued for an experimental approach and Chapter 2 presents a hypothetical travel scenario of a traveller using public transport services for her commute trip. This chapter describes how the experiments were designed and developed using this scenario.

3.1 Experimental Procedure

Recall that the experiment scenario envisages the traveller having to decide on the time to depart home to catch the bus to reach her workplace. The traveller aims to catch the service that she believes will arrive at the work place at a time closest to, but not after, the work start time, while minimising the waiting time for that service. At the same time, she has to take into account the uncertainty involving the departure times of the bus services and their in-vehicle times, which vary from day to day. She is also provided with pre-trip travel information on the bus service, and is free to use or ignore it in decision-making. Once the traveller executes her decision, the outcome or consequence will be known quickly. Specifically, the traveller will realise how long she has waited once the service departs, how long the ride is, and if she is late when she reaches her destination. On the following day, she may recall this outcome and perhaps the preceding ones as well, which will then influence the decision for the new trip.

The experiment presented this scenario as a series of choice situations, each representing a single travel day or commute trip. The participant, as the hypothetical traveller, was tasked to make a choice of the time to depart home, t_h for each day in the face of variable service departure times (t_s) and in-vehicle times (T_v), as well as in the presence of a simulated travel information service. For simplicity, the access times to and from the bus stops, T_a and T_e, are kept constant. This is so that her arrival times at the bus stop (t_b), and at the workplace (t_l) are at fixed differences from t_h and t_d (the arrival time of the service at the alighting bus stop), respectively. Once the choice was made, the variables representing the outcome: the actual service departure time (t_s), the waiting time ($T_w = t_s - t_b$), the in-vehicle time (T_v), and the arrival times at the alighting bus stop (t_d) and at the work location (t_l), were revealed immediately.

The participant was told to choose a departure time from home t_h to keep the time period between her arrival time at the work place and the work start time as short as possible, while avoiding being late. At the same time, she also needs to minimise the wait time for the service she catches. These are the typical motivations for a bus commuter. The degree to which the participant met these objectives was measured using a scoring scheme. This scoring scheme was derived from the utility formulation adapted from Small (1982). The formulation is shown in equation (3-1).

$$Score = 100 - 3T_w - SDE - 4SDL - 9L \qquad (3\text{-}1)$$

The score for each day was a base score of 100 points less penalty points. The penalty points were based on the actual values of the various outcome attributes of waiting time in minutes, early arrival at the destination (*SDE*) in minutes, late arrival at the destination (*SDL*) in minutes, and the fact of being late to work. Hence, if a participant ended up waiting at the bus stop for 5 minutes, and was then 2 minutes late for work, his score would be 68 (= 100 – 3×5 – 4×2 – 9). The ratio of coefficients in the equation in which the coefficient of *SDE* was set at 1.0, approximate that of the parameters in Small (1982), with two exceptions. First, T_v was omitted because it was not an attribute over which the participant had any influence. Second, T_w, which was not an attribute in the original framework of Small (1982), replaced T_v and was given a weight of 3.0, based on an arbitrary assumption that a traveller, when waiting, would incur close to twice the disutility of T_v, which has a coefficient value of approximately 1.6 times that of *SDE* in Small (1982).The score for each day was revealed together with the average of scores obtained up to the current day of the session.

However, introducing an explicit scoring scheme to the participant might bring about certain degree of bias towards behavioural responses, such that he might maximise the score rather than reflect his actual utility function in his real-life travel. Certainly, every participant is different and each will have his own coefficients to the travel attributes of early/late arrival and wait time. Ideally these should be estimated. Nonetheless, because the research objective is on the effects of information and learning primarily, introducing the scoring scheme provides some degree of control over the utility function to avoid subjective perception and interpretation by the participants.

This choice situation was repeated for a total of D = 20 days for a particular scenario to capture the effects of experience and learning over time. Participants were presented with scenarios that differ in the types and formats of information, and in simulated service operating circumstances, specifically in the service frequency and departure time variability.

The experiment involved repetitive choice situations and immediate feedback of decision outcomes to the participants. These requirements necessitated the experiment to be programmed and conducted on computers. The additional advantages of this approach are efficiency in data collection, standardisation of the administration of the experiment and the ability to automatically check for invalid responses. The experiment was programmed into a computer file developed on the Microsoft Excel® software using Visual Basic for Application (VBA). Figure 3-1 shows a typical screen display, with the various scenario, decision, and outcome variables indicated in yellow, green, and blue boxes respectively.

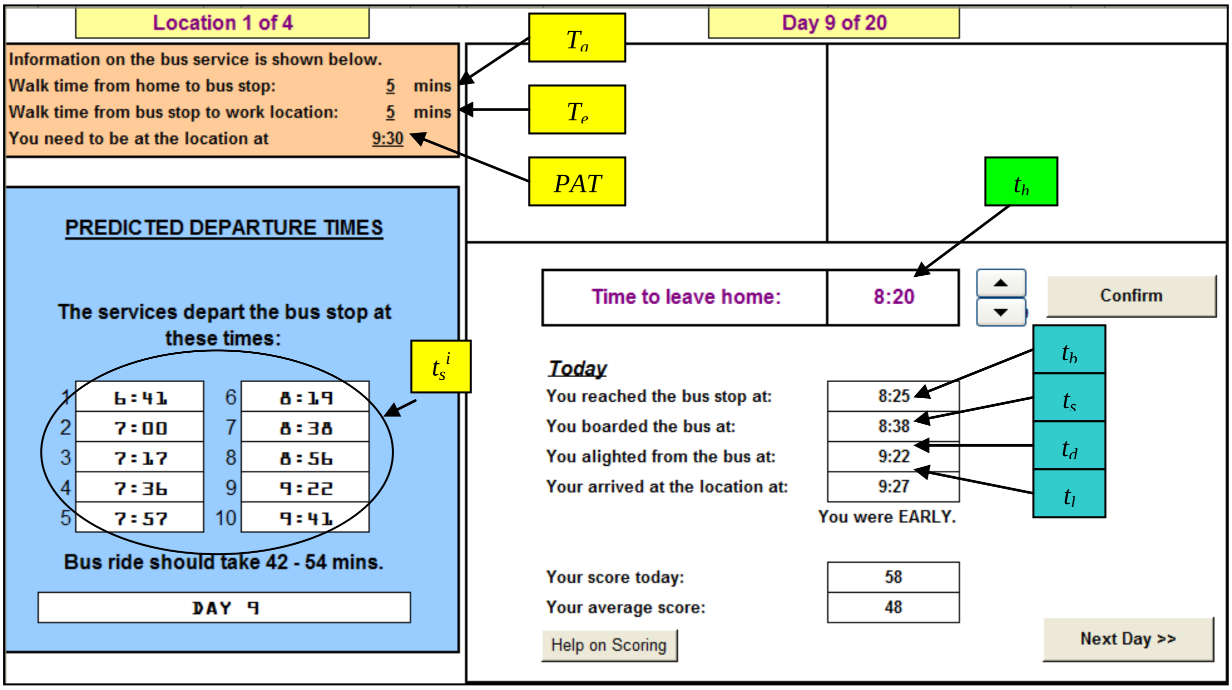


Figure 3-1 Typical Screen Display

3.2 Experimental Design

3.2.1 Independent Variables

The phenomena of research interest, namely travel information type and format, and reliability and learning, are studied through experimental factors. One factor was introduced to represent the travel information characteristics that encompass both information type and reliability, and another factor, the amount of learning or experience. A third factor on service operating characteristics was included to investigate the variations in the effects of information and learning across different service operating environments.

3.2.1.1 Factor Representing Information (*Info*)

As set out in the experiment scenario, the contents provided by the simulated travel information service relate to service departure times (t_s). This type of information content is commonly available in types and formats and from sources which are too numerous for the experiment to include in their entirety. When such information is static, it is often presented in the two formats described in Chapter 2 (Section 2.2), namely, the scheduled service intervals or headways, and scheduled service departure times at the stop, i.e., a timetable. The first format is usually used when the service frequency is deemed sufficiently high that display of specific times of service departure is considered unnecessary. The latter, on the other hand, is typically provided when headway intervals are long, although they are also not uncommon for high-frequency services. These two formats formed two conditions of the *Info* factor.

With the advent of real-time passenger travel information systems, the contents of dynamic information are increasingly varied and sophisticated, with many providing advisory and incident reporting features. However, in the context of this experimental scenario, it is assumed that dynamic information comes only in the single format of service departure times for individual services that are updated regularly. To test the effects of information reliability, the accuracy of this hypothetical dynamic information service was specified at two levels.

Hence, two formats of static information and two levels of reliability of a single format of dynamic information were constructed as four experimental conditions pertaining to service departure time information. An additional no-information condition was introduced to provide a control. The experimental conditions for service departure time information are shown in Table 3-1.

Table 3-1: Experimental Conditions for Service Departure Time Information

Information Contents	Condition	Type	Format	Reliability
Service Departure Time	*NO-INFO*	None	-	-
	HDWAY	None	Scheduled headway	-
	TTABLE	Static	Scheduled departure times	-
	DYN-UNREL	Dynamic	Estimated departure times	Unreliable
	DYN-REL	Dynamic	Estimated departure times	Reliable
In-Vehicle Time	All	Static	Estimated range	Fixed

Note that, although *HDWAY* is introduced previously as a type of static information, Table 3-1 has listed it as a condition in which no information is supplied. This is because, unlike *TTABLE*, *DYN-UNREL* and *DYN-REL*, which provide specific estimates of service departure times, whether they are static or dynamic, *HDWAY* provides no specific information that will enable the traveller to identify any particular service or its departure time. It is therefore argued that it is no different from *NO-INFO* from the traveller's perspective. Indeed, in the descriptive scheme in Chapter 2, the traveller is assumed to undergo the same behavioural processes when he is given either no information or only headway information. Nonetheless, it was retained as one of the treatment combinations because it is commonly available in the market. Certainly, given its prevalence, it would be intriguing to test if such information is indeed no better than an absence of information.

Note also that information relating to the in-vehicle time was also provided in all information conditions, but only in a single format and was not varied across treatment conditions. Its sole purpose was to define the limits within which the participant selected t_b. In other words, information on in-vehicle travel time was effectively ignored in this study context. The reason is that information on in-vehicle travel time is less prevalent in real life, and if available, is typically provided in a non-dynamic format only, and therefore does not provide for comparisons between information types and formats. Figure 3-1 (earlier) shows *Info* conditions *DYN-UNREL* and *DYN-REL* that differ only in the reliability of the information, and Figure 3-2 shows displays representing *Info* conditions *NO-INFO*, *HDWAY* and *TTABLE* in the same experimental instrument. Note that the presentations of the different *Info* conditions are designed to be largely similar. The intent is to limit the effect of information context in the experimental design, as discussed in Chapter 1, and thus focus on the content itself.

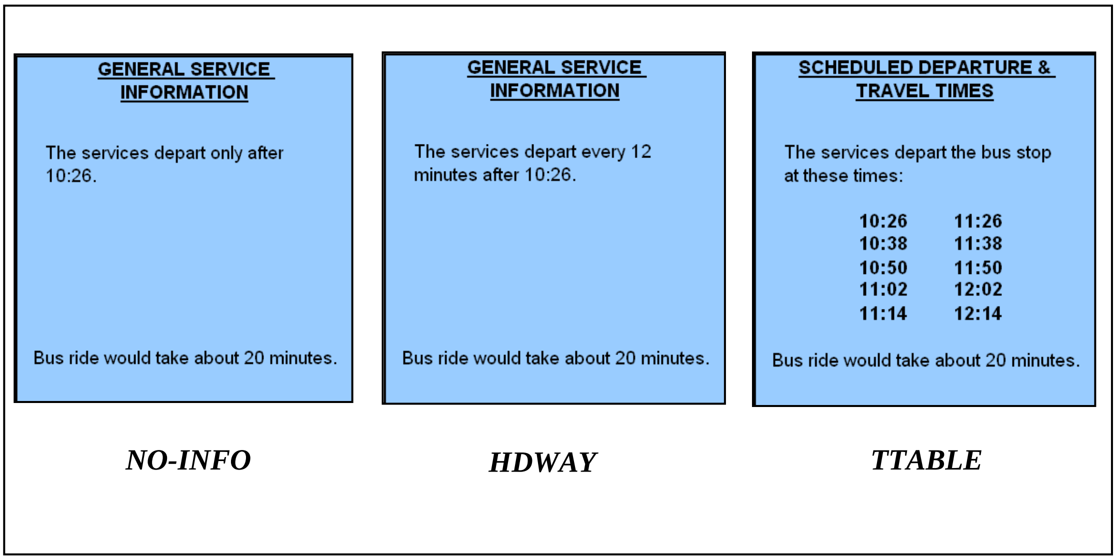


Figure 3-2 *Info* Conditions *NO-INFO*, *HDWAY* and *TTABLE* Presented in Experiment

Additional scenarios were developed by combining two of the five conditions in Table 3-1 such that one condition was presented in the first 10 hypothetical travel days before changing to the second for the last 10 days. This simulated a replacement of an existing information service with another, which was a situation that a commuter may face during his or her regular commute, e.g., the commissioning of a travel advisory service that provides dynamic estimates of service departure times to replace published timetables. Although it was possible to construct a total of 25 conditions for the simulated travel information service through factorial combinations of the five conditions, only those that represented likely real-life situations were selected. Some combinations were highly improbable in real-life, e.g., a full de-commissioning of a highly reliable dynamic travel advisory information service (*DYN-REL* to *NO-INFO*) without a substitute service. Others were omitted to attain a more parsimonious experimental design. Altogether, ten conditions of the qualitative factor, *Info* were constructed and listed in Table 3-2.

Table 3-2: Configurations of Travel Information Service as Factor *Info* Conditions

***Info* Condition**	**Condition in First 10 Days**	**Condition in Second 10 Days**	**Real Life Situation Represented**
NO-INFO	None	None	Obligations of service information provision not met
HDWAY	Scheduled average headway	Scheduled average headway	Only general service information provided
TTABLE	Scheduled departure times	Scheduled departure times	Published timetables at bus stop or distributed to commuters
DYN-UNREL	Estimated departure times – unreliable	Estimated departure times – unreliable	Dynamic travel information service on trial
DYN-REL	Estimated departure times – reliable	Estimated departure times – reliable	Fully commissioned dynamic travel information service
NO-INFO then *TTABLE*	None	Scheduled departure times	Provision of timetables when there was none previously
TTABLE then *DYN-UNREL*	Scheduled departure times	Estimated departure times – unreliable	Dynamic travel information on trial to replace timetables
TTABLE then *DYN-REL*	Scheduled departure times	Estimated departure times – reliable	Commissioning of dynamic travel information to replace timetables
DYN-UNREL then *DYN-REL*	Estimated departure times – unreliable	Estimated departure times – reliable	Commissioning of dynamic travel information after a trial period
DYN-REL then *DYN-UNREL*	Estimated departure times – reliable	Estimated departure times – unreliable	Deterioration of service levels of fully commissioned dynamic travel information service

Except for *NO-INFO* and *HDWAY*, in all *Info* conditions the information provided was in the format of individual estimates of departure time of each of the bus services and were represented by the variable t_s^i. The values of t_s^i for a particular bus service in most of the *Info* conditions were varied from day to day within the periods in which the information was dynamic (those that involve *DYN-REL* or *DYN-REL* conditions in either or both periods). However, these values were invariant within the periods in which the information was static (those that involve *TTABLE*). The variable t_s^i was not used in *NO-INFO* and *HDWAY* obviously because these were no-information conditions.

In the case of dynamic information, the values of t_s^i were drawn from discrete distributions approximating truncated normal distributions, with their means at the actual service departure time. The reliability of these estimates was captured by the standard deviation of the distribution and the levels of reliability could thus be manipulated through the adjustments of this measure of variability. Figures 3-3 and 3-4 show the distributions of the estimated departure times from this hypothetical information service, which are $f_{rel}(t_s^i)$ and $f_{unrel}(t_s^i)$ for reliable and unreliable information services respectively. Symmetrical distributions of estimates, although not entirely realistic in describing the characteristics of dynamic information services in all contexts, are also assumed in Ben-Elia *et al*. (2013) and Ettema and Timmermans (2006).

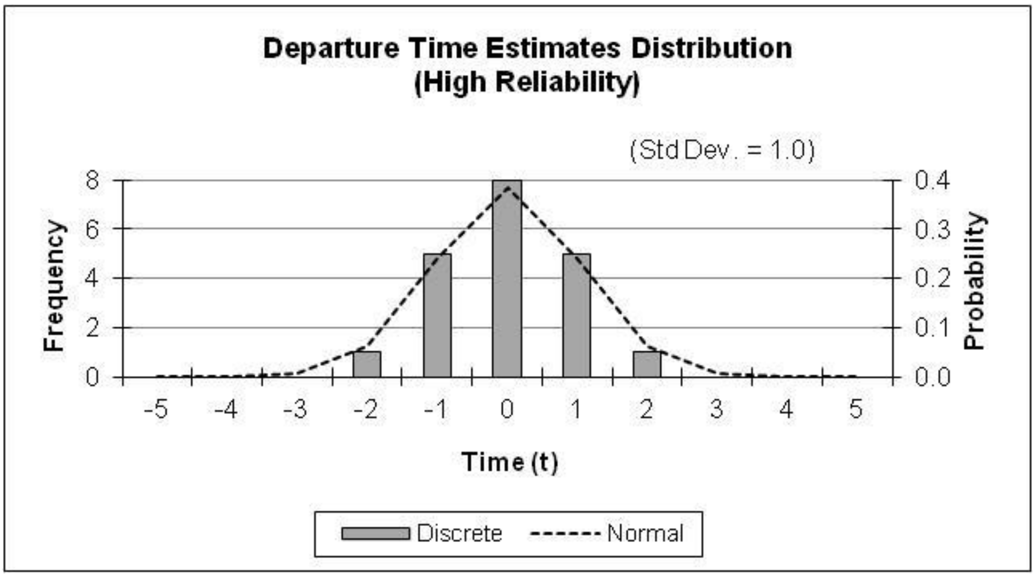


Figure 3-3: Distribution of Estimated Departure Times by "Reliable" Information Service, $f_{rel}(t_s^i)$

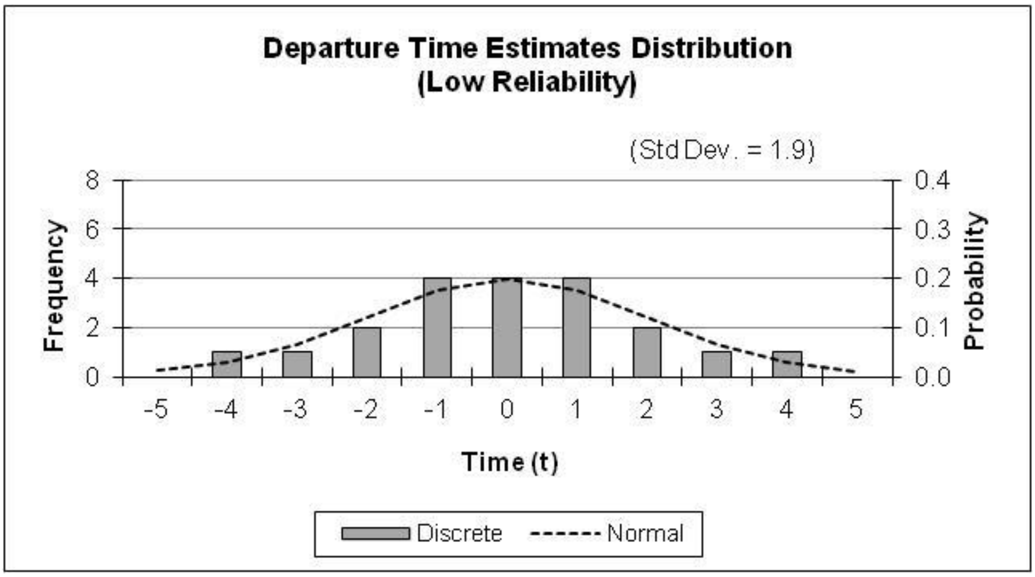


Figure 3-4: Distribution of Estimated Departure Times by "Unreliable" Information Service, $f_{unrel}(t_s^i)$

3.2.1.2 Factor Representing Learning and Experience (*Day*)

Learning and experience was represented by a non-manipulative quantitative factor *Day*. Each of its levels, d, was a hypothetical travel day or trip, and each successive day represents a gain in the level of experience or learning. The total number of days was set at $D = 20$.

3.2.1.3 Factor Representing Service Operating Conditions (*Ops*)

To simulate the variety of travel environments a traveller might face, another factor *Ops* was introduced to represent possible operating characteristics of the bus service. Six *Ops* conditions were constructed by combining three levels of bus service frequency (headway) and two levels of service arrival time variability, as shown in
Table 3-3 Table 3-3.

Table 3-3: Proposed Conditions for Factor *Ops*

Condition	Bus Service Headway	Service Departure Time Variability
H20-LOW	20 minutes	Low (Std Dev. = 2.1)
H20-HIGH	20 minutes	High (Std Dev. = 2.7)
H10-LOW	10 minutes	Low (Std Dev. = 2.1)
H10-HIGH	10 minutes	High (Std Dev. = 2.7)
H5-LOW	5 minutes	Low (Std Dev. = 2.1)
H5-HIGH	5 minutes	High (Std Dev. = 2.7)

In each *Ops* condition, there were ten services scheduled to depart the bus stop at regular headway each day, but whose actual departure times deviated from the schedule as described in the preceding paragraphs. (Correspondingly, there would be ten departure time estimates provided in *Info* conditions associated with the scheduled or dynamic information, as shown in Figure 3-1). The service departure times of each service, t_s, were drawn randomly from pre-defined probability distributions. For this experiment, discrete distributions approximating the lognormal, whose modes were set at the scheduled service departure times, were used. The distribution $f_{low}(t_s)$ with standard deviation of 2.1 was used for conditions in which the variability of t_s was low (*Ops* conditions *H20-LOW*, *H10-LOW* and *H5-LOW*), and $f_{high}(t_s)$ with standard deviation of 2.7, when variability was high (*Ops* conditions *H20-HIGH, H10-HIGH* and *H5-HIGH*). Similarly, the in-vehicle times were drawn randomly from another discrete distribution approximating the lognormal $f(T_v)$. The lognormal distribution was selected as the basis from which $f_{low}(t_s)$, $f_{high}(t_s)$ and $f(T_v)$ were derived because its asymmetry and positive skewness align closely with operating circumstances of a real life bus service, in which the bus driver tends to constrain the service's early running, but is less able to influence the operating speed to catch up with the timetable if the service is late due to congestion.

Figures 3-5 to 3-7 present the discrete distributions of t_s and T_v for over 20 travel days. All units of t_s and T_v are measured relative to the *scheduled* departure time and *scheduled* in-vehicle time, which are set to 0.

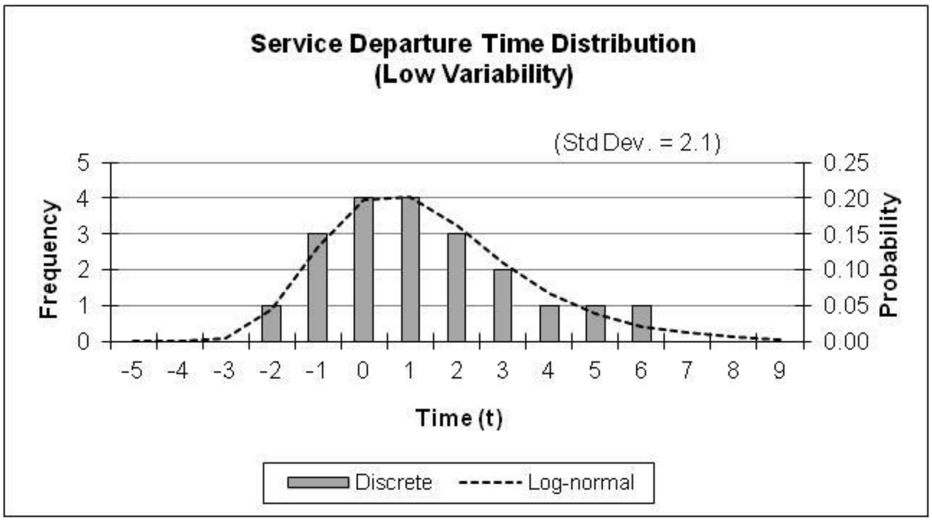


Figure 3-5: Distribution of Actual Departure Times (t_s) (Low Variability) $f_{low}(t_s)$

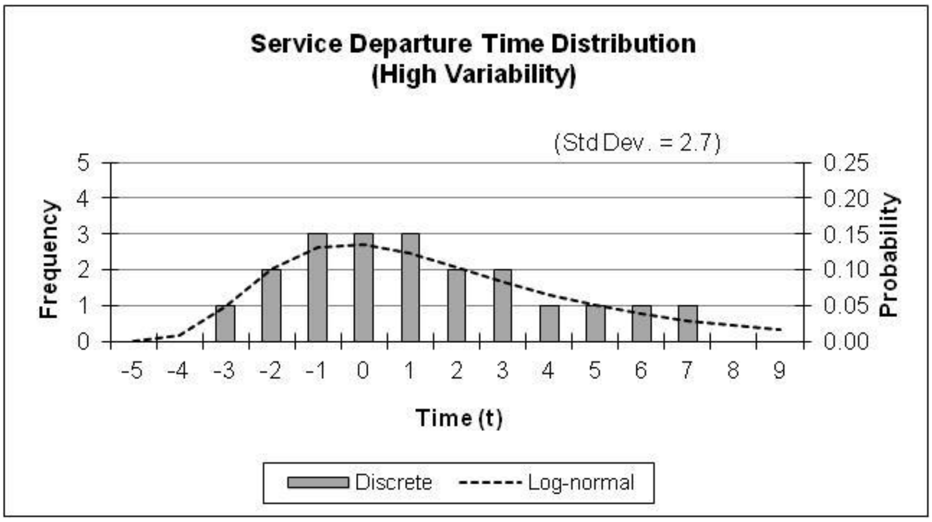


Figure 3-6: Distribution of Service Departure Times (t_s) (High Variability), $f_{high}(t_s)$

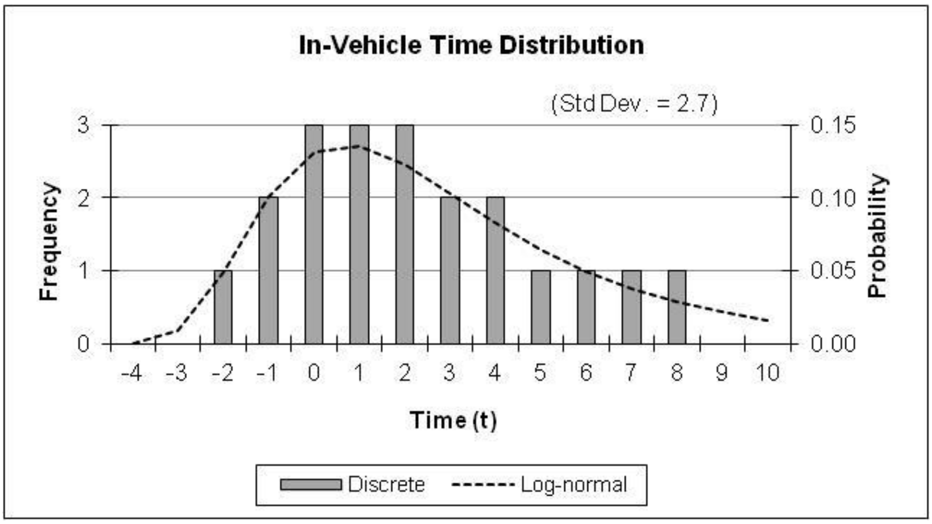


Figure 3-7: Distribution of In-Vehicle Times (T_v), $f(T_v)$

It was assumed that these distributions were stationary, i.e., they were invariant over the time periods of day and over the days of week. It is recognized that this assumption may well be violated in reality. Certain days of the week, say at the beginning of the work week, may also observe greater variability in the service departure times, than other days because of the weekly commute travel patterns. Nonetheless, the stationary assumption was used to simplify the analysis.

Although the values of T_v were derived from a single distribution $f(T_v)$, each of the 6 *Ops* conditions used a set of T_v values that were drawn independently. Similarly, separate sets of t_s values were also drawn from one of two distributions (either $f_{low}(t_s)$ or $f_{high}(t_s)$) for each *Ops* condition. Likewise, sets of t_s^i, the estimates of t_s by the information service, which were drawn for *Info* conditions involving dynamic information, differed across *Ops* conditions, even if they came from the same $f_{rel}(t_s^i)$ or $f_{unrel}(t_s^i)$ distributions. This treatment was necessary because the participant was to be subjected to more than one travel scenario in the experiment, and if the same set of values was used repeatedly in successive scenarios, he or she would be able to discern the variation patterns of the T_v, t_s and t_s^i, thus threatening the validity of the data collected.

The above discussion of the three factors of *Info*, *Day* and *Ops* may lead one easily to a conclusion that a three-factor mixed design has been proposed, with *Info* and *Ops* as between-subjects factors that are crossed with each other, and *Day*, the within-subject factor, as illustrated in Table 3-4. However, it should be noted an *Info* condition that involves dynamic information is unique to each *Ops* condition and does not repeat across other *Ops* conditions because sets of t_s^i were drawn individually for each *Ops* condition, as described in the preceding paragraph. What this means is that a condition of say, *DYN-UNREL* of *H20-LOW* condition is strictly not the same as *DYN-UNREL* of *H5-LOW*. Even *Info* conditions with static information cannot be considered identical across *Ops* conditions because the contents displayed are also associated with the *Ops* conditions they are in. Therefore each *Info* condition is nested in a single *Ops* condition, and not crossed with all *Ops* conditions as in factorial design, thus producing a nested design instead. This design is shown in Table 3-5, which is almost identical to Table 3-4, except that each *Ops* condition is associated with a unique set of *Info* conditions, instead of fully crossing with one set of *Info* conditions. In summary, ten conditions of *Info* are nested in each of 6 *Ops* conditions, such that a total of 10 × 6 = 60 treatment combinations or scenarios are constructed from these two between-subjects factors. The factor *Day* is a within-subject factor.

Table 3-4: Three-Factor (*Info* × *Ops* × *Day*) Mixed Design

Factor *Ops*	**Factor *Info***	**Factor *Day***					
		1	2	…	*d*	…	*D*
H20-LOW	*NO-INFO*						
	HDWAY						
	...						
	DYN-REL then *DYN-UNREL*						
H20-HIGH	*NO-INFO*						
	HDWAY						
	...						
	DYN-REL then *DYN-UNREL*						
…	...						
H5-HIGH	...						
	DYN-UNREL then *DYN-REL*						
	DYN-REL then *DYN-UNREL*						

Table 3-5: Three-Factor (*Info* × *Ops* × *Day*) Nested Design

Factor *Ops*	Factor *Info*	Factor *Day*					
		1	2	…	*d*	…	*D*
H20-LOW	*NO-INFO* (1)						
	HDWAY (1)						
	...						
	DYN-REL then *DYN-UNREL* (1)						
H20-HIGH	*NO-INFO* (2)						
	HDWAY (2)						
	...						
	DYN-REL then *DYN-UNREL* (2)						
…	...						
H5-HIGH	...						
	DYN-UNREL then *DYN-REL* (6)						
	DYN-REL then *DYN-UNREL* (6)						

3.3 Dependent Variables

Each choice situation at a travel day *d* under a particular travel scenario (treatment combination) yielded data for the several time variables described in Section 3.1.. From these, pertinent dependent variables were derived for each of the two broad families of relationships to be investigated.

3.3.1 Measures of Decision Outcomes

In the first family of relationships described in Chapter 2, the phenomena of interest are the outcomes of decision-making and how they are affected by the learning process and/or the presence of different types of information. The four hypotheses in this family predict that learning leads to improved decision outcomes over time and these outcomes differ depending on the type of information provided. The outcomes are the likelihood of the traveller choosing the best service of the day, and her waiting time. The first is associated with that aspect of decision-making relating to the identification and selection of the service by the traveller, and the second, the degree of her success in catching her intended service. To examine if the hypotheses can be supported, one needs to identify dependent variables that measure these outcomes.

3.3.1.1 Dependent Variable Relating to Selection of Service

A dependent variable that provides a good measurement of the likelihood of choosing the best service of the day is identified first. Now, in the experiment, and in real-life, the traveller does not provide an explicit account of the probabilities of choosing each service. On any given day, the only observation one can obtain is that he selects a service, and that service is either the best service of the day or it is not. So a binary variable can be used to indicate his choice of service, as follows:

$$\begin{cases} Svc_{best} = 1 & \text{if best service is selected} \\ Svc_{best} = 0 & \text{otherwise} \end{cases} \tag{3-2}$$

It is worth re-emphasising the point made in Chapter 2 that the selected service is defined as the service the traveller intends or targets to catch, and not the service he actually catches. As an illustration of this distinction, the traveller intends to catch a service but because of his late arrival at the bus stop, or an early departure of that service, he misses it and has to board the next service. On other occasions, he might even have caught a preceding service (perhaps unknowingly), especially if a large safety margin in arrival time has been adopted or if service bunching occurred.
In either case, the selected service is different from the service actually boarded. In other cases, the traveller catches the service he targets, and the selected and targeted services are the same. So, Svc_{best} = 1 if he targets the best service, and this is regardless of whether he manages to catch it. Conversely Svc_{best} = 0 if he catches it unintentionally, e.g., he targets and misses an earlier service and ends up catching the best service that arrives next.

This dependent variable is therefore a measure of the traveller's intent, not of the actual outcome. If it is the latter, obtaining its value is straightforward: the service boarded each day can be obtained directly from the experimental output. However, one has to infer the intended service indirectly from the only response variable, the arrival time of the traveller at the bus stop (t_b). It is reasonable to assume that t_b reflects his choice of service invariably. Surely, no traveller would choose a t_b with the intent to miss a service. So, although one is unable to know with absolute certainty which service a participant was attempting to catch on a particular day, one could still deduce it using t_b with some degree of confidence if a set of consistent and reasonable inference rules can be established. In this section, these rules to infer the service the traveller intends to target using his actual arrival time at the bus stop (t_b) are developed for scenarios in the order of (a) static information, (b) no information, and (c) dynamic information.

Scenarios with Static Information. For ease of discussion, suppose one starts with a travel scenario in which the respondent is given timetable information (*TTABLE*) in which the estimated departure time is the (invariant) scheduled departure time, $t_s^i = t_s^{sch}$. As described in Chapter 2, the traveller identifies individual services immediately using the timetable, chooses his targeted service among them, and selects t_b to catch it. For a start, one may perhaps consider a proximity inference rule: the service whose t_s^i value is closest to t_b is selected as the targeted service. Using this rule, one can easily and reasonably identify the targeted service in scenarios in which the headways between services are large, and the t_s^i values of the services are clearly apart from one another. However, it may be less straightforward if the t_b value is located midway between two consecutive t_s^i values, or if the headway is so short that any t_b value can be considered within proximity of two or more t_s^i values. This simple rule is also not entirely realistic and satisfactory because it does not take into consideration how the traveller perceives the actual departure time t_s to vary around t_s^{sch}.

The rule for determining the targeted service is first developed for the *H20-LOW* scenario (headway of 20 minutes, low t_s variability. See Table 3-3.) Consider the actual distribution of t_s, first shown in Figure 3-5, and reproduced as histogram bars in Figure 3-8. Setting t_s^{sch} of Service (i – 1) at t = 0, its t_s are distributed between $-2 \leq t \leq 6$. The service that succeeds it immediately, Service i, has t_s^{sch} at t = 20, which is one headway (H = 20) away and the t_s distribution is located between 18 and 26. Obviously, the traveller would not know the t_s distributions exactly, but would have a perception of the range within which t_s varies over time. Now, if he intends to catch Service i, he would refer to its t_s^i, which is the t_s^{sch} of that service. It is assumed that the latest time he would choose for the arrival at the bus stop (t_b) is t = 26. Thus t = 26 defines the upper limit of the range within which any choice of t_b is associated with Service i and thus its t_s^i ($=t_s^{sch}$). The lower bound is of course the upper limit of the same range for Service (i – 1), i.e., t = 6. Such an allocation rule results in that portion of the range before t_s^{sch} ($7 \leq t \leq 19$) to be larger than the one after ($21 \leq t \leq 26$). One may ask if such an asymmetry, and by extension, the rule, is reasonable. It is argued that it is so. That a larger portion of the range is before t_s^{sch} can be simply viewed as a consequence of incorporating a safety margin to address the uncertainty in $\underline{t_s}$ (Bonsall, 2004), a phenomenon that is central to the descriptive scheme.

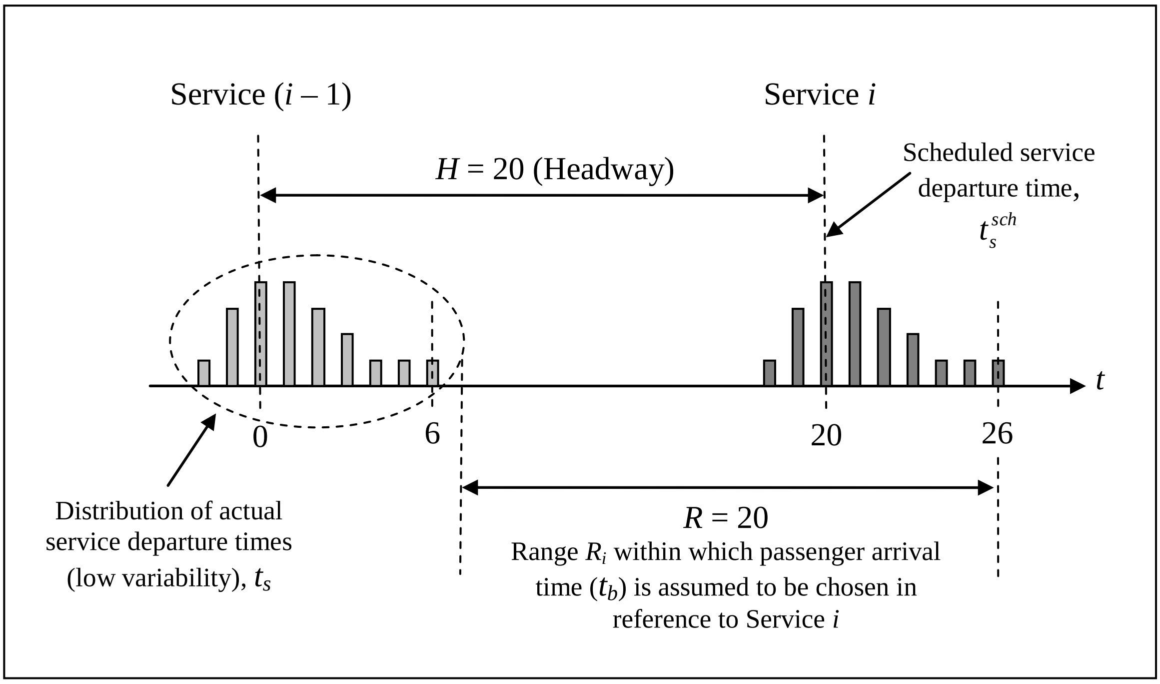


Figure 3-8 Determination of Range within which Passenger Arrival Time is chosen with reference to the Targeted Service for *H20* Scenarios

A separate rule to identify the targeted service can be formulated similarly for *H20-HIGH* scenarios following the same procedure, but using the distribution of t_s that corresponds with the *high* variability condition, and whose range is larger at 11 (compared to 9 under the *low* variability condition of *H20-LOW*). The resultant assignment ranges would be $8 \leq t \leq 27$ for Service i, $-12 \leq t \leq 7$ for Service (i – 1) and so forth. However, this represents only a shift of the boundary between the assignment range by a single unit of time. Furthermore, this shift is forward in time, implying the traveller is building *less*, not more, safety margin when there is higher variability in t_s. This is clearly counter-intuitive because one should expect him to be more cautious in the face of greater variability. Hence the rule derived using the low variability t_s distribution, described in the preceding paragraph, is used instead.

The same procedure is followed to formulate the assignment rule for *H10* scenarios. Figure 3-9 shows the low-variability distribution of t_s (in bars) for three consecutive services and the assignment range for one of them (Service *i*). The range within which t_b is assigned to a particular service is once more defined as that between upper bounds of consecutive t_s distributions. The higher-variability t_s distribution is not considered again.

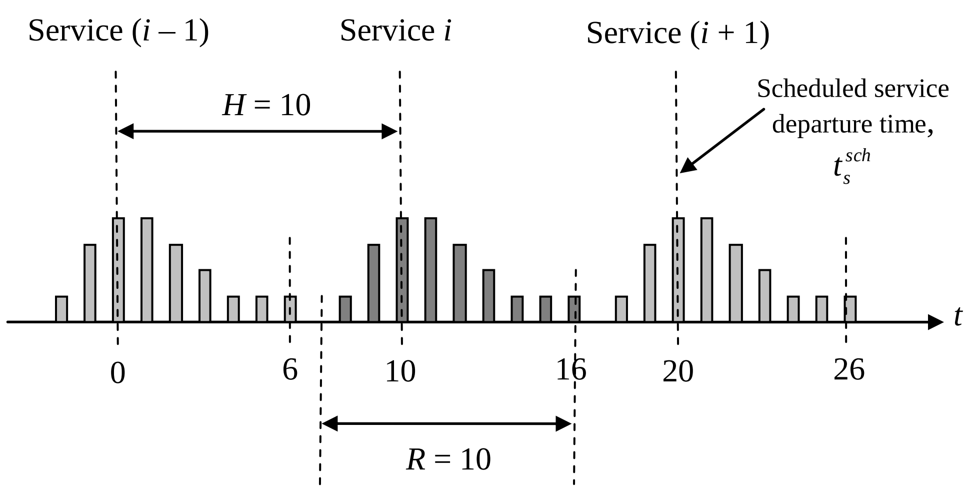


Figure 3-9 Determination of Range within which Passenger Arrival Time is chosen with reference to the Targeted Service for *H10* Scenarios

The last two operating conditions, *H5-LOW* and *H5-HIGH*, require a different set of considerations when drawing up the assignment rule. The headway, $H = 5$, is shorter than the range of t_s distribution (= 9) of a service. The t_s distribution of one service clearly overlaps with the services immediately preceding and succeeding it. This is shown in the upper panel of Figure 3-10. So, one may question if it is still admissible to set the upper bound of the t_s distribution as the boundary of the assignment range, as has been done for the other *Ops* conditions, and if not, how one should decide on the range. The answer to the first part of this question is clearly negative because the headway is shorter than the range of the t_s distribution. To address the second part of the question, the individual t_s distributions are first aggregated to produce a combined distribution, as shown in the lower panel of Figure 3-10. This distribution has peaks at the scheduled departure times t_s^{sch} (t = …, -10, -5, 0, 5, 10, …) and troughs in between these times. A logical point to define the boundary of the assignment range is at the trough, i.e., the midway point between t_s^{sch}. Interestingly, the outcome is thus the simple proximity rule, which is introduced at the beginning of this section and has been previously dismissed as unsuitable. Note that the combined t_s distribution used is again derived from individual distributions under the low variability operating condition.

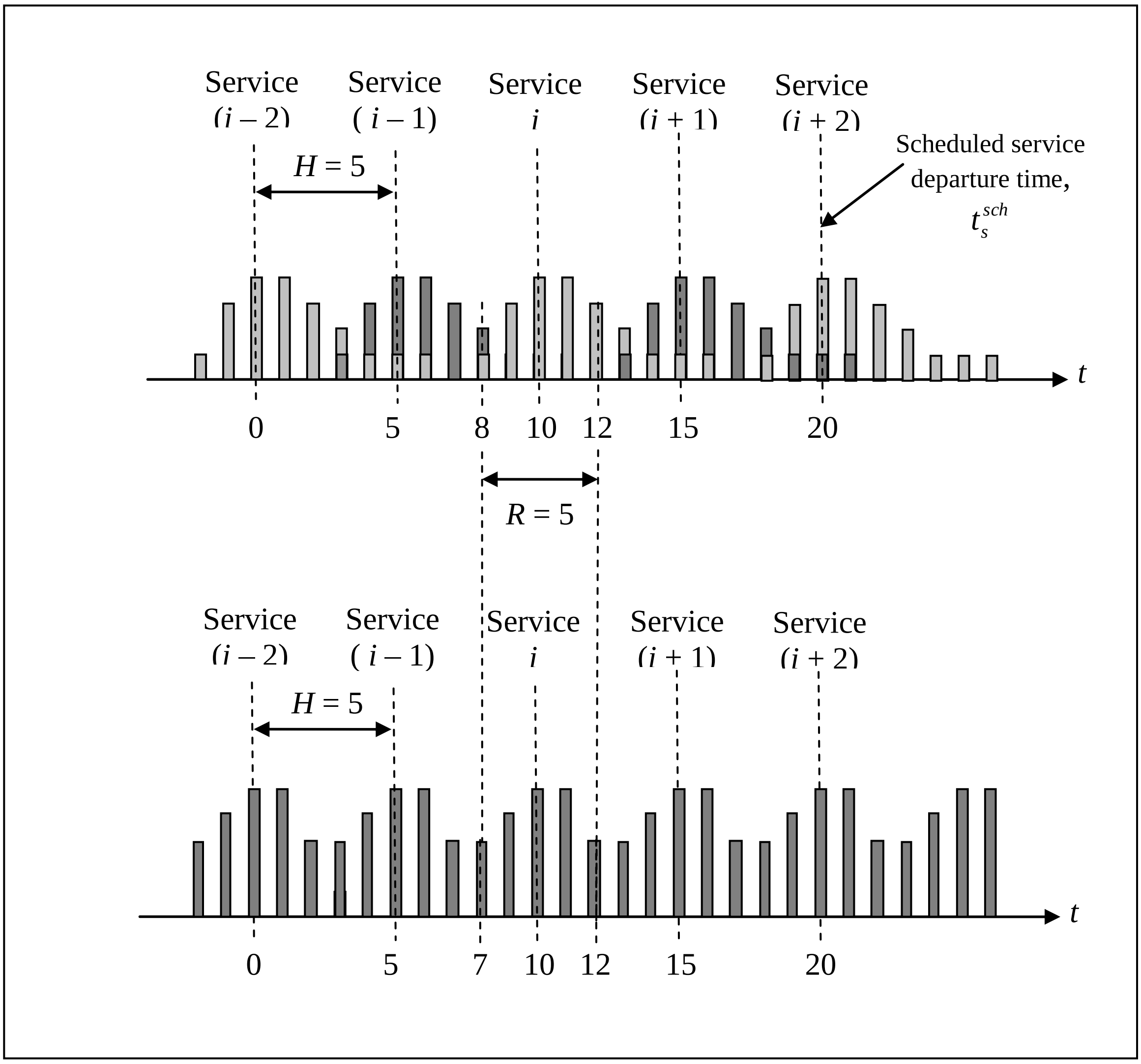


Figure 3-10 Determination of Range within which Passenger Arrival Time is chosen with reference to the Targeted Service for *H5* Scenarios

Before concluding this part of the discussion, it is interesting to highlight that, if the corresponding distributions under the high variability condition are aggregated, the resultant combined distribution can be shown to be entirely uniform. This means that from the traveller's perspective, any service he catches each day departs at random times. This outcome does not provide any useful basis to determine the location of the boundary of the assignment range. It also implies that when the service departures are frequent and highly variable, departure time estimates would have very limited utility to the traveller. This could be an interesting phenomenon to consider when analysing the choice behaviours, as is discussed later.

It is recognised that this set of assignment rules is not perfect. A traveller who intends to select Service i and thus refer to its t_s^i may opt for a very large safety margin such that his t_b is within the assignment range of the preceding Service ($i - 1$), particularly in the early travel days when he is less sure of the service characteristics. So, a conservative choice which refers to t_s^i of a service, could be misconstrued as a less conservative one relating to the preceding service. Conversely, a risk seeking choice of a t_b that is slightly beyond the upper limit of the range of the targeted service can be misrepresented as a conservative decision with the intent to catch the subsequent service. Nonetheless, such cases are expected to be few and far between. The appropriateness of the rules is also assessed and tested using the actual data in the next chapter.

<u>*Scenarios with No Information.*</u> The above rules assume the provision of information that provides static departure time estimates specific to individual services. The question to ask now is how one would deal with scenarios in which no specific information is provided, i.e., *NO-INFO* and *HDWAY.* It is argued that the traveller is still able to work out from experience, the range of t_s of at least one service (specifically the one she targets most frequently). Without a static t_s^i value as the initial anchor value, she can still use the first few t_s values she encounters to work out her perception of the t_s range and choose her t_b accordingly. Hence, the inference rules for the *TTABLE* scenarios can also be applied expeditiously to the *NO-INFO* and *HDWAY* scenarios.

<u>*Scenarios with Dynamic Information.*</u> This leaves inference rules for scenarios involving dynamic information (*DYN-UNREL* or *DYN-REL*) to be formulated. Two alternative approaches to formulating the rules are possible, depending on the assumption to be adopted. In the formulation of the above rules, it is taken that the traveller has worked out the upper and lower bounds within which t_s of a particular service is likely to vary, solely through his experience. One may extend this assumption to the current scenario such that the inference rules are the same across all scenarios. This approach applies the same inference rules to all types of information so that there can be a common and consistent basis on which the travellers' choice of service can be inferred across all scenarios.

Alternatively, one may assume that the traveller does not derive the range of t_s from experience, but instead refers to t_s^i from the dynamic information service for every decision on t_b. This will mean that the perceived ranges of t_s vary daily according to actual t_s^i, and are therefore different from the static ranges used in the scenarios with no information or static information. The rule is derived as follows. The dynamic information source provides several values of t_s^i provided each day, one for each service, and one needs to determine which of these estimates the traveller refers to when he decides on t_b. One may be tempted to adopt the expeditious approach to pick the particular t_s^i that is associated with the service he has boarded. However, this simple rule would be erroneous. As is earlier argued in Section 3.3.1.1, it is a case of intent versus outcome. If the traveller has indeed made a decision based on an estimate supplied, it should be based on the one associated with the service he has *intended* to catch, not the *actual* service she eventually boards.

One must therefore identify the '*targeted'* estimate that is associated with the service she intends to catch. This brings us to a situation analogous to that in Section 3.3.1.1 in which one needs to infer t_s^i from the data, specifically from the traveller's choice of t_b because the targeted estimate t_s^i cannot be obtained directly from the experimental output. One can easily and reasonably identify the targeted estimate if t_b is in close proximity to it. This is especially true for scenarios in which the headways between services are large, and the t_s^i values are likely to be clearly apart from one another. However, it may be less straightforward if the t_b value is located midway between two consecutive t_s^i values, or if the headway is so short that any t_b value can be considered within proximity of two or more t_s^i values.

Again one first develops the rule for *H20-LOW*. An approach similar to that used to develop the rules to infer the targeted service is adopted. However, instead of using the distributions of t_s, one now considers the actual distribution of t_s^i. Assume this distribution is the one associated with *reliable* information (*DYN-REL*), which is earlier exhibited in Figure 3-3, and reproduced as histogram bars in Figure 3-11. The t_s^i distribution is symmetrical around $\bar{t}_s$ and its range is 5 minutes, which means that on any particular day, the maximum and minimum over- or under-estimation of t_s by the information service are 2 minutes, i.e., $t_s = t_s^i \pm 2$.

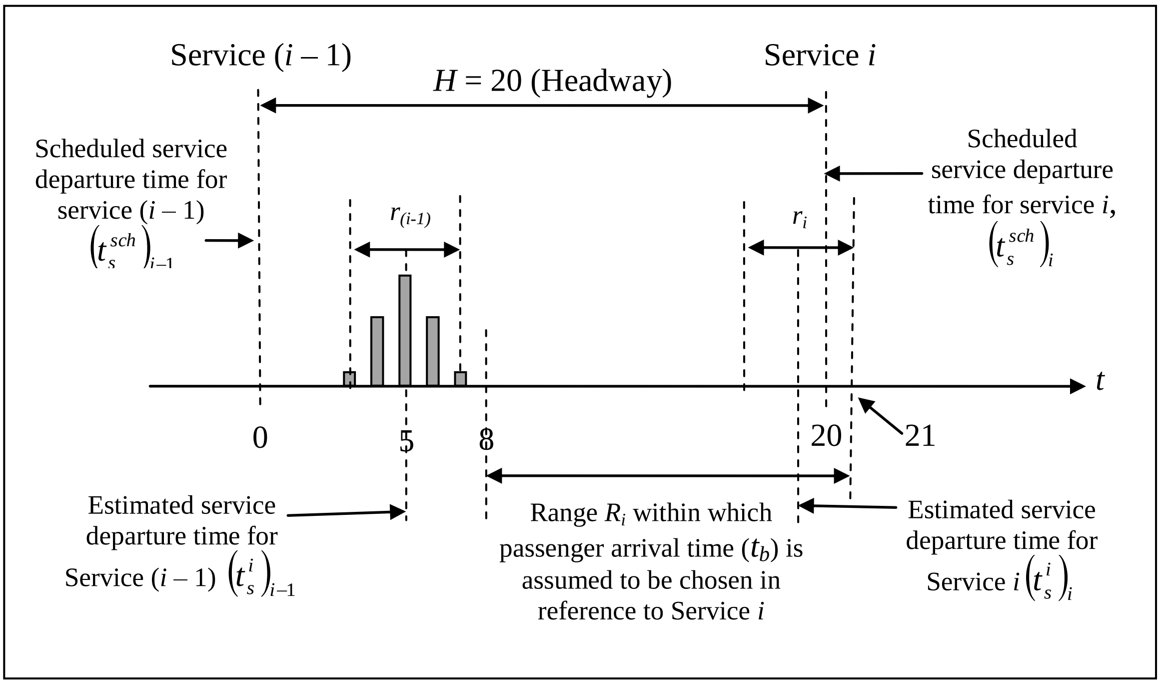


Figure 3-11 Determination of Reference Service for Dynamic Information under *H20* Scenarios

Suppose for this particular day, the estimates from the information service for services i – 1 and i are $(t_s^i)_{i-1} = 5$ and $(t_s^i)_i = 19$ respectively, and that the traveller has already formed a reasonably accurate perception of the range within which t_s^i varies. Now, if Service i is his targeted service, the latest time he is likely to arrive at the bus stop (t_b) is $t = (t_s^i)_i + 2 = 21$. Thus $t = 21$ is the upper bound of the range within which any choice of t_b is attributed to Service i and is associated with the estimate corresponding to this service, $(t_s^i)_i$. The lower bound of the assignment range is defined by the upper bound of the same range for the preceding service i.e., $t = (t_s^i)_{i-1} + 2 = 7$. In other words, if $8 \leq t_b \leq 21$, the rule infers that the traveller is targeting Service i and hence taking reference from $(t_s^i)_i$ when deciding on t_b. Note that the size of this range will differ across services and days because it depends on the t_s^i values of each pair of successive services, which are independently variable. So the range for each service has to be worked out using the above set of procedures for each of the 20 days.

Several assumptions have been made when drawing up the above rule for *H20-LOW*, and it is prudent to satisfy oneself of their reasonableness and validity before extending the rule to the other scenarios with different headways and variability. First, it has been assumed that the traveller has a fairly complete idea of the range of t_s^i, which is the basis of defining the upper bound of the assignment range. It is conceded that this assumption is questionable in the initial period when only a few trips have been completed, and the perception is still evolving with learning. Perhaps the traveller will choose a $t_b > t_s^i$ that exceeds the upper limit of the assignment range of the targeted service and is erroneously assigned to be referring to the following non-targeted service. However, this is not a major concern because the traveller is unlikely to do so even if his perception of the range of t_s^i is still sketchy during the early period. It is argued that the uncertainty in his mind is more likely to result in a more conservative choice, such that $t_b < t_s^i$.

The second assumption involves the use of the t_s^i distribution associated with a reliable information service (*DYN-REL*). One then wonders if the use of the distribution representing unreliable information (*DYN-UNREL*) would be more appropriate instead. This question is best answered by studying the resultant assignment range if the latter distribution is applied. Through a quick revisit of Figure 3-11, one can quickly discern that because the t_s^i range of the new distribution is larger (9 instead of 5), both the lower and upper boundaries of the assignment range of a service are now shifted forward along the time axis. What this implies is that if the traveller chooses a $t_b < t_s^i$, he does so with a much smaller safety margin. If $t_b > t_s^i$, he may have a t_b that deviates more from t_s^i. That the traveller can become more risk seeking in the face of more unreliable information is contrary to intuition. Unless the data supports otherwise, it may be prudent to use the t_s^i distribution of the reliable information service to establish the rule.

The third assumption is not apparent in the earlier description of the procedures to establish the assignment rule, but nonetheless is crucial as it is extended to other scenarios that have larger departure time variability and/or shorter headways. In the above illustration using *H20-LOW* condition, it has been implicitly assumed that t_s^i estimates of consecutive services are sufficiently spaced out along the time axis due to the long headway, such that the ranges $r_{(i-1)}$ and r_i in Figure 3-11 do not overlap.

However, the differences between estimates of consecutive services $(t_s^i)_{i-1}$ and (t_s^i) are smaller in *H10* and *H5* scenarios, and the earlier procedures will most likely give rise to overlapping assignment ranges for many pairs of consecutive services in these scenarios. The assignment rules derived thus far in this section will then not be admissible. Therefore, in such cases, one can fall back on the simple proximity rule: the targeted service to which t_b is referenced is determined by which t_s^i is closer to t_b.

This second approach is aligned with the key assumption used in the descriptive scheme – the information effect is present, and one that is to be tested in Hypotheses 5 described in Chapter 2. As one will see later, it is used again in the formulation of the dependent variable relating to the information effect.

Now, both approaches to infer service choice under dynamic information conditions appear plausible, so it is worthwhile to use both of them and examine the differences. To distinguish the inferred choice under each approach, the choice variable Svc_{best} is re-expressed as $Svc_{best}[1]$ and $Svc_{best}[2]$ to represent the service choice under dynamic information conditions using the first and second approaches respectively.

Once the choice of service of a traveller for a particular day is inferred from the above rules, the value of the dependent variable Svc_{best} (in the case of no-information or static information conditions) and $Svc_{best}[1]$ and $Svc_{best}[2]$ (in the case of dynamic information) (either 0 or 1) can be easily assigned.

3.3.1.2 Waiting Time (T_w)

The previous section describes the first dependent variable that captures the one aspect of decision-making that pertains to the identification of the service to board. This section introduces a measure that is concerned with the second aspect: the determination of the time to arrive at the bus stop so that the identified service can be caught successfully. This measure, which is available directly from the experimental output, is the wait time at the bus stop, $T_w = t_s - t_b$,. Its magnitude can be considered a measure of the degree of success with which the participant is able to catch the service he intends to board. If the traveller is able to catch his intended service with a short wait, or in the ideal case, with no wait at all, he would be deemed successful in catching the service. Hence, the smaller T_w is, the better the outcome in relation to this aspect of decision-making is deemed to be. Conversely, a large value indicates a poor decision outcome because the traveller has missed the service he has intended to catch and a long waiting time ensues for the next departing service. If the quality of decisions improves over time, as intuitively assumed, one possible indication could be a decreasing trend in T_w as the traveller learns about the departure times of the service. Hence T_w appears a plausible measure to track changes in the *quality* of decisions.

Through this variable, one can directly investigate the effects of the different types of information. Suppose a certain type or format of information is particularly useful to the traveller in deciding when she should arrive at the bus stop to catch the intended service, compared to other types of information. The mean values of T_w under this scenario should be significantly smaller than those with other types of information.

It is expected that, on any hypothetical day, a proportion of participants would miss their targeted service, which may have arrived earlier than they expected. The resultant distribution of T_w values for each day could be one that has a concentration of cases at the two tails. The first tail is made up of cases with small values of T_w (from those who managed to time their arrivals at the bus stop well) and the opposite, of cases with large values of T_w (from those who just missed their services and had to incur waiting time for the next departing service). Although the mean of T_w is still a good measure of the participants' quality of decision-making at the aggregate level, it should be borne in mind that its distribution is likely to be non-normal and exhibits negative kurtosis. The non-normality and negative kurtosis can be expected to be more pronounced as the headway is extended; it is likely to be especially substantial in *Ops* conditions *H20-LOW* and *H20-HIGH*. Potential problems for analysis arising from non-normality are discussed in greater detail in the next chapter.

To conclude the current section, it would be interesting to examine if there are other useful measures that are also related to the quality of decision outcomes and can be potential candidates as well.

The astute reader may have noticed that another experimental measure, the daily *score*, may also be an indicator of decision quality. After all, the higher the *score* is for a particular day, the better the quality of the decision is deemed to be. However, it is not chosen for the following reason. The formulation of *score* is reproduced below.

$$Score = 100 - 3T_w - SDE - 4SDL - 9L \qquad (3\text{-}1)$$

If the traveller has chosen the best service for the day, he will incur the minimum number of penalty points through *SDE* only, ignoring the T_w term for the time being. An earlier service would most likely result in a much too early arrival, thus incurring a higher number of penalty points through *SDE*. A later service on the other hand will lead to a late arrival at work, thus incurring even more penalty points from *SDL* and *L* (but *SDE* = 0). Unambiguously, the terms *SDE*, *SDL* and *L*, are thus associated with the first aspect of decision making: the successful identification of the correct service to catch. The reader may recall that this aspect is already covered by the first dependent variable, Svc_{best} , described in the previous sub-section. The second aspect, to successively catch the targeted service, is captured by the second term, T_w, that is the second dependent variable described in the previous two paragraphs. Hence the addition of *score* as the third dependent variable is redundant. One possibility is to substitute the earlier two measures for *score*, but this may not be the best option because *score* is an aggregate measure such that its use will result in the loss of important information relating to the respective contributions of the two important aspects of decision-making.

Given that the last three terms of equation 3-1 capture the consequence of service selection fully, one considers if a measure of ($SDE + 4SDL + 9L$) can be used in the place of Svc_{best} instead. Recall the earlier assertion in Section 3.3.1.1 that the choice of service is a measure of intent, not of outcome. On this basis, it is argued that the suggested score measure is not a suitable substitute because it captures the outcome of choice but not the intent. To illustrate, consider a traveller who has chosen and boarded the best service and another who has made the same choice but failed to catch it. Both have the same intent (and hence the same Svc_{best} value), but have different values in the said measure due to different outcomes. Next, one compares the second traveller (who chose the best service but boarded a non-best service) against a third who unintentionally caught the best service after missing his intended service that was to depart earlier (i.e., chose a non-best service but boarded the best service). The score measure will suggest the third traveller has made a better decision in the choice of service than the second when it is the opposite case. It is therefore decided that the score measure (and its components) is best left to its original purpose of informing the experimental participant of his overall performance during the experiment.

Altogether, three possible dependent variables are discussed in Sections 3.3.1.1 and 3.3.1.2. If all three variables were to be used, instead of a single one, the chances of detecting differences in effects of various information conditions on learning could potentially increase if each of them measures a different aspect of the behavioural changes. However, because these variables are likely to be correlated with each other, there would certainly be a case to reduce the number to be used for a more parsimonious analysis. The utility of each of the variables, or combination of variables, in describing the effects of information is discussed in greater detail in the next chapter.

3.3.2 Measure of Information Effect

In the second family of hypotheses, the information effect is to be studied. The hypotheses predict that the acquisition of information increases with learning and such changes depend on the type and format of information provided. Although the amount of information acquired may not be captured or measured directly, a suitable proxy can be identified.

Recall from Chapter 1 that an "information effect" resulting from acquiring information alters a perceived value of an attribute to resemble more closely the information for that attribute (Chorus *et. al*., 2006). In this experiment, the attribute is clearly the departure time of the service, t_s, and the participant's perception of it is linked to his choice of arrival time at the bus stop, t_b. As argued in Chapter 2, the information margin serves as a proxy to this effect. Therefore, the measure of the information effect is simply the absolute difference between t_b and t_s^i, the estimated departure time from the travel information, which is termed:

$$T^i = \left| t_b - t \right|_s^i \tag{3-3}$$

The smaller the value of T^i, the more closely the altered perception of t_s is to the estimate t_s^i, and the larger the information effect is deemed to be.

The information effect is only applicable in scenarios that involve the provision of dynamic departure time estimates for individual services, i.e., *DYN-UNREL* and *DYN-REL*. In a situation identical to that described in Section 3.3.1.1 one needs to determine which of the ten t_s^i estimates the traveller take reference from when he chooses t_b. The approach to do so is then no different from that in that section: the use of the same rules under approach 2 to determine $Svc_{best}[2]$ that is unambiguously associated with t_s^i to be fed into equation 3-3. All the time variables, described in Section 3.1 and dependent variables, described in Sections 3.3 are listed in Table 3-6.

Table 3-6 Experiment Measures and Dependent Variables

Measure	Description	Data Source
$(t_b)_d$	Traveller arrival time at bus stop	Participant input
$(t_s^i)_d$	Estimate of service departure time at bus stop by information service	Pre-determined density distribution $f\left(t_s^i\right)$
$(t_s)_d$	Actual service departure time at bus stop	Pre-determined density distributions $f\left(t_s\right)$
$(T_v)_d$	Actual in-vehicle time	Pre-determined density distributions $f\left(T_v\right)$
$(t_l)_d$	Destination arrival time	$(t_l)_d = (t_s)_d + (T_v)_d$
$(SDE)_d$	Early schedule delay	$(SDE)_d = \max[0, PAT - (t_l)_d]$
$(SDL)_d$	Late schedule delay	$(SDL)_d = \max[0, (t_l)_d - PAT]$
L_d	Late arrival at destination	$L_d = \begin{cases} 1 & \text{if } (SDL)_d > 0 \\ 0 & \text{if } (SDL)_d = 0 \end{cases}$
Dependent Variables relating to Learning effect		
$(Svc_{best})_d$	Choice of Service (under no information and static information conditions)	$\begin{cases} Svc_{best} = 1 & \text{if best service is selected} \\ Svc_{best} = 0 & \text{otherwise} \end{cases}$
$(Svc_{best}[x])_d$	Choice of Service (under dynamic information conditions) under approach *x*, *x* = 1 or 2, as described in Section 3.3.1.1	$\begin{cases} Svc_{best}[x] = 1 & \text{if best service is selected} \\ Svc_{best}[x] = 0 & \text{otherwise} \end{cases}$
$(T_w)_d$	Actual waiting time	$(T_w)_d = (t_s)_d - (t_b)_d$
Dependent Variable relating to Information effect		
$(T^i)_d$	Deviation of traveller arrival time at bus stop from estimate of service departure time	$(T^i)_d = (t_b)_d - (t_s^i)_d$

Subscript *d* in all terms denotes day *d*

3.4 Experimental Groups and Participants

To obtain the participants' responses, with respect to the dependent variables described in Section 3.3, to various types of information under different operating circumstances, the participants are assigned treatment combinations of *Info* and *Ops* conditions. As described in Section 3.2.1, there were a total of 60 treatment combinations. If one experimental group were to be assigned to one combination, 60 such groups, each with *n* participants, would be required. To reduce the number of participants to be recruited, 4 treatment combinations were assigned to every experimental group, i.e., each participant would have to undergo 4 different treatment combinations or scenarios, instead of one. The number of experimental groups was thus reduced to 15. In each treatment combination, the assigned values of *PAT*, T_a and

T_e, as well as the simulated values presented for t_s, T_v, $t_s^{\,i}$, are identical across participants.

For every experimental group, no operating (*Ops*) and information (*Info*) condition in any one scenario was repeated in the other three. The assignment of treatment combinations to experimental groups that ensured this condition is shown in Table 3-7. Moreover, the work start time (*PAT*), scheduled in-vehicle and access times (T_v, T_a and T_e) were assigned different values across the *Ops* conditions as an additional prompt to the participant that the scenarios in all the session were not all the same, and that he should treat them as unrelated to each other.

Table 3-7: Assignment of 60 Treatment Combinations (Scenarios) to 15 Experimental Groups

	Operating condition (*Ops*)					
Information Condition (*Info*)	***H20-LOW***	***H20-HIGH***	***H10-LOW***	***H10-HIGH***	***H5-LOW***	***H5-HIGH***
NO-INFO	1	2	3	4	5	6
HDWAY	7	8	9	10	11	12
TTABLE	13	14	15	1	2	3
DYN-UNREL	4	5	6	7	8	9
DYN-REL	10	11	12	13	14	15
NO-INFO then *TTABLE*	14	15	1	2	3	4
TTABLE then *DYN-UNREL*	5	6	7	8	9	10
TTABLE then *DYN-REL*	11	12	13	14	15	1
DYN-UNREL then *DYN-REL*	2	3	4	5	6	7
DYN-REL then *DYN-UNREL*	8	9	10	11	12	13

Each cell represents a treatment combination and the number within it refers to the experimental group to which it is assigned.

If the sequence of presentation of treatment combinations in each group were to be the same for each participant in the group, incidental effects, such as fatigue or carryover effects, are likely to occur and threaten the validity of the experiments (Keppel and Wickens, 2004). To avoid such undesirable effects, an attempt at “counter-balancing” the sequence of presentation of treatment combinations was made, such that each treatment combination should appear as the first, second, third, and fourth sessions an equal number of times within the group. However, complete counter-balancing was not achieved, and this is discussed in Chapter 4.

At the end of each session, except the last, the experimental program would display messages to announce the completion of the session and ask the participant to rate predictability of the service departure times, in-vehicle times, the usefulness and/or the reliability of the simulated information. Before the next session, the participant was also requested to complete survey questions about their socio-demographic characteristics and travel experience. The deliberate introduction of such intervening tasks between sessions was to eliminate any lingering perceptions of association of experimental scenarios of successive sessions, thus minimising any possible carrying over of perceptions across sessions.

3.5 Conduct of Experiments

3.5.1 Procedure

The participants were sent the experiment program, which is contained in a Microsoft Excel® file, and their individual passwords to the program, by email. They were instructed to pre-allocate a time period specifically for it, and to complete the experiment in a single session. They were informed that the time spent in the experiment would be tracked, and if the time spent were to be out of norm, the results might be discarded. This was to emphasise to the participants the need to keep their focus during the experiment, thus minimising extraneous interference. Data were stored in worksheets, which were protected and hidden within the same file, as the experiment progressed. Once the experiment was completed, this file would be automatically password-protected, so that the participant would not be able to access any data in it. The participants were instructed to send this file to the researcher by email.

All correspondence with the participants, including those related to recruitment and instructions, was conducted through emails sent to their workplace email addresses, whose access was controlled. This arrangement minimised the possibility that persons other than the recruited participants undertake the experiment. Exceptions were made to a minority of participants who supplied alternative email addresses after the initial exchanges using the workplace email addresses.

It is acknowledged that the experiment could be conducted expeditiously via an Internet website, as has been commonly done in many studies involving computer-based experiments. This alternative was explored but not adopted because a large proportion of potential participants did not have access to the Internet at their work places at which they were contacted for recruitment. On the other hand, all of them had access to the Microsoft Excel® software at their offices.

3.5.2 Pilot Experiment

Following extensive in-house testing, a pilot experiment was conducted to test experimental procedures, instrument design, method, and recruitment and administrative processes to identify and rectify any shortcomings. A total of 23 participants were recruited over 3 waves from the same population of candidates from which the sample for the main experiment was drawn. A mix of opt-in (first two waves) and opt-out (third wave) recruitment methods were used. For the opt-in method used in the first two waves, in which the invited participant had to provide consent to participate, the response rates were unacceptably low at 7% and 17% (both out of 54 invitees respectively). In contrast, under the opt-out method, in which each invited candidate was assumed to consent to participate and sent the experiment program unless he or she opted out explicitly, a more encouraging response rate of 42% was attained (albeit from a smaller group of 24 invitees). It was therefore decided that the opt-out method be employed in the main experiment.

In addition to testing the experiment instruments, participants in the pilot experiment were asked to provide feedback on the length, presentation and ease of understanding of the experiment in a questionnaire. An overwhelming majority of the participants rated the instructions very easy or somewhat easy to understand (8 and 15 participants out of 24 respectively), and the presentation very or somewhat clear and appealing (10 and 11 respectively). However, the length of the experiment was a challenge to many of them. Although 13 rated it “acceptable”, 9 felt it was “a little too long” and 1 thought it was “much too long”. One possible reason for the feedback is that these participants may have felt the exercise to be a bit tedious because all the scenarios they faced involved only those that did not involve mid-session changes in the information condition. It was believed that participants in the actual experiments were less affected by the monotony because some of the scenarios they underwent contained changes in the information service. Nonetheless, it was decided that the numbers of sessions and trial-days would not be reduced. Other improvements to the program, such as the layout, were made based on the participants' feedback.

3.5.3 Recruitment of Participants

A recruitment target of 300 participants was set, such that each of the 15 experimental groups would have n = 20 members. Participants were recruited from the researcher's sponsoring organisation, the Land Transport Authority (LTA) of Singapore, whose employee population has a wide range of ages and education qualifications.

A total of 1,007 LTA staff members were invited to participate over 5 waves. Among them, 338 attempted the experiment and returned the data file, giving a response rate of about 33.6%, as shown in Table 3-7, and exceeding the target of 300. Random sampling was used to select the invitees from the population, the size of which was 3,713 when the sampling frame was drawn up. Only the opt-out method was used, and those who did not opt out explicitly were randomly assigned to their experimental groups. To cater to expected non-responses, a total of 24 invitees, instead of the targeted 20, were initially aimed for in every experimental group (360 in total) in the first wave, with progressive reductions in subsequent waves as the quota in each group was filled. Waves 3 to 5 achieved higher rates than Waves 1 and 2 because of greater persistence in following up with the invited participants who did not respond initially. Wave 4 had an exceptionally high rate because it included candidates from previous waves who had requested a deferment in participation to a later date.

Table 3-8: Response Rates over Recruitment Waves

		Wave 1	**Wave 2**	**Wave 3**	**Wave 4**	**Wave 5**	**Total**
Invited	(a)	360	269	189	115	74	1007
Responded	(b)	101	78	76	57	26	338
Response rate	(c) = (a) / (b)	28.1%	29.0%	40.2%	49.6%	35.1%	33.6%

3.5.4 Incentives for Participation

The experiment scenario of a home-based work trip has been designed to closely resemble what is expected from a typical participant's actual trip experience. The instructions to the participant to select the times to depart home such that the arrival time at the work location is as close to, but not later than, the start time, is aligned with the motivation of a traveller in a typical home-based work trip. The participants were further told to respond as if they were making the hypothetical trip themselves, and that the experimental data were important in informing future travel information development in their own transport network.

To further reinforce the nexus between the experimental and real life situations, subjects were given incentives that are linked to their performance in attaining the stipulated objectives. The performance for each hypothetical day was measured by a score as described in Section 3.1. The participant with the highest average daily score over all four completed sessions in his or her own experimental group would receive a higher quantum of reward ($S9.50) than the other group members ($S7.00). For expediency of administration, the incentives were made in movie gift vouchers redeemable at local cinemas.

It is acknowledged that linking the incentive with the highest average daily score over four sessions may somewhat conflict with how the participant may behave in real life, because it may influence him to be more risk-seeking than he would be naturally. Nonetheless, this consideration is balanced with the more pertinent need of the researcher to provide sufficient incentive for the participant to take each session seriously, given the length of the experiment.

3.6 Participant Characteristics

3.6.1 Sociodemographic Characteristics

A total of 338 participants completed the experiments, of whom a slight majority were male. The majority of the participants were between the ages of 31 and 60. All participants had at least a secondary school education and more than 85% had at least a diploma or a degree. Tables 3-9 to 3-11 compare these characteristics with those of the employee population of the LTA and of the national working population. It appears that the sample of participants is fairly representative of the population from which it is drawn, in terms of age and gender distributions. However, there are disproportionately more participants with a degree in the sample than in the population, perhaps reflecting the greater propensity and confidence of more educated employees in participating in computer-based experiments. Another explanation for the discrepancies is that newly acquired educational credentials declared by some participants in the questionnaire have not been updated on their employers' records. When compared with the national workforce, the sample is over-represented in those in the age group of 30 – 39 and in those with tertiary education (Diploma and Degree) which reflects the nature of the business of its employer. As such, one could raise likely concerns of non-representativeness with respect to the general commuting public. Nonetheless, as with many studies that engage students or staff of the research institutions, the key research objective of this study is to test for the presence of the hypothesised effects and inform future research, and is not to generalise the findings to the larger population, which requires representative sampling.

Table 3-9 Gender Distribution of Participants

Gender	Frequency	%	LTA (2010)	DoS [a] (2008)
Male	180	53.3%	58.3%	56.9%
Female	158	46.7%	41.7%	43.1%
Total	338	100.0%	100.0%	100.0%

a. Department of Statistics, Singapore

Table 3-10 Age Distribution of Participants

Age (years)	Frequency	%	LTA (2010)	MOM [b] (2008a)
15-24	4	1.2%	1.0%	9.4%
25-29	34	10.1%	8.1%	10.9%
30-39	133	39.3%	33.7%	26.3%
40-49	97	28.7%	29.9%	27.2%
50-59	64	18.9%	22.7%	19.5%
60 and over	6	1.8%	4.7%	6.8%
Total	338	100.0%	100.0%	100.0%

b. Ministry of Manpower, Singapore

Table 3-11 Educational Levels of Participants

Education	Frequency	%	LTA (2010)	MOM [b] (2008b)
Below Secondary	0	0.0%	2.1%	24.2%
Secondary	12	3.6%	17.6%	23.5%
Upper Secondary	49	14.5%	9.3%	14.2%
Diploma	86	25.4%	27.9%	12.3%
Degree	191	56.5%	43.0%	25.8%
Total	338	100.0%	100.0%	100.0%

b. Ministry of Manpower, Singapore

3.6.2 Travel Characteristics

An overwhelming majority of the participants reported travelling to work on 5 workdays of the most recent week in which they worked the full number of working days (Table 3-12). They also reported the number of days a particular transport mode or combination of modes was used in that week. Public transport (public bus and/or rail [MRT/LRT]) was used most, based on the number of days of use aggregated over the entire workweek and over all participants (Table 3-13). Slightly more than half of these had "some degree of flexibility" in the time to report for work, and almost all of the remaining participants reported "no flexibility" at all (Table 3-14). This means that the majority are given some allowance to be late at work.

Table 3-12 Distribution of Weekly Commute Days

Commute Days per Week	Frequency	%
1	3	0.9%
2	2	0.6%
3	12	3.6%
4	14	4.1%
5	299	88.5%
6	6	1.8%
7	2	0.6%
Total	338	100.0%

Table 3-13 Transport Modes for Commute Trips

Transport Mode	Cumulative Number of Days of Use	%
Private vehicle (driver)	511	21%
Private vehicle (passenger)	172	7%
MRT /LRT (rail)	789	33%
Public Bus	805	34%
Taxi	66	3%
Others	39	2%
Total	2382	100%

Table 3-14 Flexibility in Determining Arrival Time at Workplace

Statement	Frequency	%
"I have no flexibility in deciding when I report for work at my workplace."	140	41.4%
"I have some flexibility in deciding when I report for work at my workplace."	190	56.2%
"I am pretty much free to decide on when I report for work at my workplace."	8	2.4%
Total	338	100.0%

Participants were also asked to estimate the travel time of their own commute trips to work in the questionnaires in between the experimental sessions. Because the experiment scenarios involve public bus travel, travel times experienced by participants who used public bus services are examined specifically. Table 3-15 shows that these times are broadly aligned with those used in the experimental scenarios, which are 5 or 10 minutes for access and egress times, 5, 10 and 20 minutes for headways (associated with waiting times), and between 25 and 50 minutes for in-vehicle times. It is acknowledged that the simulated in-vehicle times are longer than those actually experienced by the participants (with the maximum simulated in-vehicle time close to about two standard deviations more than the mean in-vehicle time experienced). Nonetheless, the simulated times are still within the range of actual times experienced.

Table 3-15 Actual Travel Times Involving Travel on Public Bus by Participants

(*n* = 187)	Access Time (mins)	Waiting Time (mins)	In-Vehicle Time (mins)	Egress Time (mins)
Mean	5.6	8.7	21.1	5.5
Median	5.0	10.0	15.0	5.0
Standard Dev.	4.1	4.6	15.6	4.6
Minimum	0.5	0.5	3.0	0.5
Maximum	30.0	25.0	80.0	50.0[1]
Experiment	5 or 10	5 to 20 (mean)	25 to 50	5 or 10

[1] An egress time of 50 minutes appears excessively long and is reported by a single participant who may have misunderstood the question. There are also two others who provided out-of-norm values (40 and 45 minutes). Nonetheless, it is possible that they could be doing an exercise walk or running an errand after alighting the bus while on their way to work. The remaining 184 reported 15 minutes or less.

3.6.3 Awareness and Use of Travel Information

Responses were also sought from the participants on their awareness of the existence of public bus travel information services, and if so, whether they made use of these services. Participants who took public transport on at least three days of the week were classified as regular public transport users and they made up about 60% of the participants. Table 3-16 shows that only a minority of these 204 regular users accessed information services in the past month. In fact, apart from the highly visible dynamic waiting time information panels, most of them were unaware of the various types of information services available, let alone using them. This is a fairly surprising finding, because Chorus *et. al*. (2006) have reported that commuters are more likely to use travel information due to the nature of their trips, and judging from the participants' responses in Table 3-14, almost all the participants' commute trips are certainly arrival time sensitive in nature. One possible explanation is that these users were not insensitive to late arrivals at work, but could have settled on a travel routine that they believed to be optimal for their commute trips, after a long period of learning. Thus, they might not perceive any incentive to know more about alternatives from the travel information sources.

Table 3-16 Awareness and Use of Existing Bus Travel Information Among Regular Public Transport Users

(n = 204)	Not aware	Aware but did not use	Used		
			1 to 5 times	5 to 10 times	> 10 times
Published Information on Service Arrivals (Scheduled Headways)	105 (51%)	60 (29%)	12 (6%)	18 (9%)	9 (4%)
Waiting Time Information via SMS	144 (71%)	22 (11%)	6 (3%)	10 (5%)	22 (11%)
Dynamic Waiting Time Information from Internet	115 (56%)	32 (16%)	13 (6%)	6 (3%)	38 (19%)
Dynamic Waiting Time Information from Display Panels	27 (13%)	96 (47%)	31 (15%)	49 (24%)	1 (0%)
Interactive Bus Service Information from Internet	119 (58%)	35 (17%)	8 (4%)	3 (1%)	39 (19%)

It is intriguing to note that the other group of 133 participants who used public transport less frequently or not at all, were generally more aware of the information services available than their counterparts (Table 3-17). It could be reasoned that, given their lower level of familiarity with public transport compared to regular users, they have a higher propensity to seek out travel information actively when they make occasional trips on public transport, and thus are more aware of the sources of information available.

Table 3-17 Awareness and Use of Existing Bus Travel Information Among Occasional Public Transport Users

(*n* =133)	Not Aware	Aware
Published Information on Service Arrivals (Scheduled Headways)	23 (17%)	110 (83%)
Waiting Time Information via SMS	29 (22%)	104 (78%)
Dynamic Waiting Time Information from Internet	66 (50%)	67 (50%)
Dynamic Waiting Time Information from Display Panels	13 (10%)	120 (90%)
Interactive Bus Service Information from Internet	59 (44%)	74 (56%)

4 RESULTS AND HYPOTHESIS TESTING

Chapter 3 sets out the design and procedures of the experiment and identifies the dependent variables. This Chapter presents the results of these experiments and describes the outcomes of the tests conducted on the data in relation to the hypotheses set out in Chapter 2. An assessment of the validity of the data is first presented. This is followed by a description of the trends of the dependent variables under the various information and operating conditions, and a comparison of the observed trends against predictions. The outcomes of hypothesis testing are then described.

4.1 Data Screening

The original target of 300 participants would have yielded data from 1,200 sessions (300 × 4 sessions). The actual response from 338 participants provided a higher-than-targeted total of 1,352 sessions. However, upon inspection, it was found that 29 of the sessions contain inadmissible data (See Table 4-1). Two different programming errors, which unfortunately did not surface during testing or the pilot experiments, were the sources of some of the errors contained in these 29 sessions. The impact of the first was limited to a small and defined group of participants who were directed to repeat a previously attempted session, thus rendering data from the repeated session inadmissible. The second produced error messages in the scores, when an input of an extreme, out-of-range value was entered. The remaining three invalid sessions were not a result of programming errors; two of them were left unattempted by a participant who withdrew after completing only 2 out of 4 sessions. The last one contains very low or negative scores in each of the 20 trial-days, which appears to be due to a misinterpretation of the scoring system by the participant who persistently made choices that led to late arrivals. Nonetheless, even after accounting for 29 sessions with inadmissible data, the total number of valid sessions exceeds the target by about 10%. See Table 4-2.

Table 4-1: Sessions with Inadmissible Data

Type of error	Number	Sessions
Error from extreme input value	12	13
Repeat session	11	11
Both input & repeat session	1	2
Incomplete	1	2
Misinterpretation of scoring	1	1
	26	29

Table 4-2: Total, Valid and Invalid Returns

Target returns	(a)	300
Target number of sessions	(b) = (a) × 4*	1200
Total returns	(c)	338
Total sessions	(d) = (c) × 4*	1352
Returns with invalid sessions	(e)	26
Total invalid sessions	(f)	29
% error	(g) = (f) / (d)	2.1%
Total valid sessions	(h) = (d) – (e)	1323
Valid sessions as % of target	(i) = (h) / (b)	110.3%

* Each return has 4 sessions.

There are 60 treatment combinations/scenarios in the experiment design (6 *Ops* conditions for each of 10 *Info* conditions). A uniform distribution of participants across all these treatment combinations was however not achieved, as shown in Table 4-3, resulting in an unbalanced design. There are three reasons. First, because both the sampling of invitees and their assignment to experimental groups were random, and also because of the opt-out method of recruitment, the response rates across both the experimental groups and across waves varied. Attempts to adjust the number of invitees for each group in each wave according to responses from preceding waves could only reduce but not eliminate fully the differences in the number of successful returns. Second, as another consequence of the opt-out method, some participants from earlier waves who did not respond despite repeated prompting submitted their returns subsequently after a long lapse of time, after the target number of responses for their experimental groups was obtained. Lastly, the omission of invalid sessions resulted in fewer responses in certain experimental groups. Nonetheless, the minimum target of 20 responses per treatment combination was attained.

Table 4-3: Sample Sizes for Treatment Combinations

	Operating condition (*Ops*)					
Information Condition (*Info*)	***H20-LOW***	***H20-HIGH***	***H10-LOW***	***H10-HIGH***	***H5-LOW***	***H5-HIGH***
NO-INFO	21	21	22	23	21	26
HDWAY	20	22	23	23	23	21
TTABLE	21	21	24	22	21	22
DYN-UNREL	23	21	26	21	22	21
DYN-REL	22	23	23	22	21	24
NO-INFO then *TTABLE*	20	22	22	22	22	22
TTABLE then *DYN-UNREL*	21	25	21	22	23	22
TTABLE then *DYN-REL*	22	22	22	21	23	22
DYN-UNREL then *DYN-REL*	21	21	23	21	24	20
DYN-REL then *DYN-UNREL*	21	22	23	22	22	21

4.2 Face Validity

Before one commences analyses of the participants' behaviours under the various experimental scenarios, it would be prudent to establish face validity of the experiments, i.e., whether the experiments captured the participants' behaviour in a valid manner. Despite measures to enhance realism of the experimental scenarios and to provide performance-linked incentives, one still needs to be satisfied that the participants had given the experiments adequate attention throughout the entire session. If frivolous behaviour were to be widespread, the validity of the experimental findings would be threatened. The presence of such behaviour, due to such factors as fatigue and inattention, cannot be discounted because the median time taken to complete the four experimental sessions and the questionnaires in between is 33.6 minutes. Although it would not be possible to obtain direct evidence that the participants had attempted the sessions seriously, a reasonably strong case can be argued that they had indeed done so.

First, the experimental program required the participant to complete all four sessions and the questionnaires before the data file could be saved, and to make the additional effort to submit that file by email. Therefore, data would not be received from those who became disinterested and dropped out during the experiment. Thus, the procedures helped ensure that those who completed the experiments would have a reasonably high level of commitment and sift out those who did not. One concern is whether those who did not complete or attempt the experiment were drawn disproportionately from a particular sub-group of the population, thus resulting in a biased sample. In the context of the current work, representativeness of sampling is not a major concern because the primary objective is to test for the presence of hypothesised effects, and not to examine the behaviour of the general traveller population. Nevertheless, it would be beneficial to gauge the level of bias as a broad indicator of the effectiveness of the opt-out method in delivering a representative sample. Tables 3-10 to 3-12 of Chapter 3 have shown that in terms of gender and age, the sample represented the population (of LTA employees) reasonably well.

More quantitative evidence to establish the face validity can be found through the examination of indicators of the participants' attitudes towards the experiment. The time to complete a session and the number of changes in t_b could be taken as two indicators of the seriousness and commitment of participants towards the experiment. It is reasonable to assume that a bored or fatigued participant would spend a decreasing amount of time and effort to review and change his previous decisions for better outcomes, as the experiment progresses. In the later sessions, he would be likely to rush through the sessions, and make fewer changes to the arrival time at the bus stop (t_b). However, if he was still able to obtain around the same score, or even improved upon it, over successive sessions, this would suggest that he became more adept at the task, rather than losing interest.

The second and third columns of Table 4-4 show respectively that the median time to complete a session and the proportion of days with departure time that differed (t_h) from the preceding day decrease as the number of completed sessions increases. (The mean time is not used because of the distorting effects of a few excessively long sessions by a few participants who took long breaks against the instructions.) Although this outcome could indicate participants getting fatigued or disinterested and rushing to complete the later sessions, data from the fourth column do not corroborate this suggestion. This column shows the mean *score**, which is the mean deviation of the actual *score* from the best possible score for the day across sessions. The overall differences in *score**across the sessions are insignificant at the 5% level (F = 2.060, sig. = 0.103), but further analyses using reverse Helmert contrasts reveal that the mean *score** of session 4 is significantly lower from the first three combined (t = – 2.307, sig. = 0.021) at the 5% level. This shows that the scores of the last session are the best of all sessions. It is apparent that the participants were learning to take progressively shorter time to make decisions of similar, if not better, quality. This outcome cannot be achieved if insufficient attention was paid by them to the experiment.

Table 4-4 Indicators of Participants' Decision Making

Session Sequence Order	Median time to complete session (s)	Proportion of days in which departure times differed from previous day	Mean deviation of score from best possible for the day, *score**
1	395	0.72	-24.06
2	287	0.63	-24.09
3	243	0.58	-24.28
4	196	0.57	-23.30

4.2.1 Assessing using Perceptions of Scenario Attributes

An additional way to assess validity is to assess if the participants had committed sufficient attention to the experiment that they were able to distinguish between related scenarios consistently. At the end of each 20-trial (day) sessions, the participants were prompted to rate their perceptions of the predictability of the service departure times (t_s) on a scale of 1 to 7, with 1 indicating the lowest level of predictability, and 7 the highest From the four sessions each participant underwent, two contained scenarios whose simulated headways were the same, but had different t_s variability (as well as different *Info* conditions). For example, he or she could encounter *H20-LOW* together with *H20-HIGH* scenarios, or *H10-LOW* with *H10-HIGH*, or *H5-LOW* with *H5-HIGH*. The order of presentation of these scenarios was varied among participants.

It is argued that an attentive participant should be able to discern the differences in t_s variability within the allocated pair of scenarios and rate them accordingly. For example, he or she would score *H20-HIGH* lower than *H20-LOW* in terms of t_s predictability, or at worst, rate both equally. To see if this is indeed so, the difference in rating score between these pairs of scenarios was computed for each participant by deducting the rating score for the low variability (more predictable) scenario (*H20-LOW*, *H10-LOW* and *H5-LOW*) from that of the high variability (less predictable) counterpart paired with it (*H20-HIGH*, *H10-HIGH* and *H5-HIGH*). If the participants were generally attentive, one would expect the majority of the individual differences in rating score to be negative or zero. Indeed, Table 4-2 reveals that slightly more than three-quarters of all scenario pairings yield a negative or zero rating score difference. More than half (52%) of the participants faced with long headway scenario pairings (*H20-LOW* and *H20-HIGH*) gave the correct relative ratings, but the proportion decreases as the headway reduces (*H10-LOW* and *H10-HIGH*, then *H5-LOW* and *H5-HIGH*). On the other hand, the proportion of participants who rated their scenarios equally has an inverse relationship with the headway. This is not unexpected because it became increasingly difficult for participants to keep track of the departure time patterns of individual services as the headway shortens. As shown in Chapter 3, at short headways, the combined departure time distribution of several services arriving in close intervals is a fairly uniform one, and the result is that the services appeared to depart at random.

Participants who rated the scenarios with higher variability as more predictable made up about a quarter of the total, with the proportion relatively stable across the *Ops* conditions. Their perceptions of t_s variability may have been influenced by the information presented and as a result, produced the counter-intuitive rating scores. Overall, based on the results in Table 4-5, one can assess that the participants have been sufficiently attentive during the experiment that the differences in variability of t_s across scenarios were discerned.

Table 4-5 Distribution of Difference in Rating Score in Scenario Pairings

***Ops* Conditions**	**Number of Scenario Pairings**	**Rating Score Difference**		
		< 0	**0**	**> 0**
H20-LOW with *H20-HIGH*	104	52%	26%	22%
H10-LOW with *H10-HIGH*	111	41%	32%	27%
H5-LOW with *H5-HIGH*	113	35%	43%	22%
Total	328	42%	34%	24%

4.2.2 Checks for Frivolous Responses

Even after arguing that the participants had attempted the experiments with sufficient seriousness, it is still necessary to scrutinise the data for individual instances of invalid responses, which need to be omitted. Although the previous section has indicated that fatigue and inattention may not constitute a serious overall concern, one cannot preclude the possibility that some individual participants may be adversely affected by them. The challenge is therefore to identify frivolous behavioural responses that are consequences of these factors.

Two possible characteristics are suggested for these so-called "problematic" responses. First, a participant who had not made a single change in the arrival time at the bus stop (t_b) for all the 20 days in a session is deemed to have exhibited 'problematic" behaviour. Second, participants who had not changed t_b after 2 consecutive late arrivals at the work place are also considered to be showing inattention or disinterest in trying their best. Out of the 1,323 valid sessions described in Section 4.1, 35 sessions are found to contain the first type of behaviour and 111, the second. These sessions are potential candidates for omission from the dataset. Table 4-6 shows their distributions by the order in which they were presented in the experiment.

Table 4-6 Sessions with "Problematic" Responses by Session Sequence

Session Sequence Order	Number of Sessions	Sessions with no change in t_b over 20 days	Sessions with no change in t_b after 2 consecutive late arrivals
1	335	0 (0.0%)	16 (4.8%)
2	335	5 (1.5%)	29 (8.7%)
3	331	12 (3.6%)	33 (10.0%)
4	322	18 (5.6%)	33 (10.2%)
Total	1323	35 (2.6%)	111 (8.4%)

The proportion of problematic sessions increases with the order of presentation, raising concern that fatigue and inattention are indeed at play. One would be tempted to omit these out-of-norm sessions to protect the validity of the dataset. However, further examination is warranted before one decides to discard them. If these problematic sessions are indeed due to frivolous and inattentive behaviour, some of their attributes can be expected to be out of the norm. To check if this is so, each of these sessions are ranked against other sessions sharing the same *Info-Ops* treatment combination and session sequence order, by attributes of median decision time, mean session score, number of late arrivals and mean wait time.

Table 4-7 shows the distribution of the problematic sessions across four quartiles for each of the attributes. In terms of *median decision time* (second column), it is no surprise here that the majority of these sessions are in the lowest two quartiles (86% for sessions with no change in t_b over 20 days, and 67% for those with no change in t_b after two consecutive late arrivals). This means that most participants in these sessions take much less time in making their decisions than their counterparts. This may imply that these participants could have attempted to complete the sessions as quickly as possible, at the attendant risk of paying insufficient attention. If this is indeed so, it should follow that they performed poorer in term of decision outcomes. However, half of these problematic sessions having *mean scores* (third column) that are in the top two quartiles (63% and 51% of sessions for those with no change in t_b over 20 days, and with no change in t_b after two consecutive late arrivals respectively). This indicates that the participants in these sessions do not appear to under-perform in their decision outcomes compared to the rest..

Table 4-7 Distribution of Problematic Sessions by Attributes

(A) Sessions with no change in t_b over 20 days (n = 35)

Quartile Group	**Median Decision Time**	**Mean Session Score**	**Mean Wait Time**	**Number of Late Arrivals**
1	66%	20%	20%	57%
2	20%	17%	20%	14%
3	11%	43%	29%	17%
4	3%	20%	31%	11%

(B) Sessions with no change in t_b after 2 consecutive late arrivals (n = 111)

Quartile Group	**Median Decision Time**	**Mean Session Score**	**Mean Wait Time**	**Number of Late Arrivals**
1	47%	27%	25%	2%
2	20%	23%	25%	8%
3	18%	28%	30%	32%
4	15%	23%	20%	59%

Examining the decision outcomes further, it can be observed that, in terms of *mean wait time* (T_w), the problematic sessions do not appear out of the norm (fourth column). The two groups of problematic sessions differ in their distributions in the *number of late arrivals* (last column). For the sessions with no change in t_b over 20 days, 57% of them are ranked among the group with the least late arrivals. On the other hand, sessions with no change in t_b after two consecutive late arrivals are over-represented among sessions with a high number of late arrivals. Regardless, both groups have mean scores comparable to those not considered to be problematic.

Table 4-7 shows that apparent frivolous behaviour may not be so on closer examination. The data do not offer compelling evidence that participants in these problematic sessions have made decisions in a frivolous or inattentive state of mind. The increase in the number of such sessions as the experiment progresses could be a manifestation of the participants' learning. This learning has resulted in the quality of decisions being maintained or even improved even as the participants took progressively shorter time to make each decision and made fewer changes to their decisions. Therefore, it was decided that data from these "problematic" sessions should be retained in the dataset.

4.2.3 Counter-Balancing of Session Sequence

In the above process of satisfying oneself with the face validity of the dataset, it is shown clearly that the order in which the scenarios were presented has a large and significant effect on the participants' responses, particularly in the response time and number of decision changes. To address such an incidental effect, one could capture it in the analysis explicitly. Alternatively, as is described in Chapter 3, one could vary the sequence of presentation of the four treatment combinations to the participants in each group such that each treatment combination appears as the first, second, third, and last sessions an equal number of times within the group. The latter approach of counter-balancing of session order was adopted.

Only partial counter-balancing was achieved. This was because the pre-requisite of having the number of participants within each group as a multiple of the number of sessions (four) was not achieved in most groups, as clearly shown in Table 4-3, because of the opt-out recruitment method described earlier. Nonetheless, in this partially counter-balanced design, the distributions of each of the *Ops* and *Info* conditions across the order of presentation were reasonably uniform, as shown in Table 4-8. There was no exceptionally skewed distribution across four sessions because every treatment combination was still presented roughly (although not strictly) an equal number of times in each order of presentation (except for a few ideal cases). The coefficients of variation (c_v) of the group size are small at 0.052 (with mean of 33.1 and standard deviation of 1.7) and 0.065 (mean 55.1 and standard deviation 3.6) for *Info* and *Ops* conditions respectively, indicating little variability in group size across experimental conditions. Hence, notwithstanding the failure to attain complete counter-balancing, one could treat the resultant design as having randomised the incidental factors present sufficiently, such that these factors no longer have any significant systematic effects on the treatment conditions.

Table 4-8 Distribution of *Info* and *Ops* Conditions by Sequence Order of Presentation

	Order of Presentation				Total
	1	**2**	**3**	**4**	
Info Condition					
NO-INFO	35	34	34	31	134
HDWAY	33	34	31	34	132
TTABLE	32	36	32	31	131
DYN-UNREL	34	33	31	36	134
DYN-REL	34	31	37	33	135
NO-INFO then *TTABLE*	31	33	33	33	130
TTABLE then *DYN-UNREL*	35	33	33	33	134
TTABLE then *DYN-REL*	35	33	33	31	132
DYN-UNREL then *DYN-REL*	34	35	33	28	130
DYN-REL then *DYN-UNREL*	32	33	34	32	131
Total	335	335	331	322	1323
				Mean	33.1
				s.d.	1.7
				c_v	0.052
Ops Condition					
H20-LOW	53	58	54	47	212
H20-HIGH	60	54	58	48	220
H10-LOW	53	62	55	59	229
H10-HIGH	58	51	57	53	219
H5-LOW	54	55	53	60	222
H5-HIGH	57	55	54	55	221
Total	335	335	331	322	1323
				Mean	55.1
				s.d.	3.6
				c_v	0.065

4.3 Predictions of Outcomes

Once satisfied with the validity of the dataset, the data are then prepared and analysed. Before the results are presented, it is useful to set out what one can expect to observe if the hypotheses are true. Such predictions serve as a benchmark against which the actual results can be compared in order to assess the extent to which the hypotheses can be supported.

In Chapter 3, three dependent variables are identified to describe a participant's (traveller's) responses under the various *Info* and *Ops* conditions. They are: the choice of service, Svc_{best}, the wait time, T_w, and the absolute deviation of passenger arrival time from the estimated service departure time, T^i. If the hypotheses were to be supported, these variables should exhibit certain differences in value and trend across *Info* conditions within a particular *Ops* condition, and also across all *Ops* conditions. The following sections draw on the predictive scheme of Chapter 3 to describe the predicted outcomes for each of the dependent variables.

The hypotheses as set out in Chapter 2 posit the outcomes of an individual traveller's decision-making over time when given different types of information. In real-life, travel information, including the bus service departure time information simulated in the current experimental scenario, is typically targeted at the general commuting public. . It is therefore necessary to examine the effect of information on decision-making of a group of travellers.

To observe the behaviour of a group of travellers that is supplied the travel information, their behaviour can be similarly tracked using the dependent variables identified earlier, i.e., Svc_{best}, T_w, and T^i. Note that the dependent variables identified earlier, Svc_{best}, T_w, and T^i are constructed at the individual level. At the aggregate level, one can use the common measures of centrality (e.g., mean, median and mode) and dispersion (e.g., standard deviation) to describe the behaviour of the group. In this case, the mean is the primary measure used. The mean values of Svc_{best}, T_w, and T^i over a day (daily mean) and over 20 trial-days (overall scenario mean) can be computed easily. Now, one can interpret the mean values of T_w, and T^i easily, but one wonders what to make of the mean of Svc_{best} that is a binary variable. At the individual level, Svc_{best} indicates whether the traveller is successful in selecting the best service (1) or not (0) in a particular trip. The mean value of this variable (between 0 and 1) of a group of travellers is simply the proportion of the travellers that chose the best service of the day. For ease of subsequent discussion, this proportion is labelled P_{best}.

Obviously, one cannot expect all travellers to be homogeneous behaviourally and respond identically when facing the same scenario and given the same information. However, if the hypotheses were to be true, one should expect the mean Svc_{best}, T_w, and T^i to vary in certain ways across the days and across *Info* conditions. The following paragraphs set out the predictions on these mean values across the different *Info* conditions using the descriptive scheme of Chapter 2.

The predicted observation of P_{best} is described first as follows. In the case in which no information (*NO-INFO* and *HDWAY*) is provided, the choice of service among a group of travellers over the entire period of interest is expected to be distributed among a number of services. It is highly unlikely that only one service is chosen by all the travellers because they have different perceptions of which service is most likely to be the best. It is assumed that individual travellers do not change their choice of service frequently in an absence of information, and so the distribution of travellers among these services should remain relatively stable. Hence, P_{best}, in the face of infrequent service changes by the travellers, is likely to fluctuate. To illustrate why this is so, suppose three services are chosen daily after the initial period in the relatively stable ratio of $a : b : c$ where $a < b < c$. Because the best service is likely to switch among one of the three, the values of P_{best}, are likely to vary among the values of a, b and c without a clear trend (i.e., flat trend). There may however be a slightly observable increase in P_{best} in the very first few days when travellers abandon services that are chosen during the first search but are found not to be obvious candidates to be the best (departing too early or too late) and select those that are likely to be. The predicted trend in P_{best} is shown by the blue line in the graph of Figure 4-1.

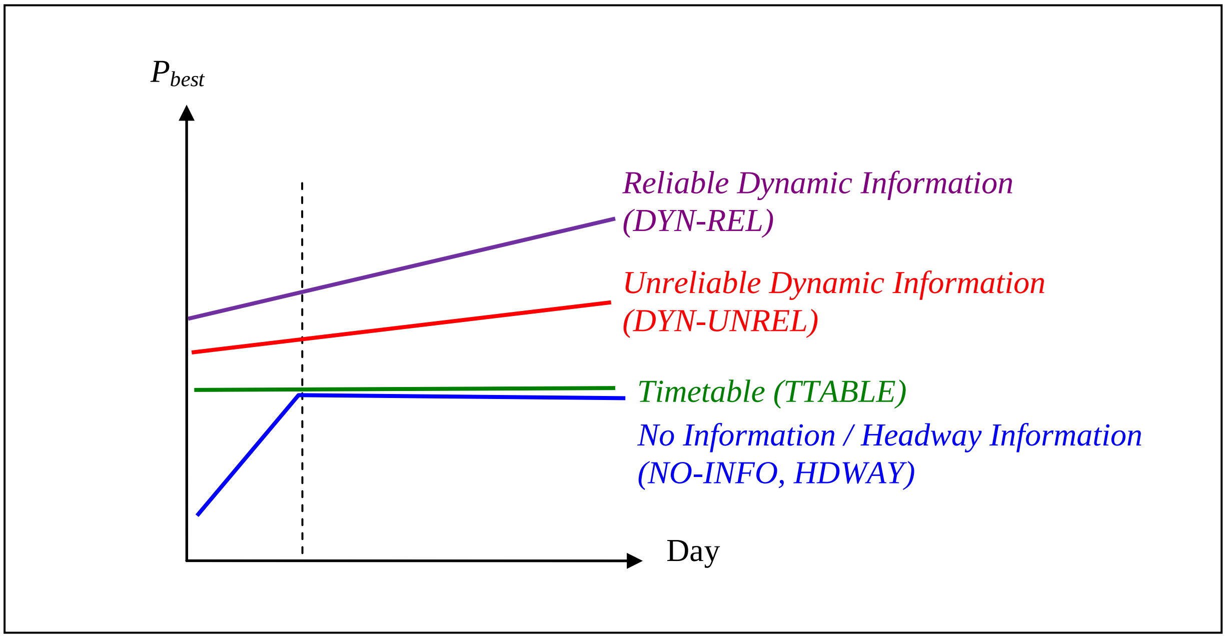


Figure 4-1 Predicted Trends of Proportion of Travellers Choosing Best Service of Day (P_{best}) based on Descriptive Scheme on Decision-Making over Time

When a timetable (*TTABLE*) is provided, the travellers omit the service search process. As a result, they can narrow down the potential candidates for the best service from the first day and can thus avoid exploring uncompetitive choices unnecessarily. In the longer term, they are not better informed on which is the best service of the day, so the trend of the variable mirrors mostly that of the no-information case. See the green line in the graph of Figure 4-1. Moving on to dynamic information, the purple and red lines in the same Figure show respectively the predicted trends of P_{best} if the dynamic information is reliable (*DYN-REL*), and if it is less so (*DYN-UNREL*). P_{best} is predicted to trend upwards also, because it has been posited in the descriptive scheme in Chapter 2 that individual travellers increase their likelihood of choosing the best service over time if the level of reliability is acceptably high. When the level of reliability is lower, it is also assumed that it is still within an acceptable range such that the trend is still upwards, but at a slower rate. The difference in *level* between these lines and those for no and timetable information reflects the postulated advantages of dynamic information over the latter *Info* conditions in that the responsive and predictive nature of the estimates of departure time t_s^i increases the overall chances of choosing the best service (and hence increases P_{best} in aggregate), especially in exceptional early or late service departures. Intuitively, an information source that is reliable has a greater beneficial effect than one that is less so.

Next, one looks at how the means T_w are predicted to vary. In the case of *NO-INFO/HDWAY*, the travellers are likely to select t_h that are widely dispersed on the first day, before narrowing them to a smaller range by the end of the service search process. During this initial period, a significant proportion of them are likely to incur long wait times (T_w) on certain days at the individual level. At the aggregate level, the mean T_w of the day will therefore be high initially but reducing quickly as the travellers locate the ranges of t_s of the services they explore. As the travellers adjust their safety margin incrementally after the initial period to reduce their individual wait times and the probability of missing their desired services, the aggregate mean T_w will then trend downwards but at a much lower rate, as shown by the blue line in Figure 4-2.

Under *TTABLE*, the travellers can identify the t_s of each service right from the first day and time their t_h to the t_s of their targeted services. As a result, the initial values of the mean T_w are expected to be lower than the corresponding ones in the no-information case. After the initial period, its downward trend should be similar to that in the latter case because in both cases, the process of adjusting the safety margin is the same. (See the green line in Figure 4-2). However, the overall mean (level) is predicted to be marginally lower in the case of timetable information (as shown by the green line being lower than the blue). This is because the timetable should enable the travellers to have a lower risk of missing a newly targeted service during (very occasional) switches between services.

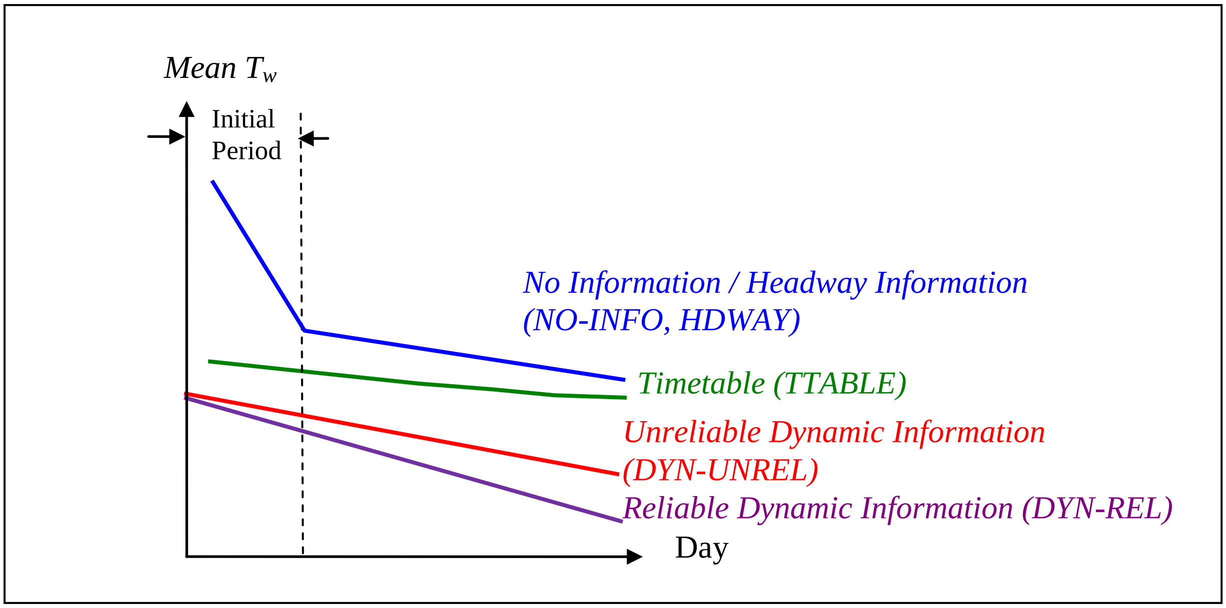


Figure 4-2 Predicted Trends of Wait Time (T_w) based on Descriptive Scheme on Decision-Making over Time

Moving on to dynamic information, the purple and red lines in Figure 4-2 show the likely trends of T_w under *DYN-REL* and *DYN-UNREL* respectively. In the descriptive scheme, T_w of an individual traveller receiving dynamic information is reduced through the narrowing of the information margin T^i. Although this behaviour appears intuitive, there is no compelling reason why this must definitely be so. After all, the terms "reliable" and "unreliable" are just descriptive labels, and the travellers' actual responses depend on the actual level of information reliability encountered by the travellers and how it is perceived, and these differ from context to context. In fact, there is an even weaker case for depicting a decreasing mean T_w (and also an increasing P_{best}) under unreliable information because the information could be so unreliable that it induces more errors in decision-making. Nonetheless, to facilitate discussion and subsequent analysis, it is assumed the travellers behave to the predictions in Figure 4-2 that the mean T_w under dynamic information are reduced at rates faster than when no or timetable information is given. As with P_{best}, the difference in *level* between all the lines represents the postulated superiority of increasing sophistication of information types. For example, dynamic information is expected to reduce the risk of missing the intended services and thus results in a lower overall T_w than other information types that are not responsive to the actual t_s.

The discussion now proceeds to the likely evolution of the information effect at the aggregate level. For the individual traveller, this effect strengthens over time when the information is reliable, and this is manifested in the decrease in the information margin, $T^i = |t_b - t_s^i|$. The measure of this effect among the group of travellers, the mean T^i , should see a similar trend to that shown in Figure 4-3. If this information is less reliable, the mean T^i may be reduced at a lower rate, not changed or even increased. However, to be consistent with the assumption used in the earlier predictions of the trends of T_w under dynamic information of different levels of reliability, the mean T^i in this case also follows a downward trend, but with a flatter slope. These predictions are consistent with those on T_w that are described in the last paragraph and are recognised to be rather questionable.

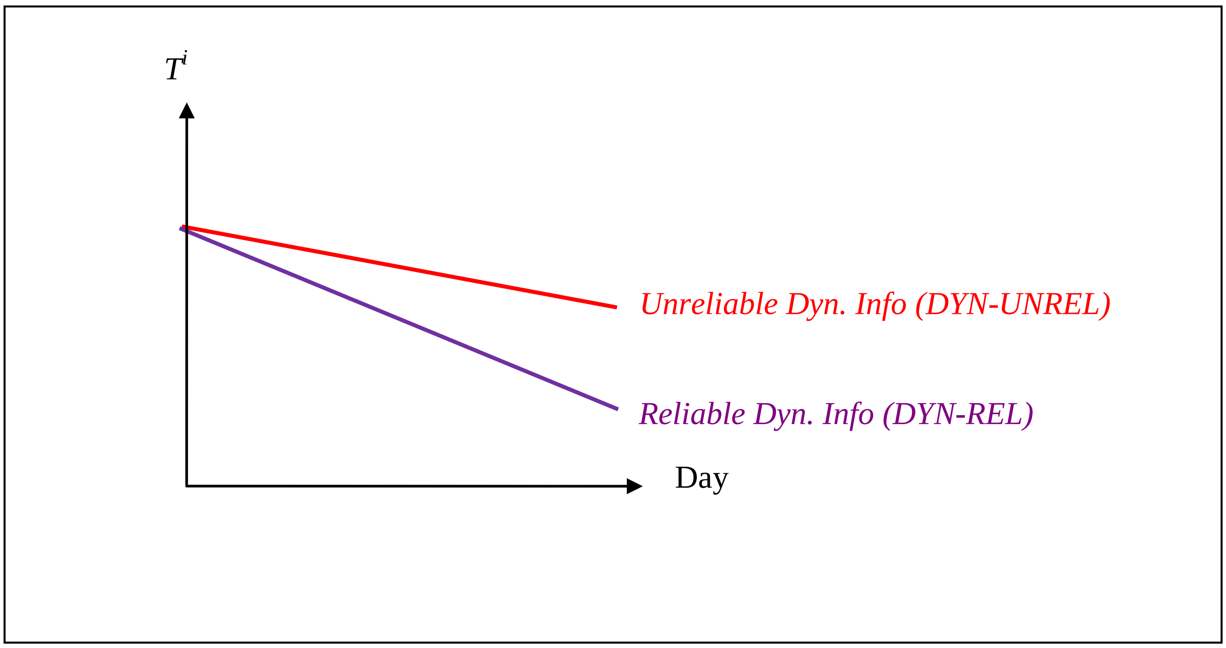


Figure 4-3 Predicted Trends of Information Margin (T^i) based on Descriptive Scheme on Decision-Making over Time

The present section describes the predicted outcomes for the three dependent variables and how they relate to the six hypotheses. They serve as a useful baseline against which the actual results can be presented and analysed. Obviously, they assume the presence of learning and information effects as set out in the hypotheses. If the learning effect is absent, the participants' perception of t_s and t_s^i will not change over time, and consequently, the postulated trends in the dependent variables will not be observed. If information does not have any effect on the participants' choice, there will be no significant difference in the mean values of the dependent variables across *Info* conditions. The next section presents the findings of the experiments and reveals if the predicted outcomes have been observed.

4.4 Hypothesis Testing

Having set out how the experimental data would be expected to present themselves through the dependent variables if the hypotheses were to be supported in Section 4.3, one can now proceed with the testing of these hypotheses. The predictions in that section are re-grouped by hypothesis. Under each hypothesis, one can draw easily from Figures 4-1 to 4-3 to set out the predicted trends for each hypothesis. The predicted observations under the various hypotheses, and the *Info* conditions to be compared and contrasted are listed in Table 4-9.

Table 4-9 Hypotheses and Predicted Observations

	Hypothesis	*Info* conditions examined		Dependent Variables	Predicted Observations	Referred Figure
		Group A	*Group B*			
1	In the absence of information, the traveller improves the outcomes of decision-making through learning and experience.	*NO INFO*	*HDWAY*	P_{best}	Initial period • Mean in *A* & *B* to trend upwards • No difference in trends between *A* & *B*. • No difference in means in *A* & *B*. Later period • No (flat) trend in mean in *A* & *B*. • No difference in trends between *A* & *B*. • No difference in means in *A* & *B*.	Figure 4-1
				T_w	Initial period • Mean in *A* & *B* to trend downwards • No difference in trends between *A* & *B*. • No difference in means in *A* & *B* Later period • Mean in *A* & *B* to trend downwards. • No difference in trends between *A* & *B*. • No difference in means in *A* & *B*.	Figure 4-2

<table>
<tr><th></th><th>Hypothesis</th><th colspan="2">Info conditions examined</th><th>Dependent Variables</th><th>Predicted Observations</th><th>Referred Figure</th></tr>
<tr><td rowspan="2">2</td><td rowspan="2">The traveller attains better outcomes of decision-making when provided with <u>static</u> information than when provided with <u>no</u> information.</td><td rowspan="2">NO INFO, HDWAY</td><td rowspan="2">TTABLE</td><td>P_{best}</td><td><u>Initial period</u>
• No (flat) trend in mean in B.
• Mean in B to be larger than in A.
<u>Later period</u>
• No difference in trends between A & B.
• No difference in means in A & B.</td><td>Figure 4-1</td></tr>
<tr><td>T_w</td><td><u>Initial period</u>
• Mean in B to trend downwards at lower rate than in A.
• Mean in B to be smaller than A.
<u>Later period</u>
• No difference in trends between A & B.
• No difference in means in A & B.</td><td>Figure 4-2</td></tr>
<tr><td rowspan="2">3</td><td rowspan="2">The traveller attains better outcomes of decision-making when provided with <u>dynamic</u> information than when provided with <u>static</u> information.</td><td rowspan="2">TTABLE</td><td rowspan="2">DYN-UNREL, DYN-REL</td><td>P_{best}</td><td><u>Both initial and later periods</u>
• Mean in B to be larger than in A.
• Mean in B to trend upwards at faster rate than in A.</td><td>Figure 4-1</td></tr>
<tr><td>T_w</td><td><u>Both initial and later periods</u>
• Mean in B to be smaller than in A.
• Mean in B to trend downwards at faster rate than in A.</td><td>Figure 4-2</td></tr>
</table>

	Hypothesis	*Info* conditions examined		Dependent Variables	Predicted Observations	Referred Figure
4	The traveller attains better outcomes of decision-making when provided with <u>reliable</u> dynamic information than when provided with <u>less reliable</u> dynamic information.	*DYN-UNREL*	*DYN-REL*	P_{best}	<u>Both initial and later periods</u> • Mean in *B* to be larger than in *A* • Mean in *B* to trend upwards at faster rate than in *A*.	Figure 4-1
				T_w	<u>Both initial and later periods</u> • Mean in *B* to be smaller than in *A* • Mean in *B* to trend downwards at faster rate than in *A*.	Figure 4-2
5	The traveller experiences a stronger information effect and this effect strengthens at a faster rate when provided with reliable dynamic information than when provided with less reliable information.	*DYN-UNREL*	*DYN-REL*	T^i	<u>Both initial and later periods</u> • Mean in *A* & *B* to trend downwards • Mean in *B* to be smaller than in *A* • Mean in *B* to trend downwards at faster rate than in *A*.	Figure 4-3

4.4.1 Possible Analysis Strategies

As explained in Chapter 3, the experiments involved three dependent variables measured repeatedly over 20 instances (days) across groups of participants assigned to various treatment combinations. For each *Ops* condition, the *Info* conditions made up the levels of the between-subjects factor, and *Day* the within-subject factor. A number of strategies could be used to analyse the data and test the hypotheses, and these are discussed in turn.

4.4.1.1 Univariate Repeated Measures ANOVA

A commonly used approach to data from mixed experimental designs such as this is to conduct a univariate repeated measures analysis of variance (ANOVA). However, the sphericity assumption is, more often than not, violated when time is the within-subjects factor and multiple readings of the same dependent variables are to be taken consecutively over time (Keppel and Wickens, 2004, Tabachnick and Fidell, 2001). To account for such a violation, one could adopt a more conservative statistical criterion through the use of such adjustments as Greenhouse-Geisser or Huynh-Feldt adjustments, but this additional stringency is brought about at the expense of lower power.

Note also that the univariate approach accommodates only a single dependent variable at any one time. Although, the use of several dependent variables in this experiment to measure the learning effect offers the advantage of a higher likelihood of discovering effects of *Info* conditions, compared to a single dependent variable, this approach necessitates a series of ANOVA tests, one for each dependent variable. If these dependent variables are correlated, there would be an inflation of Type I error, although there are approaches to address this. Also, because this approach takes no account of the relationships between dependent variables, one may not be able to detect significant differences between *Info* conditions that would only be detected when the dependent variables are tested in combination, although such situations are considered uncommon (Tabachnick and Fidell, 2001). One may turn to an alternative multivariate approach that addresses these deficiencies, the profile analysis, a short discussion of which follows.

4.4.1.2 Profile Analyses: Multivariate Approach to Repeated Measures

Singly multivariate or doubly-multivariate analyses may be used in investigating the effects of *Info* conditions on individual dependent variables (Tabachnick and Fidell, 2001), as in the univariate ANOVA approach. The singly multivariate analysis examines one dependent variable, e.g, T_w alone, but treats each observation as one dependent variable. A doubly-multivariate design examines concurrently two or more dependent variables, each of which is measured repeatedly over time. Both types of analyses are more flexible and forgiving in their assumption requirements. The doubly-multivariate design can also account for the relationships between dependent variables by analysing the combinations of dependent variables over time. For example, one can analyse the combinations of T_w and T^i on the reasoning that there may be a certain degree of correlation between them.

However, either of the singly or doubly-multivariate design requires a minimum number of participants in each experimental group that equals the number of dependent variables to be analysed (Tabachnick and Fidell, 2001). In the case of the singly multivariate design, the minimum sample size is 20, which is the number of daily observations of the experimental dependent variable in a session, and a doubly multivariate one with k dependent variables, at least $20k$. However, the largest experimental group had only 26 participants, far fewer than the minimum 40 needed to analyse just two dependent variables concurrently. Even the singly multivariate approach may not be viable because the sample sizes (20 to 26) were not substantially larger than the minimum required, and the power that could be attained might be low.

There is another strategy that would be suitable for the context of this experiment and is recommended by many such as Tabachnick and Fidell (2001) and Keppel and Wickens (2004). It is the use of trend analyses, which is discussed in the next section.

4.4.1.3 Trend Analyses and Contrasts

The third alternative strategy is the application of trend analyses and associated single degree of freedom (d.f.) comparisons (or contrasts). Recall in Section 4.4, and also from Table 4-9, that the hypotheses are expressed primarily in terms of trends of dependent variables over time, and thus lend themselves quite appropriately to the application of such a strategy. Because tests of trends and contrasts use only a single degree of freedom (d.f.), violations of the sphericity assumption, which is a key concern in the univariate approach, and of other assumptions in the multivariate approach, can be safely and elegantly sidestepped. As with its preceding counterparts, unequal sample sizes and heterogeneity of variances across groups and along the temporal dimension can be easily accommodated.

An observant reader may note that this approach also analyses only a single dependent variable, and thus offers no advantage over the two preceding candidate strategies in the ability to analyse multiple dependent variables concurrently. Perhaps, because of the design of the experiments and the number of participants recruited, the opportunity to capture the effects on combinations of dependent variables is lost. However, it is counter-argued that, as long as each of the hypotheses can be unambiguously expressed in terms of predicted trends of the key dependent variables, and these variables are well defined and specified, as has been done in Table 4-9, the analysis results should be able to describe the effects of the *Info* conditions adequately.

By expressing the hypotheses precisely and specifically in terms of how the dependent variables would behave and compare under the planned comparisons (contrasts) of trends, various treatment conditions, one can also omit the need for omnibus tests. These tests are routinely carried out in the univariate ANOVA and multivariate approaches to indicate the presence or absence of differences in effects of the treatment conditions, but they are deemed inefficient for the study of specific effects because they do not pinpoint the sources of such effects (Keppel and Wickens, 2004).

4.4.2 Analysis Plan

Thus it is decided that trend analyses and contrasts be used. To apply them, it is necessary to translate the predictions of Table 4-9 into effects to be tested. These predictions for each of the hypotheses are reproduced in the second column of Table 4-10 in which *A* and *B* represent a pair of individual or groups of *Info* conditions to be compared and are previously set out in the third and fourth columns of Table 4-9. Statistical tests are used to test for the presence of significant differences between the means or trends of these pairs of conditions or groups of conditions. In the parlance of profile analysis, one is concerned with tests of parallelism, flatness, and levels; in the jargon of repeated measures ANOVA, one is concerned with tests of trends, interactions, and between-subjects main effects (Tabachnick and Fidell, 2001). These tests are applied on single degree of freedom (d.f.) contrasts constructed to compare either a pair of trends or a pair of means. The third column of Table 4-10 lists these tests to be used on each prediction. There are three types of tests of effects, namely:

(a) Main effect of *Day* – to test the presence of a trend;
(b) Interaction of linear trends of *A* & *B* - to test the difference in trends; and
(c) Between-subjects main effect – to test the difference in levels

Table 4-10 Expected Outcomes of Tests of Hypotheses if Hypotheses are True

Hypothesis	Dependent Variables	Predicted Observations	Statistical Tests[1]	Expected Outcome
1	P_{best}	<u>Initial period</u>		
		• Mean in *A* & *B* to trend upwards	(a)	Sig.at $\alpha = 0.05$
		• No difference in trends between *A* & *B*.	(b)	Not sig. at $\alpha = 0.05$
		• No difference in means in *A* & *B*.	(c)	Not sig. at $\alpha = 0.05$
		<u>Later period</u>		
		• No (flat) trend in mean in *A* & *B*.	(a)	Not sig. at $\alpha = 0.05$
		• No difference in trends between *A* & *B*.	(b)	Not sig. at $\alpha = 0.05$
		• No difference in means in *A* & *B*.	(c)	Not sig. at $\alpha = 0.05$
	T_w	<u>Initial period</u>		
		• Mean in *A* & *B* to trend downwards	(a)	Sig. at $\alpha = 0.025$
		• No difference in trends between *A* & *B*.	(b)	Not sig. at $\alpha = 0.05$
		• No difference in means in *A* & *B*	(c)	Not sig. at $\alpha = 0.05$
		<u>Later period</u>		
		• Mean in *A* & *B* to trend downwards.	(a)	Sig. at $\alpha = 0.025$
		• No difference in trends between *A* & *B*.	(b)	Not sig. at $\alpha = 0.05$
		• No difference in means in *A* & *B*.	(c)	Not sig. at $\alpha = 0.05$

Hypothesis	Dependent Variables	Predicted Observations	Statistical Tests[1]	Expected Outcome
2	P_{best}	Initial period		
		• No (flat) trend in mean in *B*.	(a)	Not sig. at $\alpha = 0.05$
		• Mean in *B* to be larger than in *A*.	(c)	Sig. at $\alpha = 0.05$
		Later period		
		• No difference in trends between *A* & *B*.	(b)	Not sig. at $\alpha = 0.05$
		• No difference in means in *A* & *B*.	(c)	Not sig. at $\alpha = 0.05$
	T_w	Initial period		
		• Mean in *B* to trend downwards at lower rate than	(b)	Sig. at $\alpha = 0.025$
		in *A*.	(c)	Sig. at $\alpha = 0.025$
		• Mean in *B* to be smaller than *A*.		
		Later period	(b)	Not sig. at $\alpha = 0.05$
		• No difference in trends between *A* & *B*.	(c)	Not sig. at $\alpha = 0.05$
		• No difference in means in *A* & *B*.		

Hypothesis	Dependent Variables	Predicted Observations	Statistical Tests[1]	Expected Outcome
3	P_{best}	<u>Both initial and later periods</u> • Mean in *B* to trend upwards at faster rate than in *A*. • Mean in *B* to be larger than in *A*.	(b) (c)	Sig. at α = 0.00125 Sig. at α = 0.00125
	T_w	<u>Both initial and later periods</u> • Mean in *B* to trend downwards at faster rate than in *A*. • Mean in *B* to be smaller than in *A*.	(b) (c)	Sig. at α = 0.0125 Sig. at α = 0.0125
4	P_{best}	<u>Both initial and later periods</u> • Mean in *B* to trend upwards at faster rate than in *A*. • Mean in *B* to be larger than in *A*	(b) (c)	Sig. at α = 0.0125 Sig. at α = 0.0125
	T_w	<u>Both initial and later periods</u> • Mean in *B* to trend downwards at faster rate than in *A*. • Mean in *B* to be smaller than in *A*	(b) (c)	Sig. at α = 0.0125 Sig. at α = 0.0125

Hypothesis	Dependent Variables	Predicted Observations	Statistical Tests[1]	Expected Outcome
5	T^i	<u>Both initial and later periods</u> • Mean in A & B to trend downwards • Mean in *B* to trend downwards at faster rate than in *A*. • Mean in *B* to be smaller than in *A*	(a) (b) (c)	Sig. at $\alpha = 0.0083$ Sig. at $\alpha = 0.0083$ Sig. at $\alpha = 0.0083$

[1] (a) Main effect of *Day*, (b) interaction of linear trends of *A* & *B* ; and (c) between-subjects main effect.

The fourth column of Table 4-10 lists the outcomes expected if the hypotheses are true. The null hypothesis for each of these tests is that the state opposite that of the expected outcomes (fourth column) is true. When assessing the presence (or otherwise) of trends in the dependent variables across *Day* and whether there are differences between trends (tests (a) and (b)), the primary emphasis is on the linear component. A significant linear trend component indicates the presence of slope, and a significant interaction between two linear components, a difference in the rate of change in the dependent variable. Quadratic trend components may be examined as a secondary concern for the presence of curvature. Although the analysis is able to yield findings on higher order trend components, these are not considered because the current set of hypotheses does not provide for any predictions related to them. As asserted by Keppel and Wickens (2004), theories on which many behavioural studies are based do not usually warrant examination of trends of higher order than the quadratic.

Most of the hypotheses involve more than one separate test on single d.f. contrasts. Depending on the postulated relationship, these tests serve one of two different objectives. The first objective is to test for the *presence* of significant differences between the means or trends. In such a case, because the tests are inter-related and applied concurrently, there is a risk that the probability of a Type I error may increase. To prevent such an inflation of family-wise Type I error, the significance level α for each of these contrasts was lowered using the Bonferroni adjustment. In this case, the critical value was adjusted to a more stringent $\alpha = 0.05/k$, where k is the number of tests for differences for that hypothesis. The second objective is to test for evidence that there is *no* significant difference between the means or trends. For them, a more conservative approach is to adopt a more liberal critical value. In this analysis, α was retained at the nominal value, 0.05 for each of these tests of "*no* difference". One may argue for a higher value, say α = 0.10, but this would result in an excessively high family-wise Type I error rate α, if the number of tests for no difference m is 2 or more because $\alpha = 1 - (1 - 0.10)^m$.

Note that in most hypotheses, the testing is conducted on two periods, the initial and later periods. They define the periods in which exploratory activity is assumed to be conducted and when the choice behaviour is assumed to be stabilised respectively. For the purpose of this testing, the initial period is defined as the period from Day 1 to 5, and the later period, the remaining days. Although such a definition appears arbitrary, it is shown in Chapter 5 that it is not an unreasonable one.

4.5 Preliminary Findings

After describing and presenting the predicted outcomes at some length in the previous section, one can now examine the participants' actual behavioural responses to the various *Info* and *Ops* conditions presented in the scenarios under each of the four dependent variables. This section investigates the results from the first five *Info* conditions, out of the ten in total. These five conditions (*NO-INFO, HDWAY, TTABLE, DYN-UNREL* and *DYN-REL*) have been described in the preceding sections to involve only a single information type or reliability throughout the session and allow for like-for-like comparisons of the effects of different types of information. The remaining conditions contain a mid-session change of information type or reliability, and their results are discussed in Chapter 6 (Section 6.1.2.1).

Before one proceeds to test the hypotheses statistically, it would be useful to conduct a preliminary inspection of the data first to obtain a sense of how the actual behaviour adheres to the predictions. First, the mean values of each of the dependent variables in the initial and later periods in each *Ops-Info* combination were computed. Next, the mean values of each of these dependent variables over 20 days were plotted in charts to present the trends under each *Info* condition across all *Ops* conditions. Obviously, with 30 *Ops-Info* combinations, the charts are too numerous to present in their entirety in this text and are therefore relegated to Appendices 1 and 2. The discussion summarises the general findings for each dependent variable with the aid of tables and selected plots that are broadly representative of the rest.

4.5.1 *Proportion of Participants Choosing Best Service, P_{best}*

The effects of information on how the participants chose their services are examined first. Table 4-11 presents overall effects of *Info* conditions on this variable, revealing no clear relationship between the proportion of participants choosing the best service of the day, P_{best} and the *Info* condition. P_{best} is the mean value of the dependent variable Svc_{best} that can be obtained using two approaches, as described in Chapter 3. The first approach infers the traveller's choice of service using the location of t_b in relation to the scheduled service departure time t_{sch}; and the second, to the service departure time estimate t_s^i. Hence, two sets of values are derived; the values in the upper and lower halves of Table 4-11 are obtained using the first and second approaches respectively. The values of the first three *Info* conditions are identical in the two sets because the second approach applies to *DYN-UNREL* and *DYN-REL* conditions only.

Table 4-11 Proportion of Participants Choosing Best Service of Day (P_{best}) by *Ops* and *Info* Conditions

Values in **bold** indicate the highest value in each *Ops* condition.		*Ops Condition*					
		H20-LOW	***H20-HIGH***	***H10-LOW***	***H10-HIGH***	***H5-LOW***	***H5-HIGH***
P_{best} [1]							
Info condition	*NO-INFO*	0.505	**0.610**	0.316	0.352	0.233	0.181
	HDWAY	**0.553**	0.532	0.304	0.343	0.254	**0.226**
	TTABLE	0.412	0.533	0.313	0.332	**0.307**	0.193
	DYN-UNREL	0.504	0.405	0.338	0.362	0.268	0.219
	DYN-REL	0.527	0.565	**0.370**	**0.400**	0.269	0.202
P_{best} [2]							
Info condition	*NO-INFO*	0.505	**0.610**	0.316	0.352	0.233	0.181
	HDWAY	**0.553**	0.532	0.304	0.343	0.254	0.226
	TTABLE	0.412	0.533	0.313	0.332	**0.307**	0.193
	DYN-UNREL	0.528	0.502	**0.410**	0.483	0.189	0.174
	DYN-REL	0.516	0.567	0.393	**0.484**	0.245	**0.231**

The outcomes do not appear consistent with expectations that dynamic information enables more participants to pick the best service than no or static information. Each of the *Info* conditions is associated with the highest P_{best} in at least one *Ops* condition.

Earlier predictions of the outcomes are silent on the effects of *Ops* conditions because they are not the primary focus of this study. Nonetheless, it would be useful to compare across the *Ops* conditions to see if the data are consistent with intuition. One can easily see that the ratios decrease with decreasing headway, and that, except in *H20* conditions, only a minority of participants chose the best service. A possible explanation is that when the headway is long, it is much easier to deduce which is the most likely service that will yield the best outcome. Any earlier and later services will have a very high probability of resulting in a very substantial schedule delay (early and late respectively) due to the large scheduled intervals between services. As the headway is reduced, two or more services will be perceived as viable alternatives.

The ratios of Table 4-11 show only the overall effects and do not shed light on the trends of P_{best} over time. To this end, the values of P_{best} are plotted across the 20 days and these plots are contained in Appendix 1. Disappointingly, it is difficult to discern trends from these plots, let alone trends that have been predicted for each of the *Info* conditions, as illustrated by Figures 4-4 to 4-6. Figure 4-5 presents P_{best} under the first approach, but the corresponding plot under the second approach shows almost identical patterns (or lack of), and is therefore not shown. The large variations in the variable under some of the scenarios, as shown starkly by Figure 4-6, are also a phenomenon on which further examination is warranted (and, as is discussed in Chapter 5, is conducted).

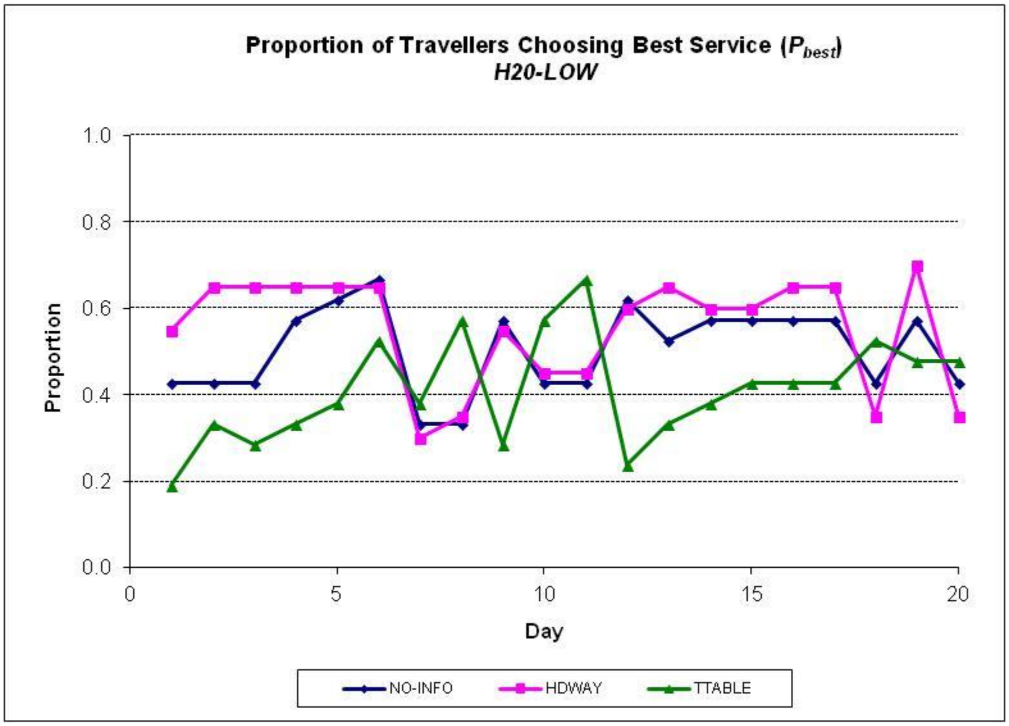


Figure 4-4 P_{best} for *NO-INFO, HDWAY* and *TTABEL* in *H20-LOW* Scenario

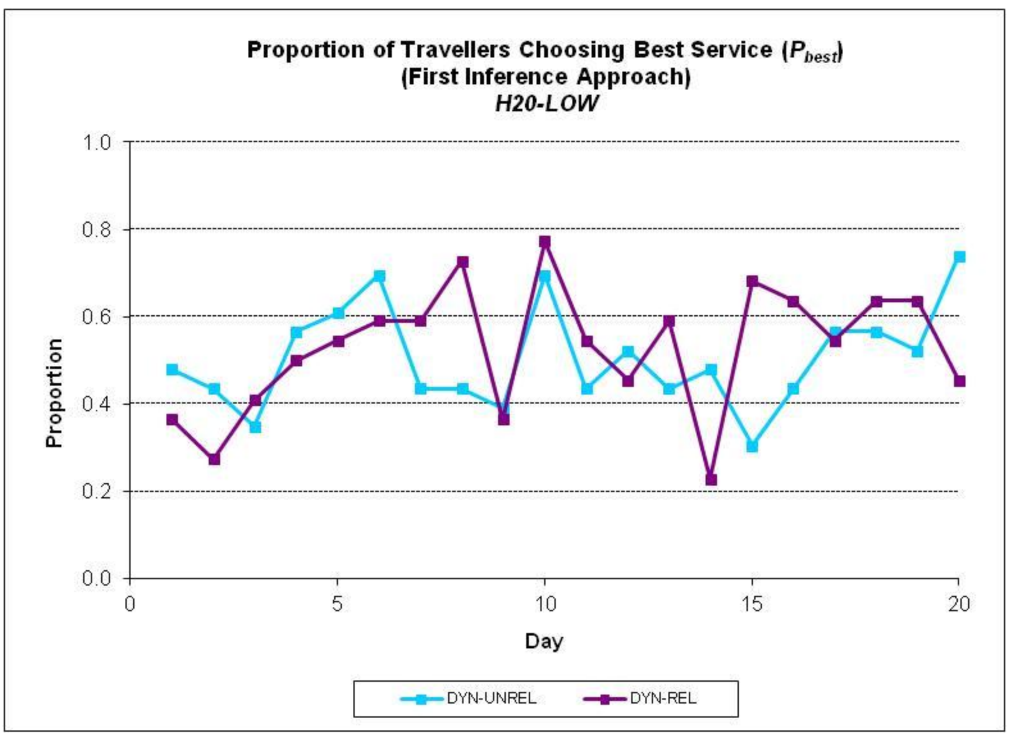


Figure 4-5 P_{best} for *DYN-UNREL* and *DYN-REL* in *H20-LOW* Scenario

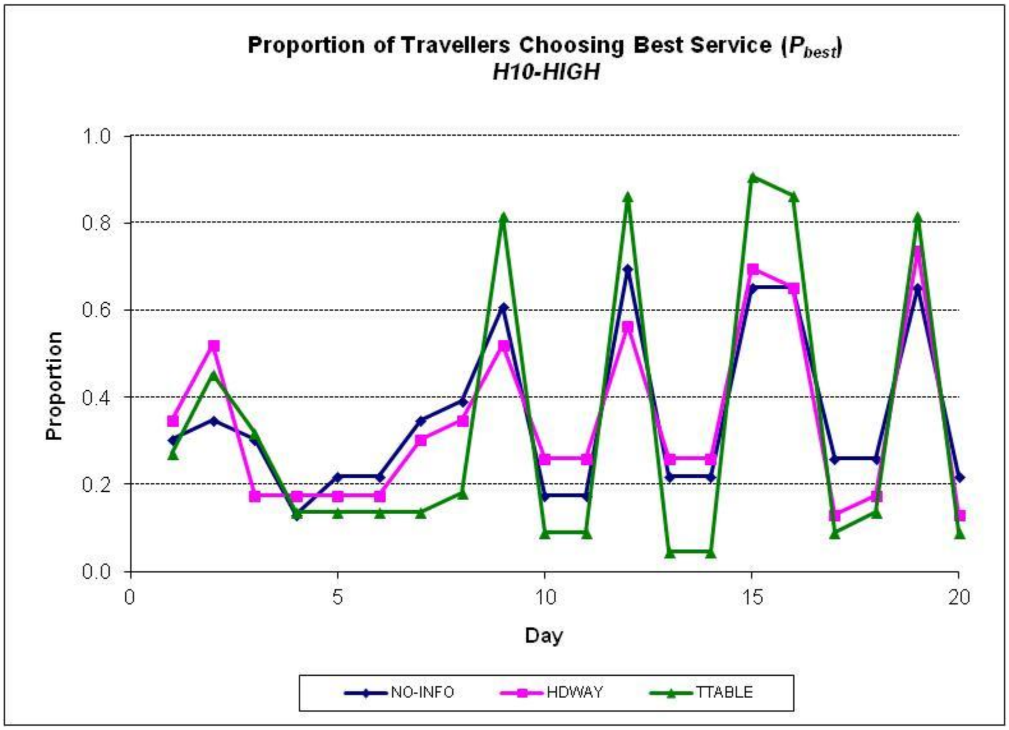


Figure 4-6 P_{best} for *NO-INFO, HDWAY* and *TTABEL* in *H10-HIGH* Scenario

4.5.2 Wait Time, T_w

In contrast to the less than obvious outcomes in P_{best}, Table 4-12 provides a clear picture of the overall effects of *Info* conditions on the wait time, T_w. Generally, T_w reduces as one progresses from no provision of information (*NO-INFO*) to the most reliable dynamic information (*DYN-REL*). It lends support to the prediction that supplying static information (*TTABLE*) does not bring about a clear reduction of wait time, compared to providing no or non-specific information (*NO-INFO* and *HDWAY*). The advantage of dynamic information over static (and no) information is more obvious, particularly that of reliable dynamic information. In all *Ops* conditions, reliable information (*DYN-REL*) clearly outperforms its unreliable counterpart (*DYN-UNREL*). This is certainly in accordance with one of the predictions and in line with the general paradigm in the literature.

Table 4-12 Mean Wait Time (T_w) by *Ops* and *Info* Conditions

Mean T_w (minutes)		***Ops Condition***					
		H20-LOW	***H20-HIGH***	***H10-LOW***	***H10-HIGH***	***H5-LOW***	***H5-HIGH***
Info condition	*NO-INFO*	8.6	9.8	4.9	5.7	2.8	3.7
	HDWAY	8.3	8.8	5.6	5.6	2.8	3.5
	TTABLE	8.3	8.4	5.6	5.9	2.7	3.3
	DYN-UNREL	7.5	8.2	5.3	4.7	2.3	3.4
	DYN-REL	**5.5**	**6.2**	**4.5**	**4.0**	**2.3**	**3.1**

Values in **bold** indicate the lowest mean in each *Ops* condition.

Scanning across the *Ops* conditions, it is apparent that the mean T_w is inversely related to service frequency; the shorter the headway (higher the frequency), the shorter is the mean wait time. This is expected because the mean T_w values should always be less than the headway unless the traveller at the bus stop skips the first immediate service to depart for the second, which is impossible in the experimental scenario. Also consistent with intuition is the observation that, the mean wait times, when the variability of the service departure times is low (*H20-LOW*, *H10-LOW* and *H5-LOW*), are generally shorter than when the variability is high (*H20-HIGH*, *H10-HIGH* and *H5-HIGH*). This can be explained by participants adopting a smaller safety margin when choosing the arrival time at the bus stop when the service departure times are perceived to be more predictable. This fits into the description of how the traveller responds to variability in t_s in the descriptive scheme. Also, if the service departures are more variable, there will be a greater likelihood of the participant just missing the desired service and needing to incur a longer than intended wait for the service.

One may contemplate whether these outcomes, particularly of the attainment of the shortest wait time when given reliable dynamic information, are due to the participants adhering closely to the estimates from the information service. This is one of the few questions to explore when the last dependent variable T^i in the next section.

The plots of the mean wait time T_w over days are contained in Appendix 2. One can notice that the means of the *NO-INFO*, *HDWAY* and *TTABLE* in each of the *Ops* condition are typically in the same range and seem to fluctuate almost in tandem with each other, as illustrated in Figure 4-7. The key predictions are not realised: there is neither a large but reducing T_w trend in the initial period in the *NO-INFO* and *HDWAY* conditions, nor a general reduction in T_w in the later period across all conditions.

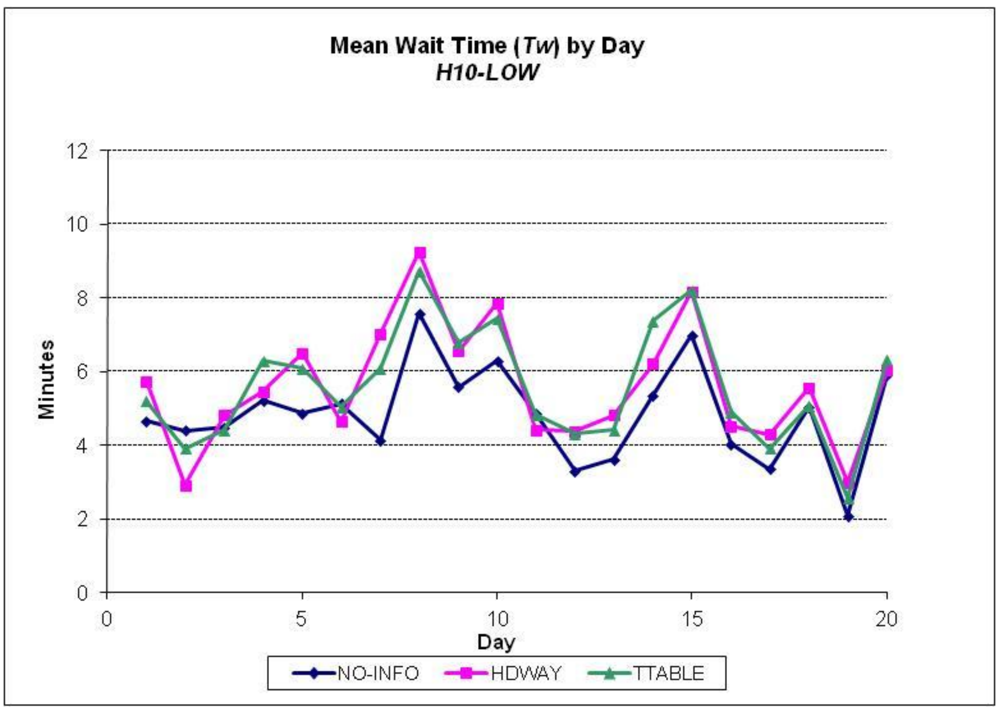


Figure 4-7 Mean T_w for *NO-INFO*, *HDWAY* and *TTABLE* in *H10-LOW* Scenario

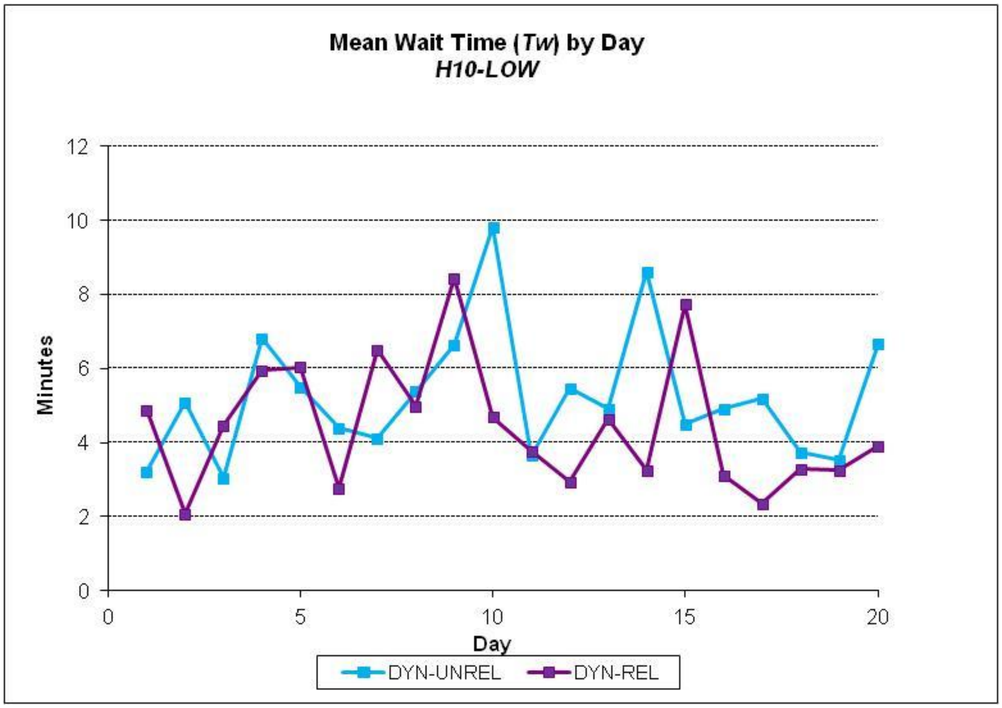


Figure 4-8 Mean T_w for *DYN-UNREL* and *DYN-REL* in *H10-LOW* Scenario

The trends in the *DYN-UNREL* and *DYN-REL* are expected to be different from the three other *Info* conditions and from each other. Specifically, the mean of *DYN-REL* is expected to have a steep downward trend. Figure 4-8 shows the trends of the mean for the *DYN-UNREL* and *DYN-REL* in the same *Ops* condition as the previous three *Info* conditions. However, it is difficult to distinguish between the two trends. In fact, across all *Ops* conditions, the mean values have large day-to-day fluctuations and the observation of their overall trends proves very challenging.

4.5.3 Absolute Deviation of Arrival Time at Bus Stop from Departure Time Estimates, T^i

The last dependent variable of T^i is the only measure of the information effect. This observation is confirmed by presenting the overall means across all *Info-Ops* combinations, as in Table 4-13. In five out of the six *Ops* conditions, the overall mean T^i over 20 days in the *DYN-REL* condition is lower than that in its *DYN-UNREL* counterpart. This is consistent with the prediction that a reliable information source brings about a better outcome than a less reliable one. What is somewhat puzzling is that the mean value for *DYN-UNREL* is lower than *DYN-REL* in the *H5-LOW* condition, and only marginally higher in the *H5-HIGH* condition. To this observation, perhaps one can offer the explanation that when the headway is at such a low level, the services appear to depart at random times. As a result, their departure time estimates by the dynamic information source also appear to vary randomly such that the participants can discount them in their decision-making. The results may be just an outcome of random t_b choices.

Table 4-13 Absolute Deviation of Arrival Time at Bus Stop from Departure Time Estimates (T^i) by *Ops* and *Info* Conditions

Mean T^i		***Ops* Condition**					
20 days		***H20-LOW***	***H20-HIGH***	***H10-LOW***	***H10-HIGH***	***H5-LOW***	***H5-HIGH***
Info condition	*DYN-UNREL*	3.6	5.1	2.1	2.2	**0.9**	1.8
	DYN-REL	**2.6**	**3.3**	**2.0**	**2.1**	1.2	**1.8**

Values in **bold** indicate the lower mean in each *Ops* condition.

Under the same *Info* condition, the mean T^i is consistently larger in an *Ops* condition with higher departure time variability (*HIGH*) than its counterpart with the same headway but of lower variability (*LOW*). This suggests the participants have adopted a larger information margin in response to the greater uncertainty in the service departure time, t_s. One wonders why this should be so. After all, the departure time estimates t_s^i are distributed around the actual t_s and should be equally reliable (or unreliable) in both low and high t_s environments. One possible reason is that the participants do not know if this is the case, just as the real-life public transport commuter is not likely to appreciate the algorithm used by a real life dynamic information service to predict the wait time. A second reason is that the participant may not work out his t_b choice based solely on the t_s^i given, but could factor in his own perception of the variability of t_s. If he believes t_s to be highly unpredictable, he may still consult t_s^i but build in an additional margin. If this is so, the assumption in the descriptive scheme that the participant decides on her t_b using either her perception of t_s (when specific estimates are not available) or t_s^i (when the estimates are available) is too simplistic. It is likely that her perceptions of both the trip attribute and the information service interact during the decision-making process.

Hypothesis 5 predicts that the mean value should trend downwards over time as the participant learns more about the information characteristics and that the rate of reduction is higher when the information is reliable. However, it is clear that the actual results do not reveal such a trend. Figure 4-9 presents a typical plot of the mean T^i. The plots of mean T^i for all *Info-Ops* conditions are contained in Appendix 3. What is more apparent is that the mean value for *DYN-UNREL* is lower than *DYN-REL* on most of the days. That is to say, the information effect is stronger when the information is reliable than when it is less so. This is consistent with Table 4-13.

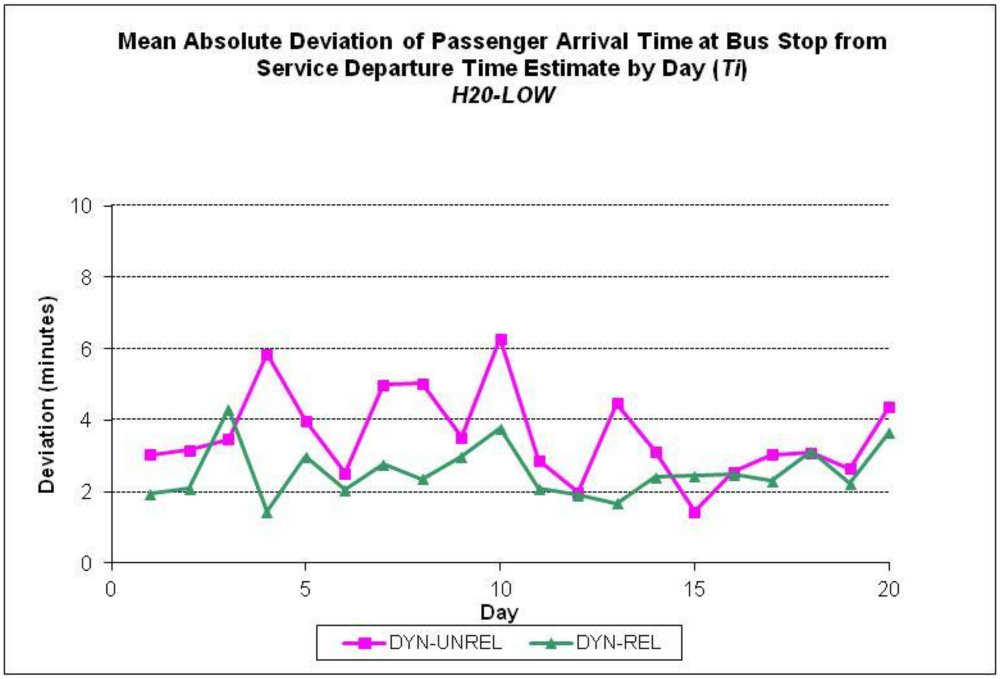


Figure 4-9 Mean T^i for *DYN-UNREL* and *DYN-REL* in *H20-LOW* Scenario

Based on the results presented in the previous three sub-sections, it appears that many of the predictions contained in the descriptive scheme and postulated in the hypotheses have not been observed. On the other hand, there are also certain findings that are to expectations and suggest the presence of predicted effects. These include the effect of different types/reliability of information on the overall wait time T_w, and the presence of an information effect. There are still others whose trends cannot be discerned easily by visual inspection from the data plots, and need to be analysed statistically.

4.5.4 Findings of Analysis

To complete this stage of analysis, the statistical testing of hypothesis is formally conducted to determine if the effects that are believed to be present are indeed significant and to ascertain the presence of the trends. For completeness, effects that are found to be absent against predictions will still be tested. The outcomes of tests on the hypothesised effects are summarised in Tables 4-14 and 4-15. These tables indicate whether the test outcomes for each *Ops-Info* treatment combination were aligned with those described earlier in Table 4-10, and listed in the "Exp. *p*" columns. If there is sufficient evidence that all the predictions are true, each of these tables should have indicated the test outcomes to be as expected, i.e., been populated fully with the symbol “*”. It is apparent that this is not the case in any of the hypotheses that were tested. In summary, there appears insufficient evidence to reject all of the null hypotheses, which are that:.

1. In the absence of information, the traveller does not attain better outcomes of decision-making over time through learning and experience.

2. The traveller does not attain better outcomes of decision-making and learning when provided with static information than when provided with no information.

3. The traveller does not attain better outcomes of decision-making and learning when provided with dynamic information than when provided with static information.

4. The traveller does not attain better outcomes of decision-making and learning when provided with reliable dynamic information than when provided with less reliable dynamic information.

5. The traveller does not experience a stronger information effect or this effect does not strengthen at a faster rate when provided with reliable dynamic information than when provided with less reliable information.

This finding is consistent with the general conclusion made on observations described in the previous section. It appears that the effects of information and learning have not been manifested in the manner predicted. One wonders why a substantial proportion of the hypothesised effects, especially those postulated in Hypotheses 3 to 5, are found to be insignificant. Perhaps there is indeed no strong information or learning effects, regardless of the *Info* or *Ops* condition involved. While it would be easy to form such a conclusion simply from the statistical tests, it would be premature to do so. It might be useful at this juncture to take a step back and recall that Table 4-12 has shown clearly the mean wait time T_w is the lowest across all *Ops* conditions when reliable dynamic information (*DYN*-

REL) is provided. Similarly, Table 4-13 shows that T^i is generally lower in this condition (*DYN-REL)* than in its less reliable counterpart (*DYN-UNREL*). Surely, these cannot be random outcomes. One can argue that the effects of information are present, but not necessarily in the form or manner postulated in this Chapter. A different approach to examining the data is called for, and this is discussed in Chapter 5.

Table 4-14 Significance Values of Tests for Hypotheses 1 and 2 (with "*" indicating outcome as expected)

Hypo-thesis	*Info* Tested	Per-iod	Tests[1]	$P_{best[1]}$							T_w							T^i						
				Exp. *p*	*H20-LO*	*H20-HI*	*H20-LO*	*H20-HI*	*H20-LO*	*H20-HI*	**Exp. *p***	*H20-LO*	*H20-HI*	*H20-LO*	*H20-HI*	*H20-LO*	*H20-HI*	**Exp. *p***	*H20-LO*	*H20-HI*	*H20-LO*	*H20-HI*	*H20-LO*	*H20-HI*
1	*NO-INFO* Vs *HDWAY*	Initial	(a)	≤ .05	.028 *	.017 *	.000 *	.002 *	.321	.008 *	≤ .025	.142	.192	.053	.000 *	.000 *	.018 *	n.t.	-	-	-	-	-	-
			(b)	>.05	.315 *	.915 *	.028 *	.367 *	.321 *	.861 *	>.05	.778 *	.060 *	.276 *	.814 *	.646 *	.648 *	n.t.	-	-	-	-	-	-
			(c)	>.05	.358 *	.836 *	.099 *	.802 *	.670 *	.116 *	>.05	.792 *	.528 *	.340 *	.542 *	.980 *	.443 *	n.t.	-	-	-	-	-	-
		Later	(a)	>.05	.049	.794 *	.000	.057 *	.075 *	.515 *	≤ .025	.090	.034	.000 *	.016 *	.001 *	.359	n.t.	-	-	-	-	-	-
			(b)	>.05	.575 *	.389 *	.970 *	.959 *	.482 *	.934 *	>.05	.819 *	.053 *	.405 *	.596 *	.674 *	.299 *	n.t.	-	-	-	-	-	-
			(c)	>.05	.559 *	.230 *	.645 *	.726 *	.401 *	.402 *	>.05	.795 *	.147 *	.027	.915 *	.662 *	.513 *	n.t.	-	-	-	-	-	-
2	*NO-INFO + HDWAY* Vs *TTABLE*	Initial	(a)	>.05	.005	.000	.000	.000	.688 *	.000	n.t.	-	-	-	-	-	-	n.t.	-	-	-	-	-	-
			(b)	n.t.	-	-	-	-	-	-	≤ .025	.080	.956	.518	.694	.423	.897	n.t.	-	-	-	-	-	-
			(c)	≤ .05	.037 *	.470	.590	.921	.807	.605	≤ .025	.822	.128	.457	.987	.338	.916	n.t.	-	-	-	-	-	-
		Later	(a)	n.t.	-	-	-	-	-	-	n.t.	-	-	-	-	-	-	n.t.	-	-	-	-	-	-
			(b)	>.05	.239 *	.653 *	.610 *	.137 *	.254 *	.622 *	>.05	.903 *	.319 *	.801 *	.096 *	.979 *	.842 *	n.t.	-	-	-	-	-	-
			(c)	>.05	.022	.726 *	.869 *	.627 *	.051 *	.938 *	>.05	.917 *	.292 *	.240 *	.283 *	.089 *	.019	n.t.	-	-	-	-	-	-

[1] (a) Main effect of *Day*, (b) interaction of linear trends of *A* & *B* ; and (c) between-subjects main effect.

Table 4-15 Significance Values of Tests for Hypotheses 3 and 4 (with "*" indicating outcome as expected)

Hypo-thesis	*Info* Tested	Per-iod	Tests[1]	$P_{best[1]}$ / $\underline{P_{best[2]}}$							T_w							T^i						
				Exp. *p*	*H20-LO*	*H20-HI*	*H20-LO*	*H20-HI*	*H20-LO*	*H20-HI*	**Exp. *p***	*H20-LO*	*H20-HI*	*H20-LO*	*H20-HI*	*H20-LO*	*H20-HI*	**Exp. *p***	*H20-LO*	*H20-HI*	*H20-LO*	*H20-HI*	*H20-LO*	*H20-HI*
3	*TTABLE* Vs *DYN-UNREL + DYN-REL*	Initial	(b)	≤ .0125	.541	.347	.013	.059	.222	.560	≤ .0125	.703	.932	.730	.475	.064	.507	n.t.	-	-	-	-	-	-
			(c)	≤ .0125	.867	.242	.950	.761	.882	.777	≤ .0125	.071	.019	.474	.054	.302	.270	n.t.	-	-	-	-	-	-
			(b)	≤ .0125	*.462*	*.613*	*.019*	*.447*	*.628*	*.748*	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			(c)	≤ .0125	*.795*	*.583*	*.644*	*.280*	*.750*	*.570*	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		Later	(b)	≤ .0125	.416	.189	.658	.002 *	.820	.649	≤ .0125	.128	.206	.307	.030	.567	.725	n.t.	-	-	-	-	-	-
			(c)	≤ .0125	.042	.226	.030	.187	.630	.941	≤ .0125	.002 *	.002 *	.001 *	.000 *	.214	.255	n.t.	-	-	-	-	-	-
			(b)	≤ .0125	*.285*	*.468*	*.106*	*.043*	*.874*	*.005* *	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			(c)	≤ .0125	*.118*	*.502*	*.965*	*.125*	*.912*	*.164*	-	-	-	-	-	-	-	-	-	-	-	-	-	-
4 and 5	*DYN-UNREL* Vs *DYN-REL*	Initial	(a)	n.t.	-	-	-	-	-	-	n.t.	-	-	-	-	-	-	≤ .0083	.093	.044	.681	.243	.005 *	.091
			(b)	≤ .0125	.636	.579	.021	.178	.190	.376	≤ .0125	.489	.906	.988	.922	.100	.752	≤ .0083	.376	.333	.413	.682	.769	.320
			(c)	≤ .0125	.578	.139	.551	.661	.579	.781	≤ .0125	.352	.025	.909	.794	.721	.575	≤ .0083	.161	.324	.635	.608	.318	.504
			(b)	≤ .0125	*.706*	*.404*	*.134*	*.496*	*.483*	*.428*	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			(c)	≤ .0125	*.200*	*.400*	*.157*	*1.00*	*.597*	*.864*	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		Later	(a)	n.t.	-	-	-	-	-	-	n.t.	-	-	-	-	-	-	≤ .0083	.437	.071	.145	.080	.042	.003 *
			(b)	≤ .0125	.307	.184	.989	.054	.014	.183	≤ .0125	.147	.026	.106	.384	.027	.343	≤ .0083	.187	.130	.116	.261	.119	.165
			(c)	≤ .0125	.279	.061	.101	.339	.723	.624	≤ .0125	.007 *	.028	.013	.019	.989	.187	≤ .0083	.278	.030	.706	.668	.189	.956
			(b)	≤ .0125	*.220*	*.486*	*.990*	*.388*	*.500*	*.033*	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			(c)	≤ .0125	*.529*	*.469*	*.834*	*.988*	*.068*	*.073*	-	-	-	-	-	-	-	-	-	-	-	-	-	-

[1] (a) Main effect of *Day*, (b) interaction of linear trends of *A* & *B* ; and (c) between-subjects main effect.

Underlined values are for $P_{best}[2]$. n.t. stands for "not tested"

5 FURTHER ANALYSES

Chapter 4 presents the preliminary findings of the experiment and reports the outcomes of statistical tests on the six hypotheses. The test results are mainly not in accordance with predictions contained in the descriptive scheme. It is suggested that the effects of information could be present but do not manifest in ways predicted. This Chapter re-examines the choices of the participants in greater detail, specifically first, of their arrival time at the bus stop, and next, their choice of service.

5.1 Analysis of Passenger Arrival Time at Bus Stop (t_b)

The re-examination of the participants' behavioural responses can start with the only response variable that is directly obtainable from the participant in the experiments, which is the departure time from home (t_h). By itself, the variable t_h provides no indication of the quality of outcome that is the focus of the hypotheses. Nonetheless, it is useful to examine it to see if there are certain behavioural patterns that are not detected by the three dependent variables discussed in Chapters 3 and 4.

In the following discussion, the arrival time at the bus stop (t_b) is used instead. This is admissible because it is related directly to t_h by $t_b = t_h + T_a$, in which T_a, the access time to the bus stop, is set as a constant in the experiment. The discussion starts with the scenario in which the services depart from the bus stop at long intervals of 20 minutes (*H20-LOW*). The plot of mean t_b under *NO-INFO* condition is presented in Figure 5-1. The *NO-INFO* plot serves as a baseline against which the other *Info* conditions, and hence the effects of information, are compared. Three different graphs related to t_b are plotted: its mean, standard deviation and the proportion of participants who changed t_b from the previous day. The first is presented in Figure 5-1 and the latter two in Figure 5-2. In Figure 5-1, the vertical scale measures the time in minutes relative to *PAT*, with the negative values denoting time earlier than *PAT*. The horizontal dotted lines represent the scheduled departure times (t_s^{sch}) of two consecutive services. One of them is coloured red to indicate that it is the service that will bring the participant to end the trip at a time closest to, but not later than, the *PAT* on most of the 20 days. In other words, it is the best service of the day on most, but not all, days. Its significance and how it relates to the choice of service is discussed in the next section.

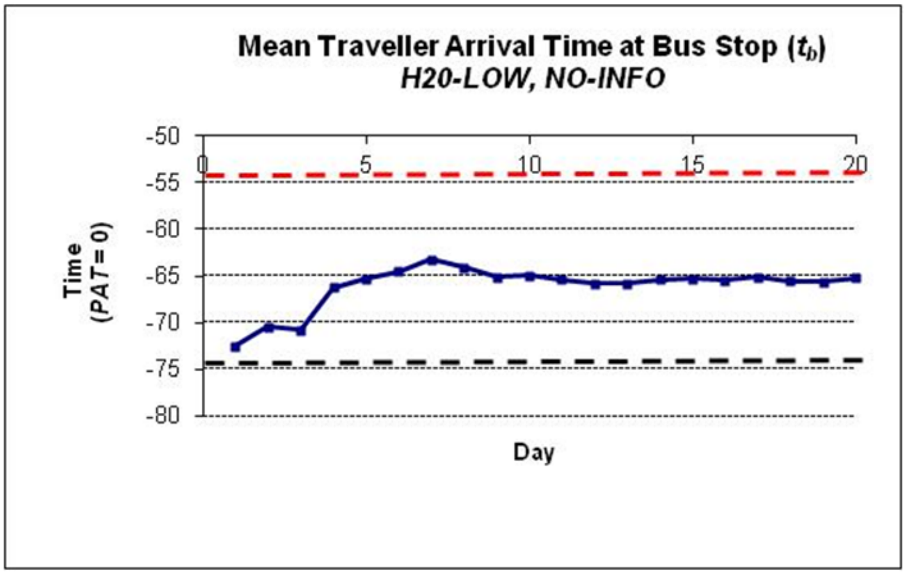


Figure 5-1 Traveller Arrival Time at Bus Stop t_b for *H20-LOW*, *NO-INFO* Scenario

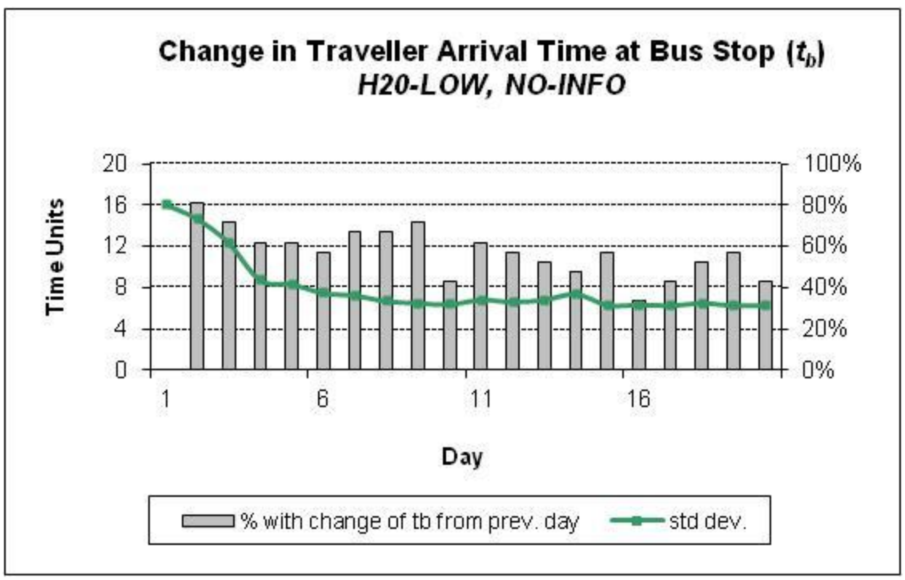


Figure 5-2 Standard Deviation of t_b and Proportion of Participants with Change in Arrival Time at Bus Stop from Previous Day for *H20-LOW, NO-INFO* Scenario

Figure 5-1 shows that, on average, the participants appeared to be mostly catching the best service indicated by the red dashed line, because they are about 10 minutes too late for the preceding one. Of course, the variability in the service departure times could mean that some would board the earlier service, indicated by the black dashed line, if it arrived substantially earlier than scheduled, especially during the initial days when the participants arrived earlier on average. It also shows that the mean t_b trends upwards arriving later towards t_s^{sch} of the maximising service (i.e., later arrival times at the bus stop) for an initial period before the graph out and fluctuates around its longer term level. This coincides approximately with the 5-day period identified earlier in Chapter 4 as the 'initial period'. There is also an observable reduction in the s.d. within the same period (Figure 5-2). As with the t_b trend, the s.d. also stabilises after that. The proportion of participants making changes to t_b from the preceding day is also generally higher in this period compared to the later days. These observations indicate a large but rapidly diminishing dispersion of t_b values and frequent decision changes over successive days in the initial period.

The observations made in Figure 5-2 suggest that the participants had engaged in an exploratory process about t_s in the first several days. This is because they had no information on when the services were scheduled to depart on the first day. They could, of course, infer that the service they believe they should be catching must depart no later than a certain time to avoid arriving late at the destination based on the information on estimated range of T_v (See Figures 3-1 and 3.2). However, they would not be certain when that service would depart, hence they made frequent changes in t_b to locate it. It can be argued that such an exploratory behaviour is evidence of the 'service search' process postulated in the descriptive scheme in Chapter 2. The spread of t_b then becomes smaller over consecutive days, as shown by the reduced s.d., and the frequency of changes to t_b also reduces, indicating the cessation of this process. This is also postulated in the descriptive scheme.

If the ‘service search’ process is deemed present, how about its counterpart, the ‘safety margin reduction’ described in the same descriptive scheme? Recall in Chapter 2, in the latter process, because the traveller is highly uncertain of his perception about t_s initially, he builds in a ‘safety margin’ in his decision making that is manifested by the initial t_b being substantially earlier than t_s^{sch} of his targeted service. This margin is then reduced progressively as he becomes more certain about t_s through experience. The upward trend in the mean t_b in the initial period appears to support this description. That this trend does not persist subsequently can be explained by the retention of a minimum safety margin by the participants because the perceived uncertainty with respect to t_s cannot be eliminated fully despite the experience gained about the service.

The observations appear to be somewhat consistent with the ‘service search’ and ‘safety margin reduction’ processes in the descriptive scheme. However, these are from only one scenario. The plots of the 11 other *Info-Ops* combinations involving *NO-INFO* and *HDWAY* are examined to examine if similar outcomes can be observed in other operating conditions when no information on the service departure time is provided. (Given the large number of charts to be presented requires them to be exhibited in the Appendix 4 rather than with the text.) The observations on t_b plots are mixed. Some show similar upward trend in the first several days and a relatively flat trend subsequently (*H10-HIGH* and *H5-HIGH* with *NO-INFO*). Most of the others do not share such trend characteristics, however. Figure 5-3 shows a typical plot in which the trend of mean t_b is not very discernible, and Figure 5-4, another one in which t_b trends upwards and downwards over time. In all cases, the day-to-day fluctuations are not pronounced.

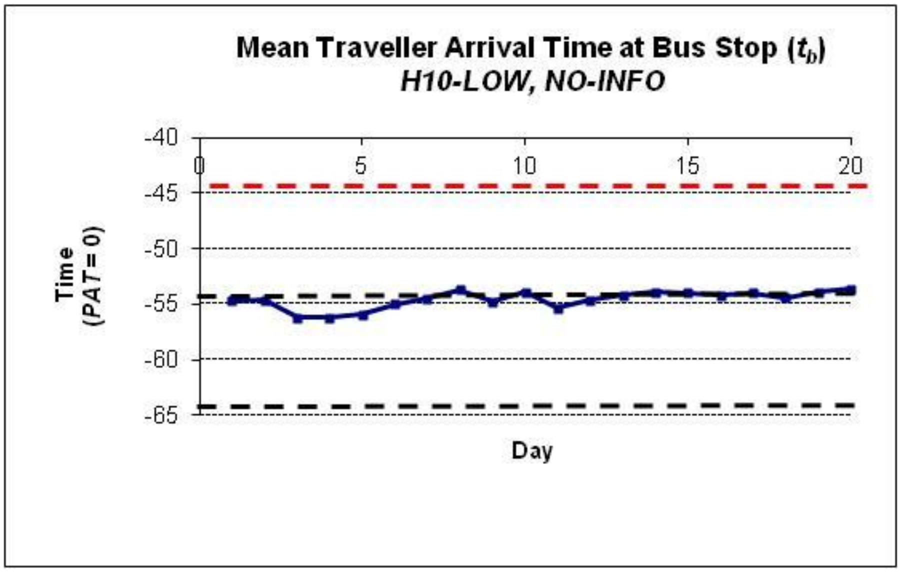


Figure 5-3 Traveller Arrival Time at Bus Stop t_b for *H10-LOW, NO-INFO* Scenario

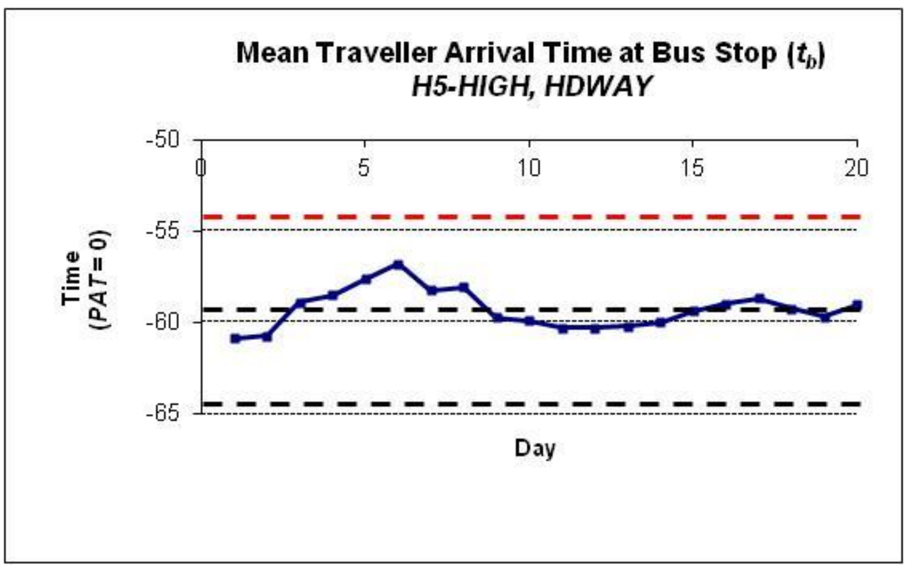


Figure 5-4 Traveller Arrival Time at Bus Stop t_b for *H5-HIGH, HDWAY* Scenario

There are more similarities in the plots of the s.d. and proportion of participants making changes to t_b from the preceding day though. Most of the plots show generally higher values in s.d. within the initial period than in the remaining period, although in some, the s.d. is elevated for at most two or three days. By comparison, all plots show the progressive reduction in the proportion of participants changing their t_b choices.

Having examined how participants responded without the presence of information in *NO-INFO* and *HDWAY* conditions, one can now explore how the provision of information affects the learning and response of the participants. The effect of static information is first investigated. Plots of the same three measures described earlier but under the *TTABLE* condition are examined. Visual inspection of these plots does not reveal any substantial difference in how the participants under this *Info* condition have responded compared to their counterparts (See Appendix 4). Figures 5-5 and 5-6 show two of these plots for the *TTABLE* condition that show very similar trends as those for *NO-INFO* and *HDWAY* conditions (Figures 5-1, 5-3 and 5-4).

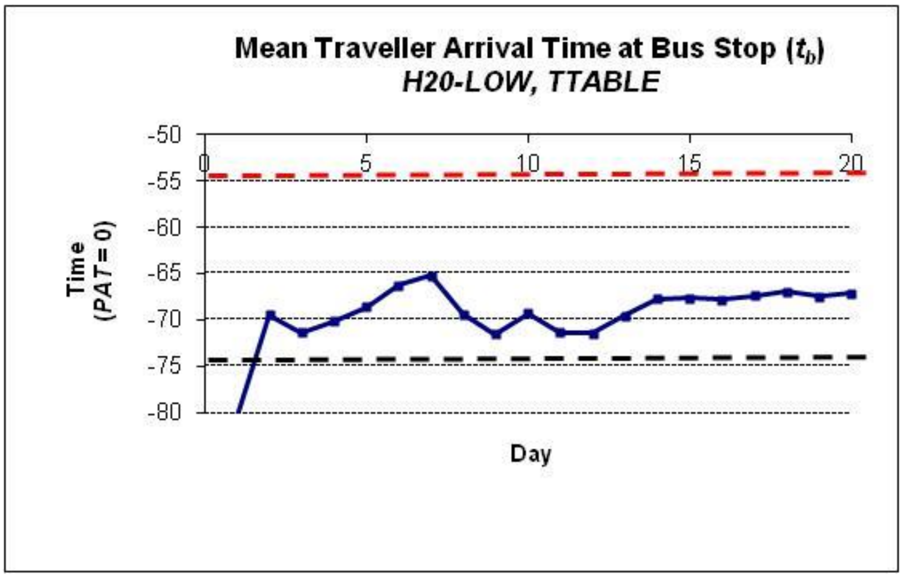


Figure 5-5 Traveller Arrival Time at Bus Stop t_b for *H20-LOW, TTABLE* Scenario

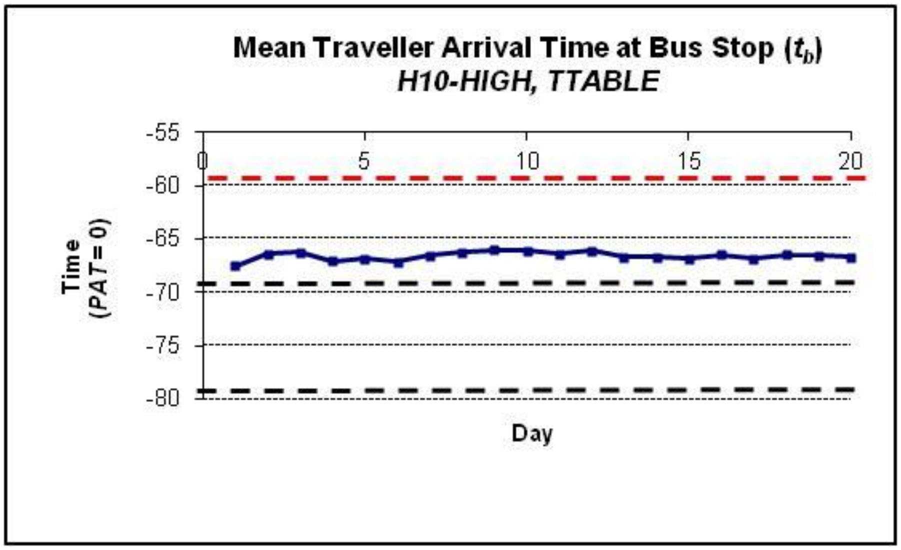


Figure 5-6 Traveller Arrival Time at Bus Stop t_b for *H10-HIGH, TTABLE* Scenario

There are no clear trends in the t_b plots across the *Ops* conditions, as in the case of *NO-INFO* and *HDWAY*. On the other hand, the high but reducing s.d. in the first several days, and the progressive reduction in the proportion of participants engaging in t_b changes are discernible. It appears that the participants have engaged in the exploratory process in the initial period, like their counterparts with *NO-INFO* and *HDWAY* conditions. This is somewhat unexpected that such a process appears also to occur in the *TTABLE* scenarios. One may have anticipated that the provision of estimates of service departure times specific to each service, even if it is static, would eliminate the need for the participants to engage in the exploratory behaviour. Apparently, this is not so.

The discussion moves on to the effects of dynamic information. Consider first the effects of reliable information, as represented by the *DYN-REL* condition. Two noteworthy observations can be made in this condition in relation to the preceding three *Info* conditions. First, greater day-to-day fluctuations in the mean t_b are observed across all *Ops* conditions. Figure 5-7 is an example. Unlike the other three *Info* conditions in which the larger changes in mean t_b were mainly restricted in the initial period, the fluctuations in t_b under this *Info* condition were sustained throughout the 20 days. It appears that the participants were responding to the varying service departure time estimates t_s^i, and persistently so.

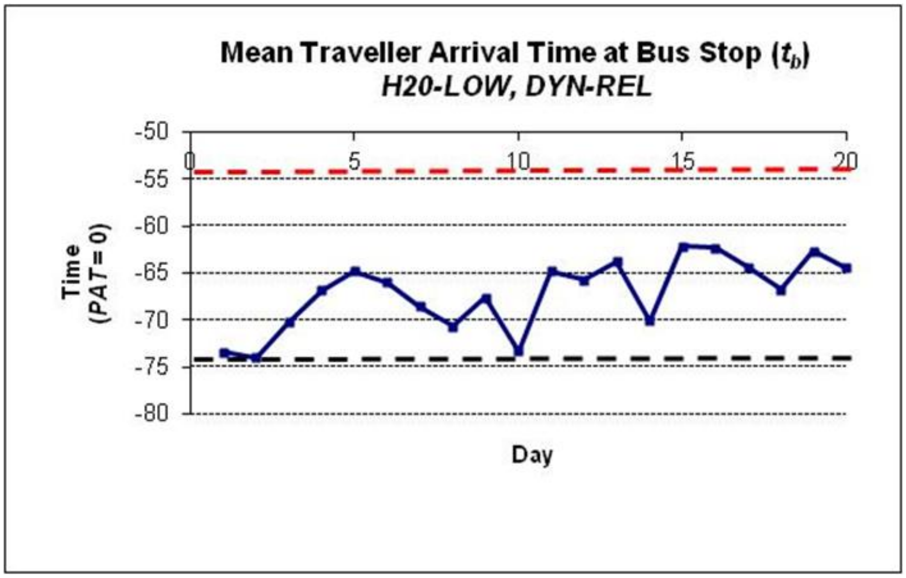


Figure 5-7 Traveller Arrival Time at Bus Stop t_b for *H20-LOW, DYN-REL* Scenario

Second, the proportion of participants who made changes to their t_b choices in the *DYN-UNREL* and *DYN-REL* conditions was sustained at a high level throughout the 20 days across all *Ops* conditions. A quick visual inspection revealed that, with few exceptions, more than 60% of the participants made changes on any given day, and this high proportion was sustained at this high level after the initial period. See Figure 5-8 for an example. In comparison, the number of days in which the proportion exceeds 60% in *NO-INFO*, *HDWAY* and *TTABLE* conditions is substantially fewer, and they occur mainly in the first 10 days when the learning process took place.

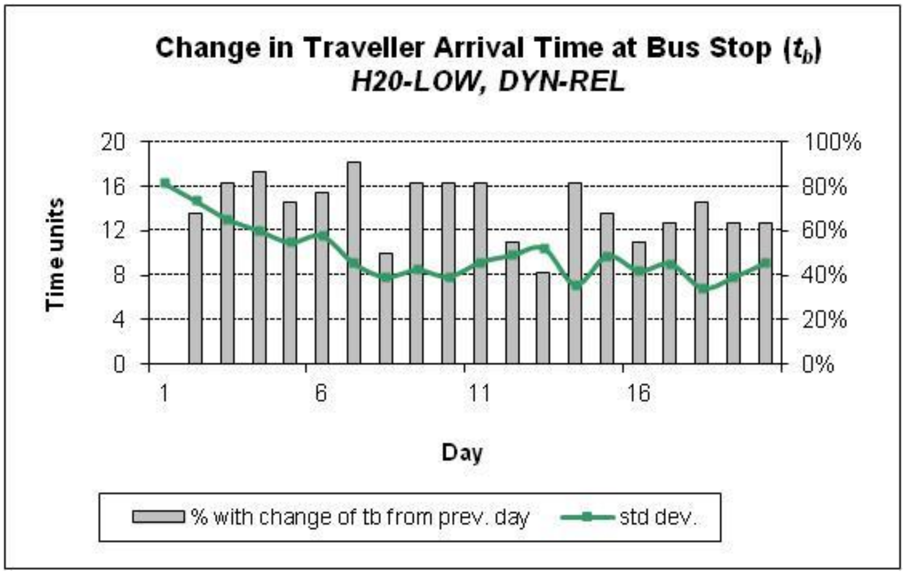


Figure 5-8 Standard Deviation of t_b and Proportion of Participants with Change in Arrival Time at Bus Stop from Previous Day for *H20-LOW, DYN-REL* Scenario

That the participants' t_b choices changed frequently in response to the varying t_s^i under *DYN-REL* is unsurprising. After all, the t_s^i estimates were fairly reliable (±2 minutes of actual t_s, see Figure 3-3), and using them should help them time t_b to be as close to actual t_s of their targeted service. In the case of *DYN-UNREL* in which t_s^i were ±4 minutes of actual t_s (Figure 3-4), and therefore less reliable, it is reasonable to assume that the participants would have a higher likelihood of setting their t_b too early from the actual t_s or too late (and thus missing the service) if they were to rely on unreliable t_s^i to the same degree as that on reliable t_s^i. Hence, it follows that they would not base their t_b decisions on t_s^i as much as in the *DYN-REL* condition. However, visual inspection of the overall trends of the mean t_b, its day-to-day fluctuations and the proportion of participants changing t_b is not able to yield strong evidence that participants in *DYN-UNREL* were less responsive to t_s^i than those under *DYN-REL*. It is highly likely that the participants were not able to discern the difference in reliability.

Table 5-1 shows the mean proportion of participants who made changes to their daily t_b decisions over 20 days, by *Ops-Info* combination. Its last two rows in fact suggest the contrary: that participants in *DYN-UNREL* appear to be more responsive to t_s^i than those in *DYN-REL* in 4 out of 6 *Ops* conditions. It is also obvious from Table 5-1 that in all six *Ops* conditions, those receiving dynamic information (*DYN-REL* and *DYN-UNREL*) have proportions (62.5% - 81.8%) that are substantially higher than their static and no-information counterparts (33.3% - 70.2%). These differences between the two groups are significant statistically (p = 0.000 for all at α = 0.05). It appears that the participants responded to t_s^i, regardless of the service characteristics (*Ops* condition), and more interestingly, also regardless of the reliability of the information as well.

Table 5-1 Mean Proportion of Participants with Change in Arrival Time at Bus Stop, t_b from Previous Day over 20 Days by *Ops* and *Info* Conditions

Mean proportion of participants with change in t_b from previous day (%) over 20 days		***Ops Condition***					
		H20-LOW	***H20-HIGH***	***H10-LOW***	***H10-HIGH***	***H5-LOW***	***H5-HIGH***
Info condition	*NO-INFO*	57.1	70.2	52.4	39.8	41.6	55.5
	HDWAY	45.3	33.3	58.1	41.9	47.4	48.9
	TTABLE	50.9	53.1	49.3	44.5	51.6	46.4
	DYN-UNREL	**79.2**	77.2	**81.8**	70.2	**77.5**	**69.2**
	DYN-REL	70.3	**79.9**	75.1	**77.0**	65.9	62.5

Values in **bold** indicate the highest proportion in each *Ops* condition.

A better way to describe how participants have responded to t_s^i is to examine how the choice of t_b deviates from t_s^i, using a dependent variable discussed in Chapter 4. Here, a small but useful digression is made to return to the discussion of T^i (= $t_b - t_s^i$). If the participants were less responsive to t_s^i in *DYN-UNREL*, its mean T^i should be higher than that in *DYN-REL*. Recall in Chapter 4 that one of the hypotheses postulates that T^i will decrease over time and that the rate of decrease is significantly higher in *DYN-REL* than in *DYN-UNREL*. It follows that the mean T^i should then be significantly lower in *DYN-REL* than in *DYN-UNREL*, and vice-versa, particularly in the stabilised period (Day 6 onwards). However, the hypothesis tests reveal otherwise (See Table 4-15 – test (c) for T^i under Hypotheses 4 and 5) – the mean T^i is not significantly lower in *DYN-REL* than in *DYN-UNREL*, in both the initial and stabilised periods. Again this outcome does not support the view that participants respond more to a reliable source of dynamic information than to a less reliable one.

What one can observe thus far is that there appears no discernible pattern in which the participants' choice of t_b differ among *NO-INFO*, *HDWAY* and *TTABLE*, i.e. *Info* conditions that involve no or static information. In most of the scenarios involving them, the changes in the mean t_b are not pronounced, particularly after the initial period. There appears a short period of exploratory behaviour in the first few days, characterised by a comparatively large but rapidly decreasing s.d. of t_b. An increasingly smaller proportion of participants changed t_b as they gained experience. In contrast, the presence of dynamic information is associated with frequent changes in the mean t_b as well as a high proportion of participants making changes to their t_b, both of which are sustained throughout the 20 days.

There is another way in which one may also observe how the participants' responses to dynamic information differ distinctly from those to the other types of information. In Chapter 3, it is mentioned that there are other experimental scenarios in which there is one *Info* condition in the first 10 days before switching to another in the last 10 days, in order to simulate a replacement of an existing information service with another. In two of these scenarios, the initial *TTABLE* condition was switched to either *DYN-UNREL* or *DYN-REL* conditions. Both Figures 5-9 and 5-10 show marked and sustained increases in the proportion of participants changing their t_b choices once they were exposed to dynamic estimates after Day 10.

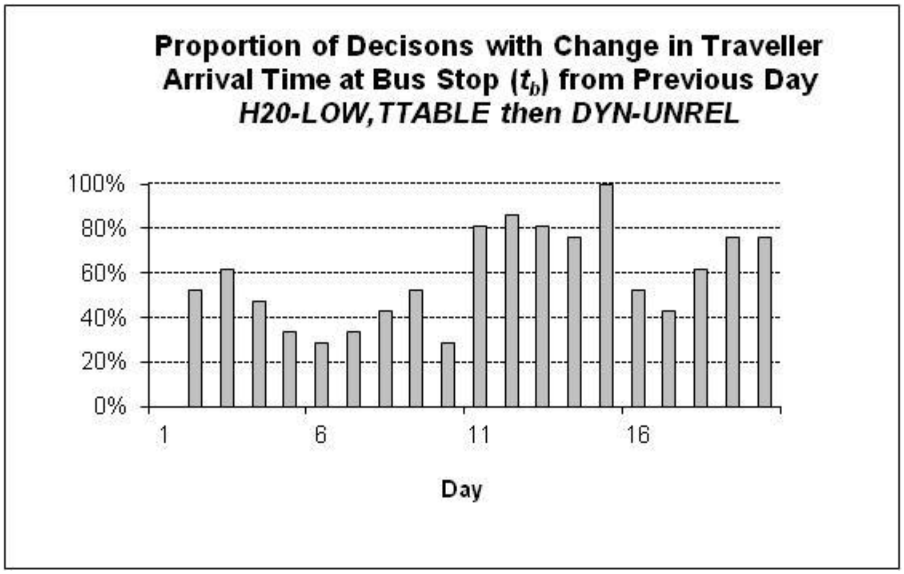


Figure 5-9 Proportion of Participants with Change in Arrival Time at Bus Stop from Previous Day for *H20-LOW, TTABLE to DYN-UNREL* Scenario

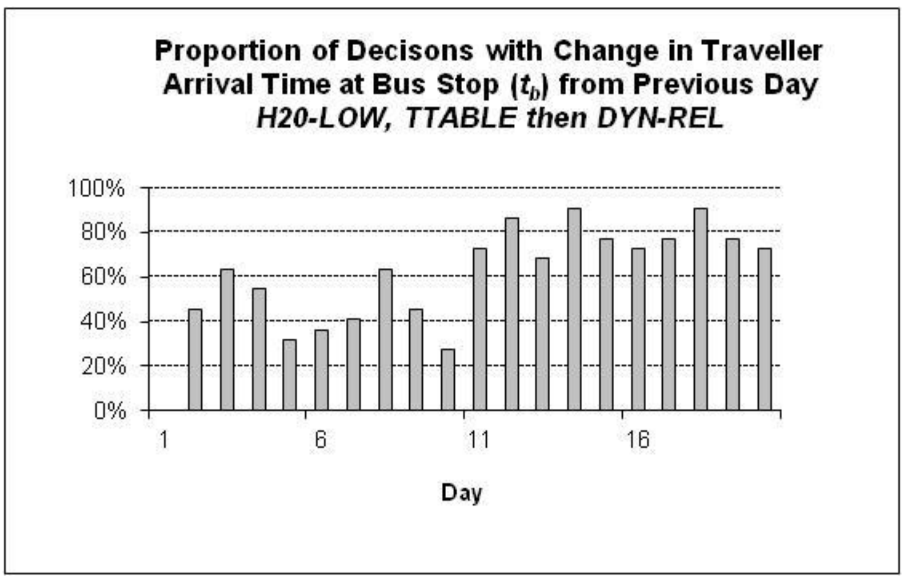


Figure 5-10 Proportion of Participants with Change in Arrival Time at Bus Stop from Previous Day for *H20-LOW, TTABLE to DYN-REL* Scenario

For comparison, one can examine another scenario (under the same *Ops* condition of *H20-LOW* condition) in which the switch is from *NO-INFO* to *TTABLE* (Figure 5-11). The introduction of static estimates did not appear to trigger any significant change in the participants' responses. The downward trend in the proportion of participants changing t_b continues, as in the case when there is no change in the *Info* condition (Figure 5-2).

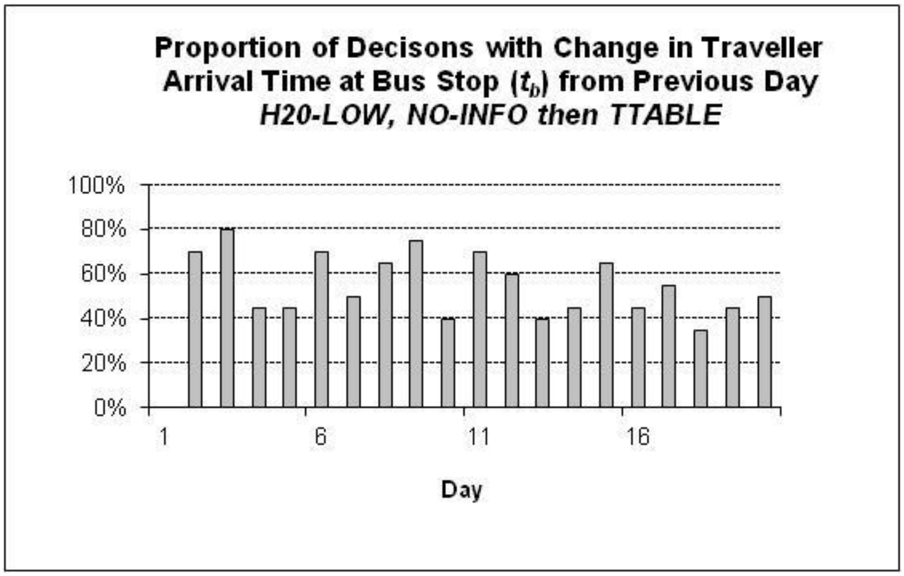


Figure 5-11 Proportion of Participants with Change in Arrival Time at Bus Stop from Previous Day for *H20-LOW, NO-INFO to TTABLE* Scenario

There is another more interesting observation from the t_b data. The observant reader may have noted that the range within which the mean t_b varies relative to the scheduled departure time, t_s^{sch} of the services differs according to the headway. When the headway is long at 20 minutes (*H20-LOW* and *H20-HIGH*), this range is located about half-way between the red and black horizontal lines, i.e., between the t_s^{sch} of the service that is the one that is the best service of the day for most of the 20 days (the 'red' service) and the one immediately preceding it. (See Figure 5-1) On the other hand, at shorter headways of 10 and 5 minutes (*H10* and *H5*), the mean t_b fluctuates around the t_s^{sch} of the earlier of the two services. (See Figures 5-3 and 5-4)

For ease of comparison across all *Info* and *Ops* conditions without resorting to inspecting all the t_b plots, Table 5-2 provides the mean deviation of t_b from the t_s^{sch} of the 'red' service over 20 days of each *Info-Ops* combination. These values provide a quick indication of the range within which the daily mean t_b fluctuates. A value of $-x$ means x minutes earlier than t_s^{sch} of the 'red' service. In the *H20-LOW* conditions, the t_s^{sch} of the 'red' service and of the service preceding it are at 0 and -20 respectively. The corresponding ranges of actual departure times t_s are $-2 \leq t_s \leq +6$ and $-22 \leq t_s \leq -14$. (Refer to Figure 3-5 for the distribution of t_s under the low t_s variability condition). Now, because the mean t_b values for these conditions are between –10.0 and –15.3 (third column of Table 5-2), one can argue that the participants are most likely to be attempting to catch the 'red' service. In the *H20-HIGH* conditions (fourth column), the means are between –11.1 and –14.9. When compared with the actual t_s ranges, one can similarly infer that the targeted service is more likely to be the 'red' service ($-3 \leq t_s \leq +7$) instead of the preceding one ($-23 \leq t_s \leq -13$) (Refer to Figure 3-6 for the distribution of t_s under the high t_s variability condition).

Table 5-2 Mean Deviation of Passenger Arrival Time from Scheduled Departure Time of 'Red' Service over 20 Days by *Ops* and *Info* Conditions

Mean over 20 days		***Ops* Condition**					
		H20-LOW	***H20-HIGH***	***H10-LOW***	***H10-HIGH***	***H5-LOW***	***H5-HIGH***
Info condition	*NO-INFO*	-12.1	-11.1	-10.6	-9.5	-7.5	-7.7
	HDWAY	-10.0	-12.4	-11.0	-7.6	-6.5	-5.3
	TTABLE	-15.3	-11.6	-9.9	-7.6	-5.1	-6.6
	DYN-UNREL	-13.4	-14.9	-9.3	-8.0	-6.3	-7.2
	DYN-REL	-13.1	-12.0	-8.4	-8.0	-5.8	-5.7

In contrast, in the *H10* scenarios, the conclusion is different if the same inference approach is used. With mean values between –7.6 and –11.0, the likely targeted service is the service before the 'red' service ($-12 \leq t_s \leq -4$ for *H10-LOW*, and $-13 \leq t_s \leq -3$ for *H10-HIGH*) instead of the 'red' service itself ($-2 \leq t_s \leq +6$ and $-3 \leq t_s \leq +7$ respectively). In the *H5* scenarios, the t_s ranges of successive services overlap substantially and the same inference approach is therefore not admissible. Nonetheless, with mean values of between –5.1 and –7.7, the most likely targeted service is the service before the 'red' service again, by reason of their proximity to its $t_s^{sch} = -5$.

Now, it appears, from the locations of the mean t_b, that the participants were attempting to catch the 'red' service when the headway was long (20 minutes), but an earlier service when the headways were shorter (5 and 10 minutes). To explain such a phenomenon, one could perhaps suggest that, in *H20* scenarios, participants perceived the 'red' service as the only viable option because taking the earlier service would have resulted in them arriving at the destination excessively early (around 20 minutes). However, they also could not afford to miss the 'red' service; the consequence of missing it would be a long wait of about 20 minutes for the next service and the near certainty of being late for work. In consideration of this cost of missing the service and the variability of its t_s, they adopted one of the strategies described by Bonsall (2004) and in the descriptive scheme of Chapter 2: to build in a 'safety margin' that was manifested in the gap between the mean t_b and t_s^{sch} of the targeted 'red' service.

In contrast, when faced with shorter headways in *H10* scenarios, the participants appeared to choose the service preceding the 'red' service. Perhaps they had deemed arriving at the destination slightly more than 10 minutes earlier as acceptable. The interesting observation is that, unlike their counterparts in *H20* who arrived substantially earlier before t_s^{sch} of their targeted ('red') service, they did not appear to introduce much of a safety margin when attempting to catch their intended service. This could be seen by the mean t_b values that were inside the range of t_s of the targeted service. One can argue that a safety margin still existed in their decision-making; it was embedded in their choice of service. After all, they could miss their service on a number of days by choosing to arrive very close to the t_s^{sch}, but because the next available service is the 'red' service, they could still avoid being late. The same reasoning applies to *H5* scenarios.

Plausible as the above description appears, it is still not satisfactory. It offers an explanation for the presence of the safety margin in *H20* scenarios, but does not explain why that safety margin is so large. Notice that the earliest possible t_s of the 'red' service was -3 (in the high variability condition) while the mean $t_b \leq -10$, implying that the participants were willing to incur long wait times generally. Even in *TTABLE*, *DYN-UNREL* and *DYN-REL* conditions in which the participants were given an indication of the location of t_s, they still chose t_b that were very much earlier than was necessary. One may also question why the participants in *H5* and *H10* did not attempt to catch the 'red' service. It is highly unlikely that all of them were averse to catching the 'red' service. Again with t_s no earlier than -3, they could have found a range of t_b that offers a suitable safety margin to catch the 'red' service, without needing to seek safety in the choice of a service that was 10 minutes earlier and clearly, less rewarding.

By now, the reader would have realised a flaw in the approach to use the mean t_b to infer the choice of service. This approach is admissible if the participants were relatively homogeneous in their choice behaviour, and the distribution of t_b is such that the aggregated mean is representative of their collective choice. The distributions of t_b are examined again. Figure 5-12 shows the distribution of the choices of t_b aggregated across all the participants and all days for one of the 30 *Info-Ops* combinations, *H20-HDWAY* scenario. As mentioned earlier in this Chapter, the scheduled departure time of the 'red' service, t_s^{sch} was set at zero, hence negative values on the time t axis of this histogram denote units of time which are earlier than this departure time, and positive values, later. The t_s^{sch} of all services in this scenario are at t = -60, -40, -20, 0 ('red'), 20 and so on, the locations of which are indicated by the vertical dotted lines.

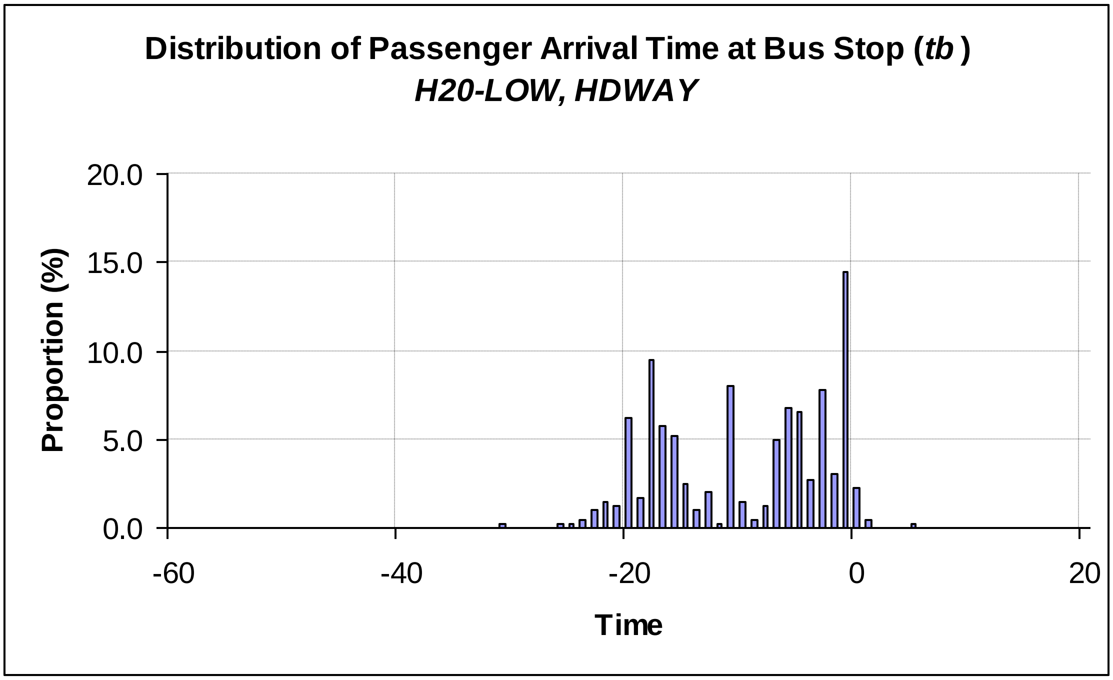


Figure 5-12 Histogram showing Distribution of Arrival Time Choices under *H20-LOW, HDWAY* Scenario

The histogram reveals a distinctly bimodal distribution of t_b values, with most of these values clustering close to either t = -20 and t = 0, i.e., over 20 days, the participants chose t_b mostly close to the t_s^{sch} of the 'red' service or the service preceding it. It clearly illustrates that it is erroneous to assume that the participants targeted the 'red' service, as has been done previously. Those who did attempt to catch this service did not appear to adopt a large safety margin, also earlier assumed, because the mode is actually at t = -1, just 1 minute away from t_s^{sch} of the service.

Moving to a scenario with a shorter headway of 10 minutes (*H10-LOW*) and 5 minutes, the distributions differ from the preceding one substantially. Figures 5-13 and 5-14 show the histograms for *H10-LOW* and *H5-LOW* respectively, under the *HDWAY* condition. No longer is the bimodal distribution apparent. Most of the clustering now occurs close to t_s^{sch} of the service immediately before the 'red' service (t = -10 for *H10-LOW* and t = -5 *H5-LOW*). This set of observations appears to support the earlier conclusion on the choice of service in *H10* and *H5* scenarios. However, it is noted that not an insignificant proportion of t_b values are located within the vicinity of t_s^{sch} of the 'red' service and of the second service before the ‘red’ service. So there is still the presence of heterogeneity in the choice of service.

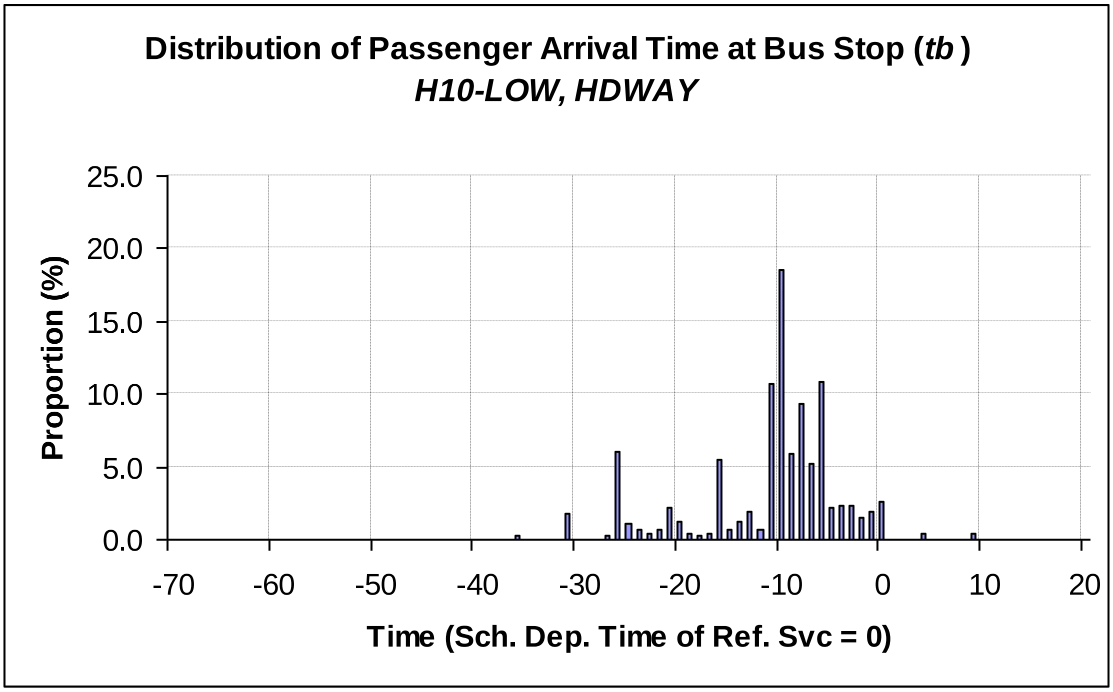


Figure 5-13 Histogram showing Distribution of Arrival Time Choices under *H10-LOW, HDWAY* Scenario

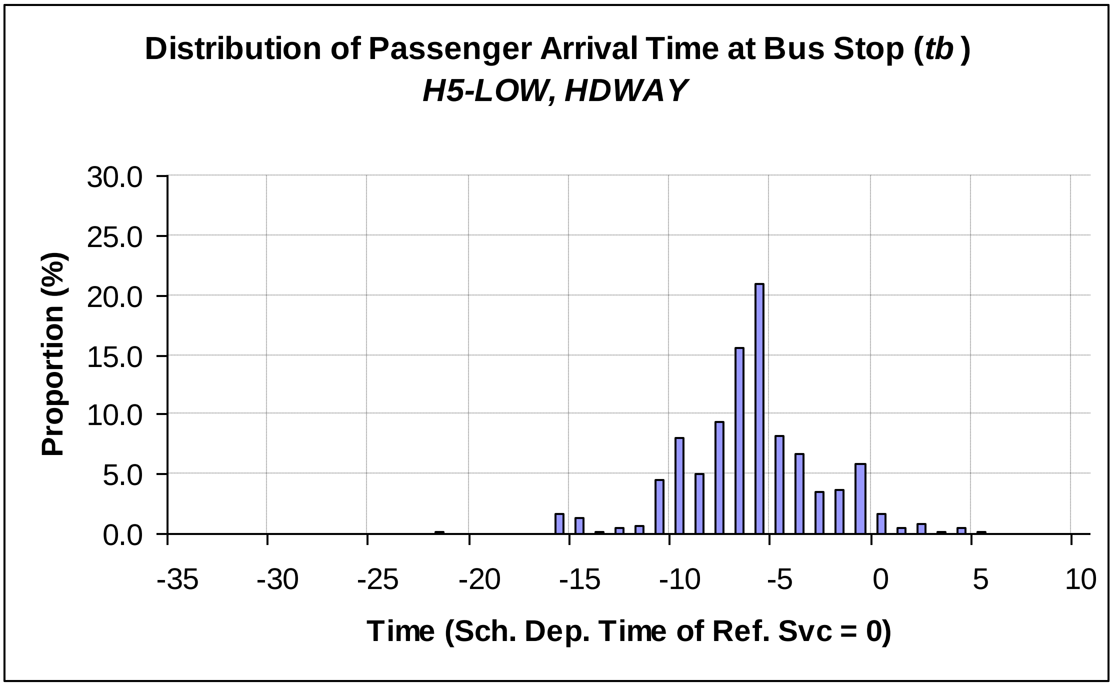


Figure 5-14 Histogram showing Distribution of Arrival Time Choices under *H5-LOW, HDWAY* Scenario

The histograms of t_b in Figures 5-12 to 5-14 are able to shed some light on the participants' actual choice of service, and demonstrates that it could be a better approach than using the mean t_b over 20 days to infer (erroneously) the (one and only) service the participants chose. However, subjecting oneself to scrutinise visually all the 30 histograms (5 *Info* conditions for each of the 6 *Ops* conditions) and making a subjective assessment of which service the participant has likely chosen from the t_b data points, is an exhaustive and exhausting effort. Fortunately, there is a more fruitful and expedient way to do so, and it has already been carried out previously. As the discussion has already progressed into the choice of service, it is now the opportune time to examine it in greater detail.

5.2 Analysis of Passenger Choice of Service

Recall in Chapter 3, a set of rules has been formulated (Section 3.3.1.1) to infer the choice of service using t_b for each and every instance of decision-making to determine if the best service of the day is chosen. Recall that the rules define the assignment ranges of successive services. If t_b falls within the range of a particular service, it is deemed that that service is chosen (see Figures 3-8 to 3-10). This is now the opportune time to use these rules to investigate how participants decide on their service. To demonstrate their application, the boundaries of the assignment ranges are overlaid onto the histograms of t_b in Figures 5-12 to 5-14. The histogram of *H20-LOW, HDWAY* in Figure 5-15 is reproduced from Figure 5-12, with the boundaries of the assignment ranges, marked by the dotted lines, introduced. One can see the boundaries broadly match the troughs in the distribution, and such an observation provides one with a quick visual assessment that the rules have been reasonably formulated.

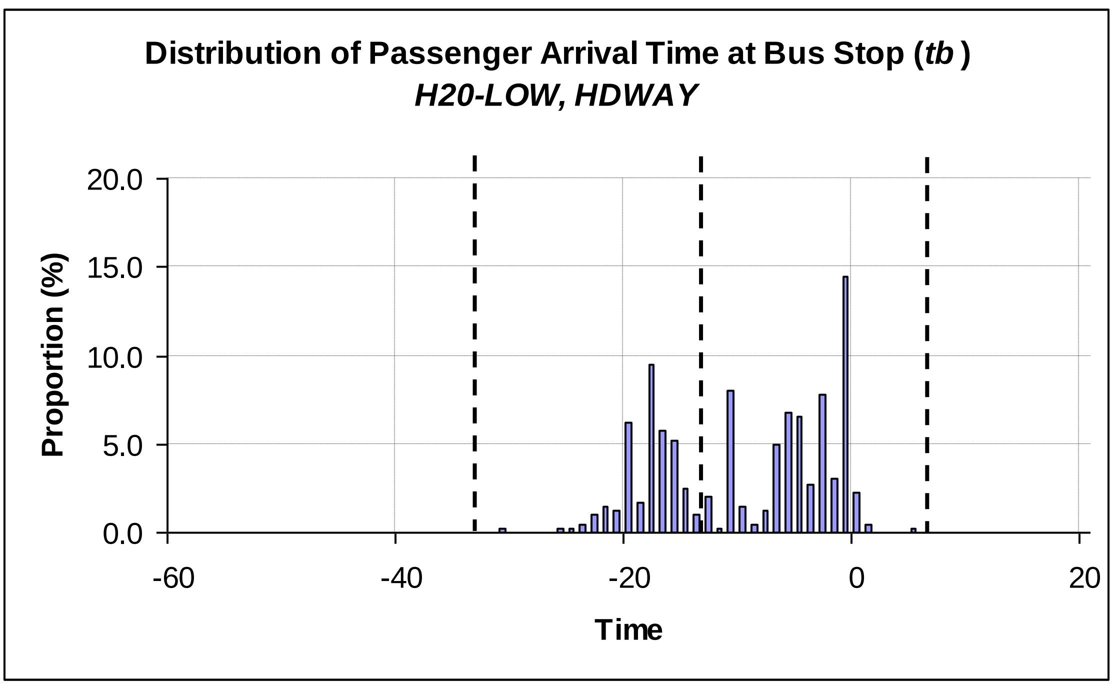


Figure 5-15 Application of Assignment Rule on *H20-LOW, HDWAY* Scenario

It is less apparent if this set of rule agrees with the actual observations of shorter headway scenarios as well as it does with those in Figure 5-15. This is because most of the t_b values in the *H10-LOW, HDWAY* and *H5-LOW, HDWAY* scenarios cluster mostly around only a single t_s^{sch} (that of the service before the 'red'), unlike in *H20-LOW* scenario in which the bimodal distribution predominates. Nevertheless, as illustrated by Figures 5-16 and 5-17, the inference rules are still able to partition the t_b distribution into reasonable clusters.

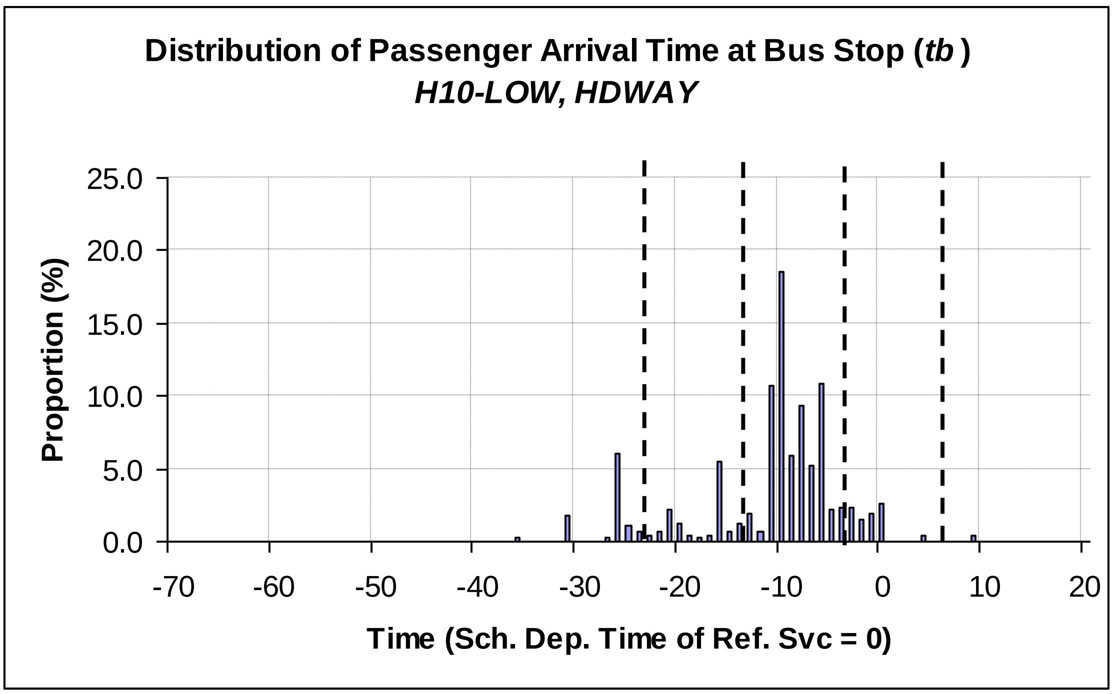


Figure 5-16 Application of Assignment Rule on *H10-LOW, HDWAY* Scenario

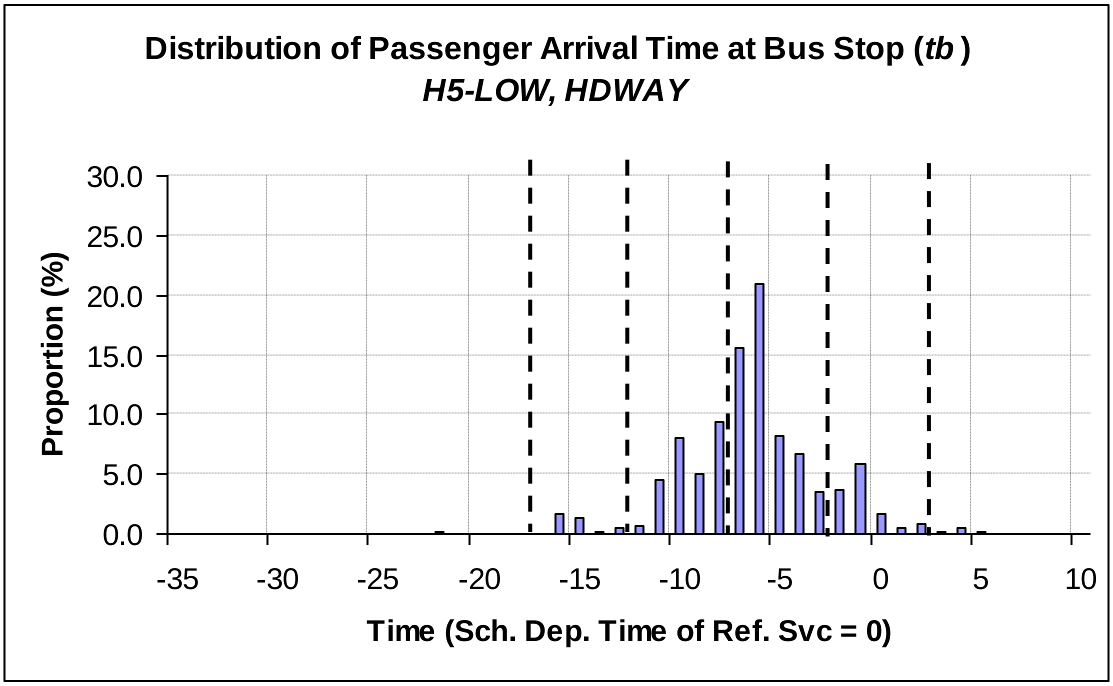


Figure 5-17 Application of Assignment Rule on *H5-LOW, HDWAY* Scenario

Using these inference rules, histograms of targeted services can be derived from the histograms of t_b. For example, the latter histograms shown in Figure 5-15 to 5-17 are transformed to the former, as shown in Figure 5-18 to 5-20. These histograms reveal a clearer picture of the choice of services by the participants over 20 days under each *Info-Ops* scenario. They show that, across all scenarios, the participants' choices did not concentrate on a single service; there are at least two services that have been chosen frequently. The 'red' service, labelled as 'Service 0', is a competitive choice in the *H20-LOW, HDWAY* scenario (Figure 5-18), but not the only one as is originally described. On the other hand, the service before the 'red' service is the superior option in the corresponding *H10* (Figure 5-19) and *H5* (Figure 5-20) scenarios, as predicted earlier. However, it is again not the only choice.

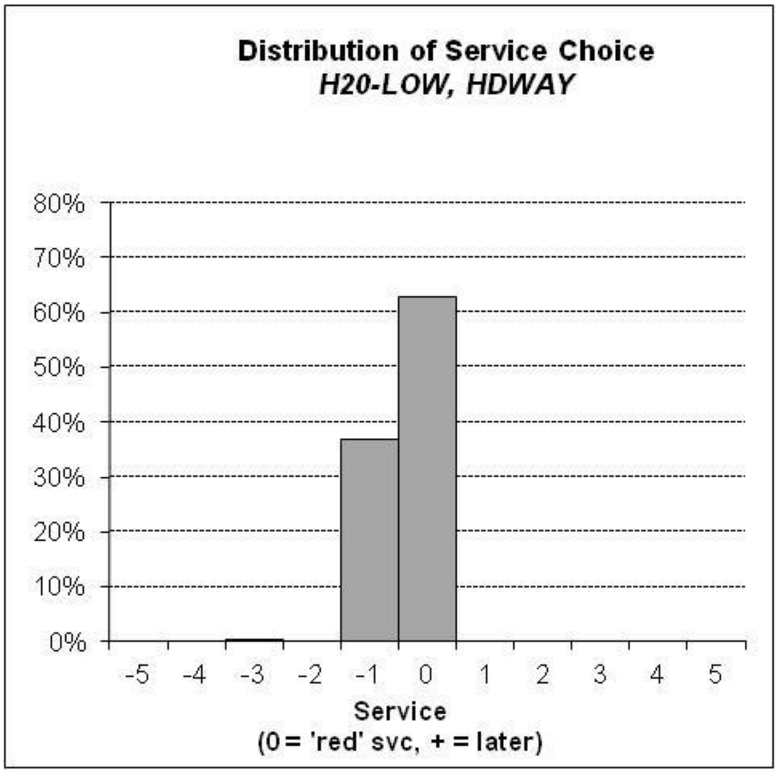


Figure 5-18 Distribution of Targeted Services for *H20-LOW, HDWAY* Scenario

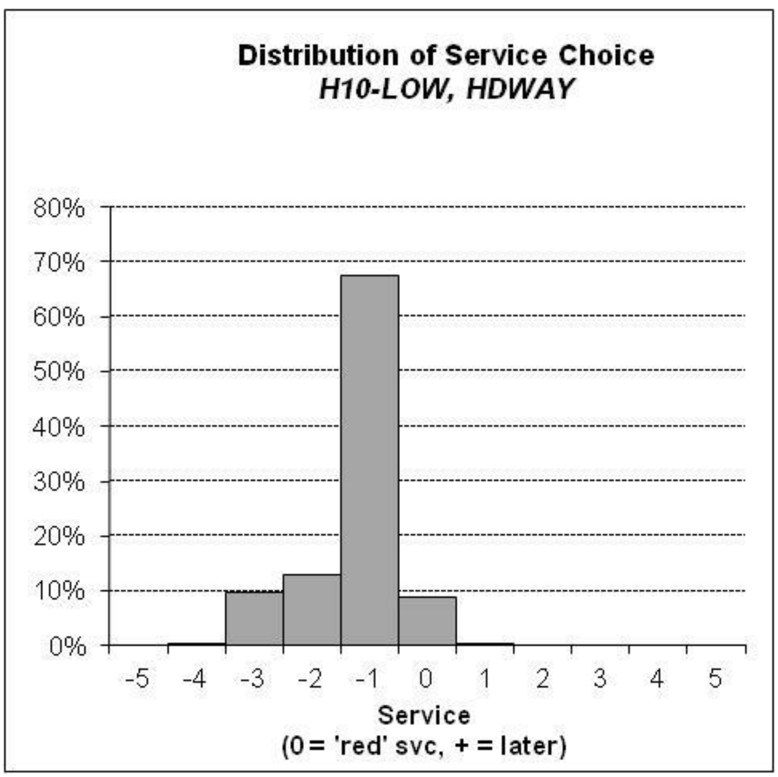


Figure 5-19 Distribution of Targeted Services for *H10-LOW, HDWAY* Scenario

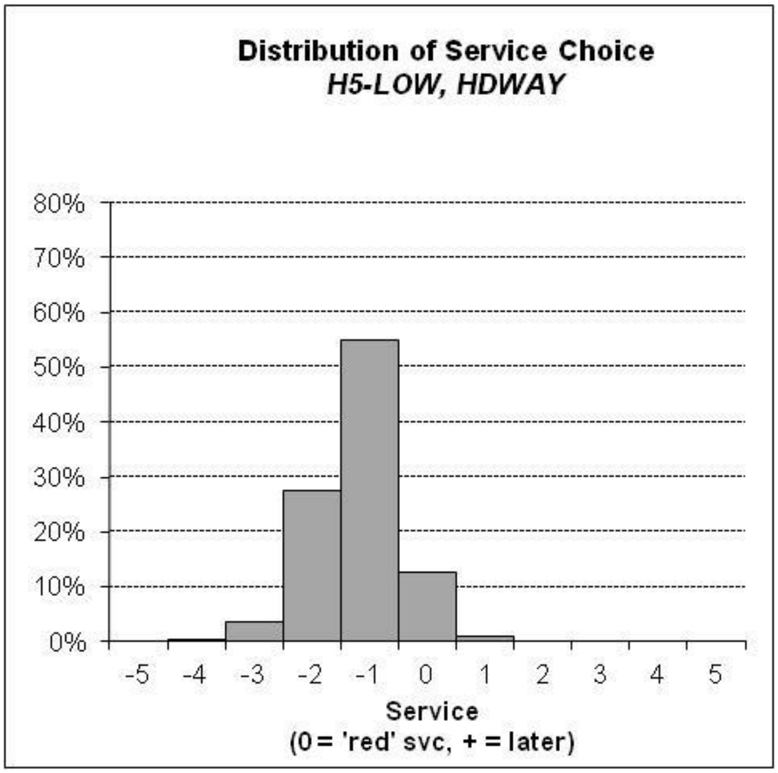


Figure 5-20 Distribution of Targeted Services for *H5-LOW, HDWAY* Scenario

In lieu of presenting the histograms of all *Info-Ops* combinations, the distributions of the targeted services by *Ops* and *Info* conditions are shown in Table 5-3. Only three services are shown because they account for almost all of the choices. It is observed that the participants have not chosen a particular service exclusively but selected two or more services over 20 days across all scenarios. In all but five *Info-Ops* combinations, the service immediately preceding the 'red' service is the most popular choice over 20 days. The 'red' service is a competitive choice only when the headway is 20 minutes, but even so, it is the first choice in only 5 out of 10 scenarios with a 20-minute headway.

Table 5-3 Distribution of Targeted Service over 20 Days by *Ops* and *Info* Condition

***Info* condition**	**Choice of Service**	***Ops Condition***					
		H20-LOW	***H20-HIGH***	***H10-LOW***	***H10-HIGH***	***H5-LOW***	***H5-HIGH***
NO-INFO	*Second before 'Red'.*	2%	0%	17%	7%	31%	18%
	First before 'Red'.	41%	35%	**78%**	**62%**	**44%**	**55%**
	'Red'	**57%**	**64%**	4%	26%	15%	12%
HDWAY	*Second before 'Red'.*	0%	1%	13%	5%	28%	16%
	First before 'Red'.	37%	46%	**68%**	**67%**	**55%**	**58%**
	'Red'	**63%**	**53%**	9%	25%	13%	20%
TTABLE	*Second before 'Red'.*	2%	0%	13%	5%	15%	40%
	First before 'Red'.	**58%**	42%	**72%**	**80%**	**53%**	**41%**
	'Red'	38%	**57%**	10%	14%	22%	17%
DYN-UNREL	*Second before 'Red'.*	4%	2%	12%	20%	31%	20%
	First before 'Red'.	**49%**	**60%**	**77%**	**46%**	**45%**	**46%**
	'Red'	46%	37%	9%	33%	19%	19%
DYN-REL	*Second before 'Red'.*	2%	1%	7%	14%	27%	28%
	First before 'Red'.	**52%**	**50%**	**67%**	**52%**	**45%**	**48%**
	'Red'	45%	48%	23%	32%	21%	20%

Earlier, it has been inferred from the mean t_b (Table 5-2) that the service being targeted by the participants is the 'red' service when the headway is long (20 minutes), and the preceding one when the headways are shorter (5 and 10 minutes). It is further interpreted that when selecting the 'red' service, the participants adopted a large 'safety margin' in when deciding on their t_b whereas they did not appear to do so if the intended service is the one preceding the 'red' service. The findings from Table 5-3 show that the first interpretation on the choice of service is inaccurate. However, it would be interesting to know if the second interpretation on the 'safety margin' is valid.

Table 5-4 lists the mean deviations of t_b from the scheduled service departure time t_s^{sch} of the targeted service. The mean values for choices targeting the 'red' service are in standard font, and those for the remaining non-'red' services in *italics*. A negative value indicates a t_b that is earlier than t_s^{sch}. In all the scenarios, the non-'red' services are, with very few exceptions, those that depart before the 'red' service.

Table 5-4 Mean Passenger Arrival Time Relative to Scheduled Departure Time of Targeted Service by Scenario

		***Ops* Condition**					
***Info* conditions**	**Service Targeted**	*H20-LOW*	*H20-HIGH*	*H10-LOW*	*H10-HIGH*	*H5-LOW*	*H5-HIGH*
NO-INFO	'Red' Service	-5.99	-7.24	-1.68	-1.91	-1.16	-0.83
	Others	*1.35*	*2.13*	*0.94*	*1.38*	*-0.27*	*-0.15*
HDWAY	'Red' Service	-4.90	-5.12	-1.17	-1.35	-0.88	-1.05
	Others	*1.68*	*-0.40*	*1.69*	*2.24*	*-0.26*	*0.11*
TTABLE	'Red' Service	-4.38	-5.63	-1.11	-0.79	-0.62	-0.68
	Others	*-0.19*	*0.55*	*1.81*	*2.10*	*-0.03*	*-0.27*
DYN-UNREL	'Red' Service	-3.09	-5.22	-1.14	-0.90	-1.31	-0.54
	Others	*0.44*	*0.39*	*1.34*	*2.40*	*0.09*	*-0.29*
DYN-REL	'Red' Service	-1.88	-3.45	0.20	-0.60	-0.76	-0.63
	Others	*-0.47*	*0.27*	*1.23*	*1.45*	*-0.13*	*0.07*

One can easily notice an interesting relationship: without exception, the mean value for the 'red' service is less than that for the other earlier services. This means that, relative to the scheduled departure time, the participants chose to arrive earlier on average when participants targeted the 'red' service than when they selected the earlier services. In other words, one is witnessing an interesting phenomenon in which the choice of a riskier service (in terms of being late) is associated with more conservative arrival time choices, whereas less risky service choices appear to lead to greater willingness to bear a higher risk of missing the service. As postulated earlier, the possible reason is that if a participant attempts to catch a service before the 'red' service, he may have perceived that, even if he were to miss this service, he would still not be likely to be late by boarding the 'red' service that departs next. Hence he could afford to be more risk-taking, simply because his safety margin is already embedded in his choice of service. In contrast, if he targets the 'red' service, he would be cognisant of the fact that he does not have a safety margin in the service choice, and would therefore adopt a larger safety margin in the arrival time instead.

5.2.1 Analysis of Choice of Service over Time

One can make further inference pertaining to the choice of service from Table 5-3. There can be two possible interpretations of the findings. The participants could have chosen a number of services in the early period, but gravitate increasingly towards one of them, i.e. towards homogeneity in the choice of service over time. Another opposing interpretation is that most participants decide on just one particular service in the initial period and do not change their choice subsequently even with learning, or sustained heterogeneity. However, the findings in Table 5-3 are not informative because it aggregates all the choices over all 20 days in a session, and one cannot discern how the choice evolves over time, if at all. To confirm which of these two arguments is more valid, and also to have a more complete understanding of participants' behaviour, one needs to examine their choice(s) of service over time.

One may recall that the evolution of the participants' choice of service over time has been investigated previously. This is with respect to whether the best service of the day is chosen. In Chapter 4, it has been hypothesised that in all *Info* conditions except *TTABLE*, the proportion of participants choosing the best service of the day (P_{best}) will increase over time in general (see Figure 4-1). However, statistical tests have revealed insufficient evidence that such trends exist (See Tables 4-14 and 4-15).

Perhaps, it is unrealistic to expect the participants to be able to identify the best service of the day consistently and improve on their ability to do so, even with experience and the availability of information. After all, they have to face not only the variability in t_s, but also in the in-vehicle time, T_v. Even if the participant were to be given perfectly reliable (dynamic) estimate of t_s ($t_s^i = t_s$) or were prescient about t_s of each and every service, the service she selects could still result in her being late due to an out-of-norm T_v.

To examine how the choice of service evolves, it may be instructive to consider how Avineri and Prashker (2006) and Ben-Elia *et al.* (2008) analyse the participants' choices. In their studies, the participant chooses between two routes, with one of them having a lower mean travel time. If the hypothetical traveller were to maximise his utility, he would consistently choose the route with the lower mean travel time. Note that the faster route does not necessarily have the lower travel time every single day because of the variability of travel times along both routes. So, even if a participant seeks to maximise utility by choosing the faster route every day, he would have ended up with the worse of two options occasionally. Whether the participants choose the faster route *on any given day* is not an issue of concern. Instead, the proportion of participants choosing the route that is faster *in general* is examined for the presence and evolution of utility maximising behaviour over time. This proportion is labelled the maximisation rate.

It might be fruitful to follow similar line of investigation and see if there is insight to be found by framing the analysis as one that is analogous to the choice situations of Avineri and Prashker (2006) and Ben-Elia *et al.* (2008) and contrast the findings of that study with those just described for this study. But, one would wonder how the choice behaviour relating to services in a bus route be comparable to that relating to two alternative driving routes in their studies. In the current scenario, the public transport user also has to make a choice, but in a service out of ten possible ones on the same bus route. As in the route-choice scenarios, the current one should also have one of the bus services with the lowest disutility, and the proportion of participants choosing it can also be tracked over time. Identifying this bus service is straightforward. Recall that there were ten services from which the participant had to pick one that she believed was the most appropriate to meet her travel objectives. Indeed, the experiments were intentionally designed to contain one particular service in each *Ops* condition whose scheduled departure time at the stop and scheduled in-vehicle time would most likely result in the traveller ending her trip at a time closest to, but not later than, the *PAT*. However, given the variability in departure and in-vehicle times, selecting this service might not actually result in the best possible outcome every single day. This service would be associated with the highest score among all other services for most, but not all, of 20 days. In other words, it is the 'red' service that has been mentioned extensively in this Chapter. For ease of subsequent discussion, this service is termed the utility-maximising service or '*maximising'* service in short henceforth.

Table 5-5 shows the number of days in which the highest score among all services was attained and the number of days in which the arrival of the traveller at the destination would be late over 20 days for this maximising service across all six *Ops* conditions, and for comparison, for the two services preceding it. The scores in the table were computed assuming the waiting time was zero. The total number of days with highest score exceeds 20 in a few *Ops* conditions because of ties. Note that in certain instances, especially in *H20-LOW* and *H20-HIGH*, a service that arrives late at the destination may still have the highest score among all the services, and hence the numbers of highest score days and of late arrival days for a particular service do not necessarily add to 20. Also, in both *H5-*

LOW and *H5-HIGH*, the first service after the maximising service has the highest score on 2 days, but this information is not shown. It confirms that the 'maximising' service has the largest number of days on which it has the highest score in all *Ops* conditions. On the other hand, choosing only this service over the entire 20-day period will result in the traveller being late to work between 4 and 9 days, significantly higher than any of its counterparts. It can be easily distinguished from the other services by any or all of these measures. Hence, this maximising service is a risky choice but one that is most rewarding overall.

Table 5-5 Mean Score, Number of Days with Highest Score and with Late Arrivals for Selected Services across *Ops* Conditions

Service	**Highest score days**	**Late arrival days**	**Highest score days**	**Late arrival days**
	H20-LOW		*H20-HIGH*	
Maximising	14	8	18	7
First before Maximising	6	0	3	0
Second before Maximising	0	0	0	0
	H10-LOW		*H10-HIGH*	
Maximising	13	9	14	6
First before Maximising	8	0	6	0
Second before Maximising	0	0	0	0
	H5-LOW		*H5-HIGH*	
Maximising	11	7	14	4
First before Maximising	6	2	4	2
Second before Maximising	1	0	1	0

As in Avineri and Prashker (2006) and Ben-Elia *et al.* (2008), one can track the proportion of participants choosing the maximising service, or the maximisation rate, over time. The findings in these studies could be used to provide a useful benchmark for comparison. However, one must be mindful of an important difference between two experimental settings even as it is asserted that that route choices and bus service choices are analogous. In the work of Avineri and Prashker (2006) and Ben-Elia *et al.* (2008), not only are the travel times of the alternative routes not the same, their variability also differs generally. In contrast, the current experimental scenarios draw the departure times of each service from the same distribution. This is not unrealistic because the bus user is unlikely to differentiate between successive services of the same route by their departure time variability. This difference poses a challenge in the attempt to make a meaningful contrast. Fortunately, out of the three route travel time scenarios in Ben-Elia *et al.* (2008), one of them (labelled the "Low-Risk" scenario) has the two routes having the same deviation of ±5 minutes around the means of the routes that are 25 minutes and 30 minutes for faster and slower routes (Route *F* and Route *S*), respectively. Under this scenario, the participant was given no information except for the post-choice feedback of the actual travel time of his selected route. The counterpart received simulated dynamic travel time information in the form of a variable range of estimated travel times for each of the routes, in addition to the feedback. The findings are that the faster route *F* was more likely to be chosen by both groups of participants with and without information. The group without information learnt over time that Route *F* was faster and the proportion of the group that chose this alternative with higher utility, i.e., the maximisation rate, increased progressively. The effect of providing information was apparent, especially in the initial period when the difference in the maximisation rate between the two groups was the largest. See Figure 5-21.

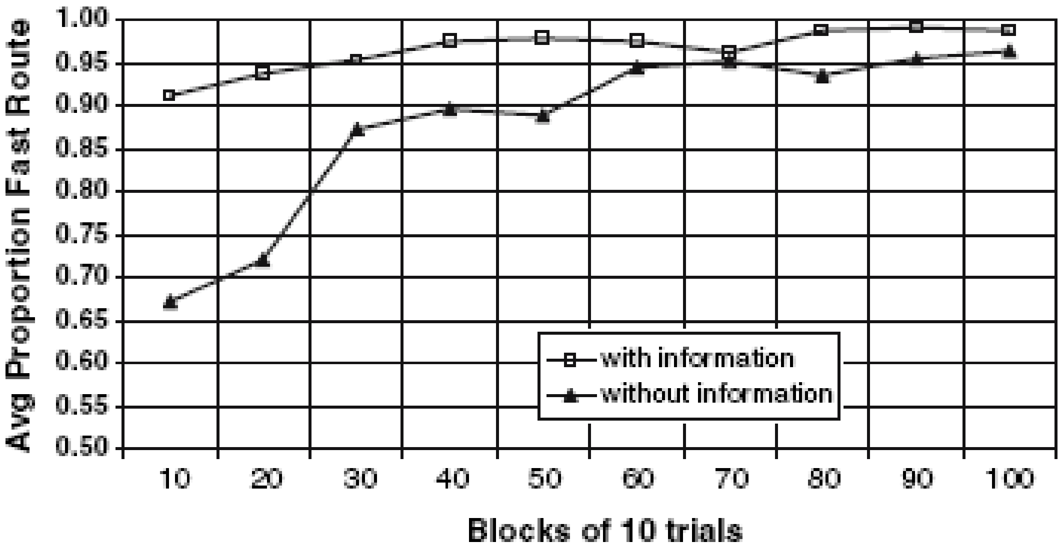


Figure 5-21 Chart of Maximisation Rate for the "Low-Risk" Scenario from Ben-Elia *et al.* (2008)

To examine if the maximisation rate increases in the current setting, i.e., whether the maximising service is being increasingly chosen with experience, the proportion of participants selecting the maximising service are plotted over the 20 days for all *Info-Ops* scenarios. See Appendix 5. The *NO-INFO* and *HDWAY* conditions can be treated as equivalent to the 'Without Information' condition in Ben-Elia *et al*. (2008), and *DYN-UNREL* and *DYN-REL*, to the 'With (Dynamic) Information'. There is no equivalent condition for *TTABLE* in the work of either Avineri and Prashker (2006) or Ben-Elia *et al*. (2008). Although the former study involves static information, it does not contain a scenario in which the two routes have the same travel time variability, as in the "Low-Risk" scenario in Ben-Elia *et al*. (2008) that allows meaningful comparison.

Figure 5-22 shows the plots for *NO-INFO* and *HDWAY* under the *H20-LOW* condition. The proportion of participants showed a small upward trend within, and slightly beyond, the initial period, discussed in Section 5.1, during which there is also a substantial number of changes in t_b. This lends some support to the postulate that the participants have been engaging in the exploratory process to identify the most appropriate service to catch. A net increase of participants switched from the original choice of a non-maximising service towards the maximising service. The upward trend in the maximisation rate flattens out after the initial period. Again, the flattening of the trend line coincides with the stabilisation in the mean t_b and in the proportion of participants changing t_b. The curves of *NO-INFO* and *HDWAY* in Figure 5-22 appear to resemble that of its "Without Information" equivalent in Figure 5-21 to some extent, i.e., an initial increase before stabilising. In the corresponding plots of *H20-HIGH* (Figure 5-23), the plot for *NO-INFO* show a similar trend, but the *HDWAY* plot shows a downward trend instead.

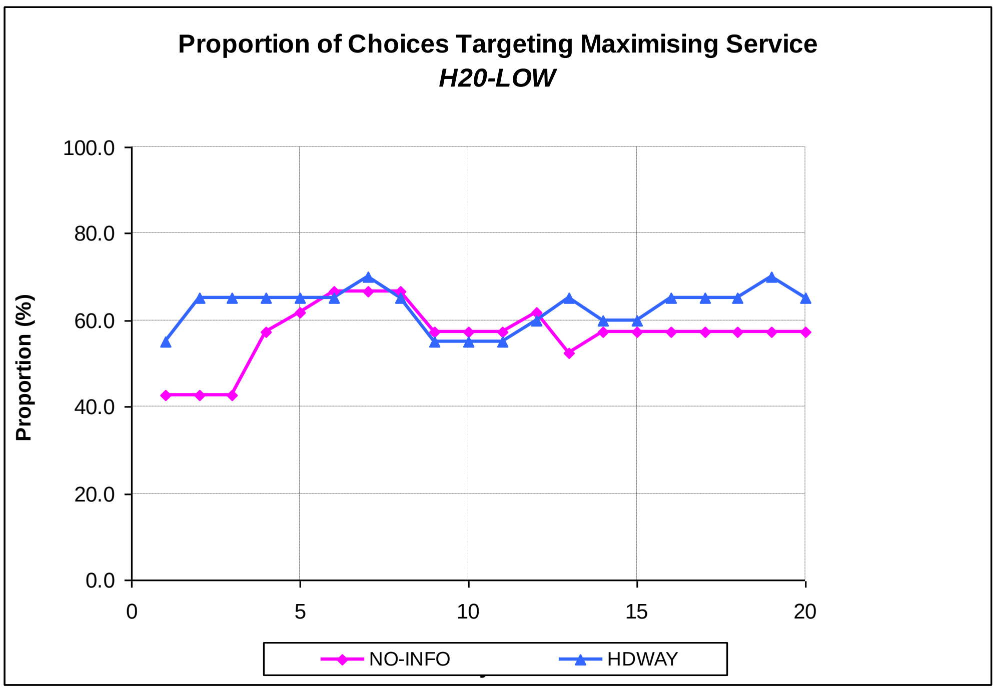


Figure 5-22 Proportion of Choices Targeting Maximising Service by Day for *NO-INFO* and *HDWAY* conditions under *H20-LOW* scenario

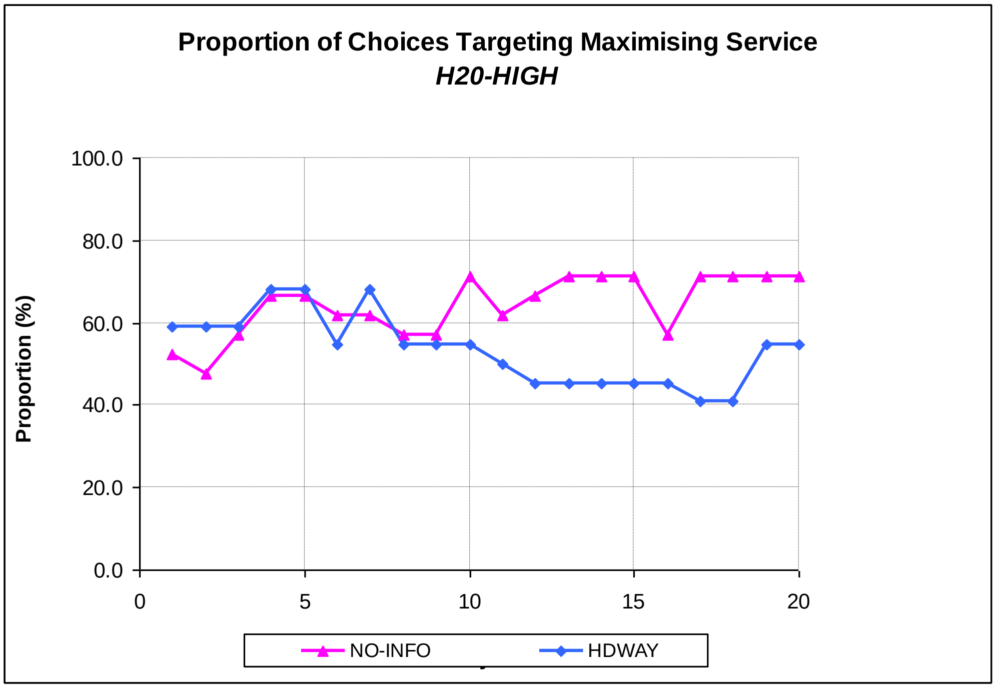


Figure 5-23 Proportion of Choices Targeting Maximising Service by Day for *NO-INFO* and *HDWAY* conditions under *H20-HIGH* scenario

The observations clearly deviate from those in the *H20* scenarios when the headway is reduced. In the *H10* and *H5* conditions, the maximisation rate follows a clear downward trend and varies within a range at a much lower level. Figures 5-24 and 5-25 are typical examples. In addition, even during the initial days, the maximisation rate rarely exceeds 0.5, one that is lower than the corresponding maximum in the *H20* scenarios. In fact, in some, e.g., the *NO-INFO, H10-LOW* scenario, the rate is no higher in the initial period than in the subsequent period. Unlike the *H20* scenarios, it appears that the majority of participants have opted *not* to maximise their utility.

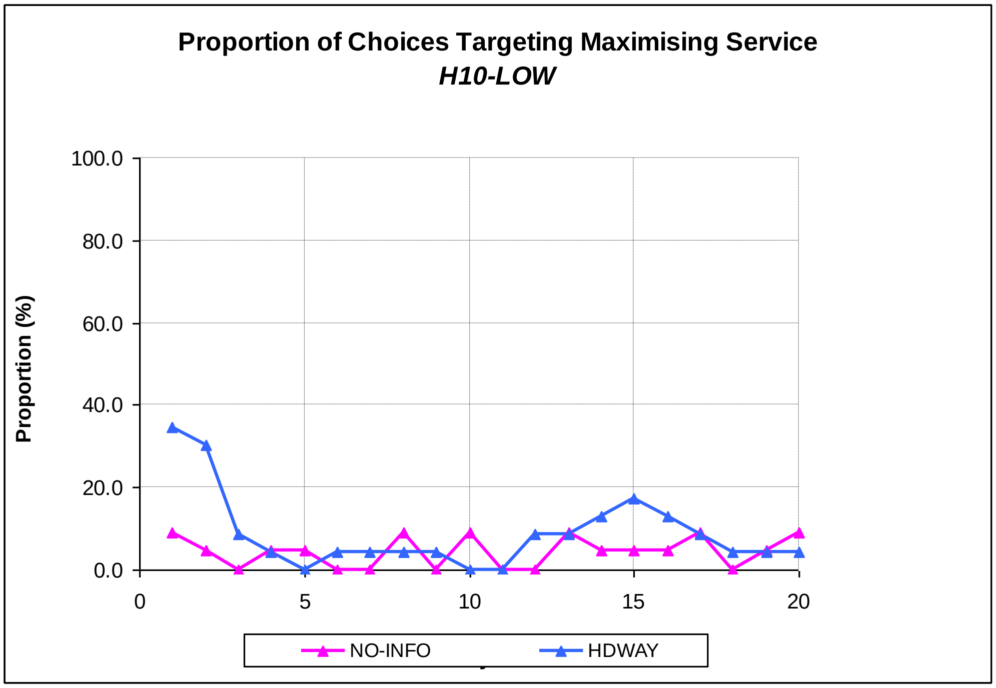


Figure 5-24 Proportion of Choices Targeting Maximising Service by Day for *NO-INFO* and *HDWAY* conditions under *H10-LOW* scenario

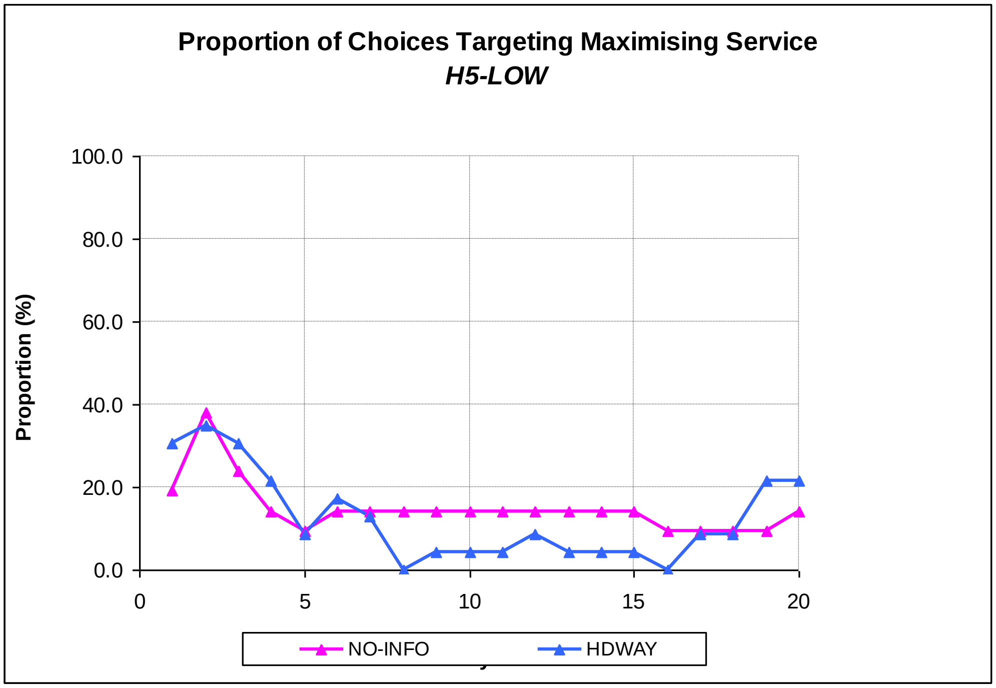


Figure 5-25 Proportion of Choices Targeting Maximising Service by Day for *NO-INFO* and *HDWAY* conditions under *H5-LOW* scenario

The discussion now moves on to scenarios involving dynamic information (*DYN-UNREL* and *DYN-REL*). Figure 5-26 shows an example of the plots under these two conditions in the *H20-LOW* scenario. Similar to *NO-INFO* and *HDWAY* plots in the same *Ops* condition (Figure 5-22), the proportion of participants choosing the maximising service shows an increase in the initial period, but no obvious upward trend subsequently. The key difference is that the plot exhibits substantially larger day-to-day fluctuations. This finding is consistent with the observations of large fluctuations in the mean t_b associated with these two conditions, as discussed in Section 5.1. A visual inspection of all the *DYN-UNREL* and *DYN-REL* plots in the remaining *Ops* conditions reveal that their overall trend mirrors those of its *NO-INFO* and *HDWAY* counterparts generally, except for more pronounced day-to-day variations. To complete the picture, the plots of *TTABLE* are also examined. Again, their trend characteristics do not appear dissimilar to those of *NO-INFO* and *HDWAY*.

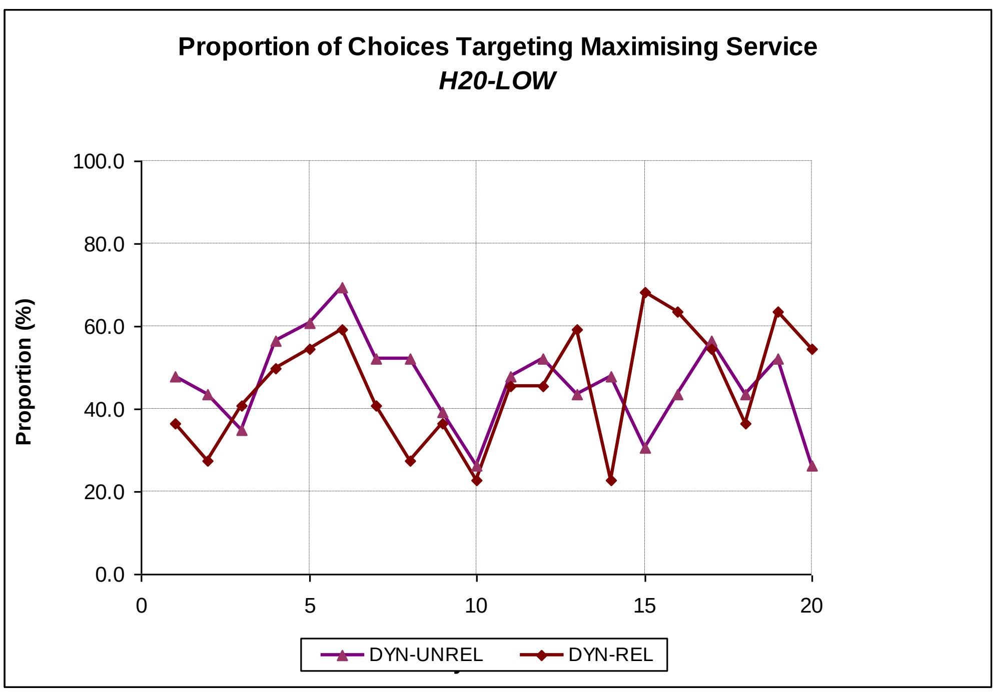


Figure 5-26 Proportion of Choices Targeting Maximising Service by Day for *DYN-UNREL* and *DYN-REL* conditions under *H20-LOW* scenario

Without resorting to statistical testing of trends, one can come to a conclusion quickly through visual comparison that the trends in the maximisation rate in the current experimental conditions have little similarity to those in Ben-Elia *et al.* (2008). From Figure 5-21, one can see that the proportion of participants choosing the Route *F* (the more 'maximising choice) increases persistently over time in both 'With Information' and 'Without Information' conditions. This proportion is consistently larger in the 'With Information' condition than the 'Without Information' condition across all the 10-day blocks, although the gap narrows over time. Although the corresponding plots in the *H20* scenarios of this study also show an upward trend, it is not sustained beyond the initial period of about 5 days, unlike those in Ben-Elia *et al.* (2008). In addition, the overall maximisation rates under the *DYN-UNREL* and *DYN-REL* conditions (equivalent to 'With Information') are not substantially higher than those under the *NO-INFO* and *HDWAY* conditions (equivalent to 'Without Information'), a finding opposite to those of Ben-Elia *et al.* (2008). In fact, in the *H20-LOW* condition, the former conditions attained much lower mean maximization rates of 46% and 45% respectively than the 57% and 63% in the latter, and in the *H20-HIGH* condition, similar observations are made (mean rates of 37% and 48% compared to 64% and 53%) (see Table 5-3). The discrepancies between the two experiment settings are even more apparent when the observations in the *H10* and *H5* conditions are considered. In these plots, there is no upward trend in the maximisation rate in the initial period. Instead of a continued rise, the rate declines and stabilises at a lower level from the peak of the initial surge. What is most noteworthy is that the upper limit of the variation in the maximisation rate is 0.4 in general, and at most 0.5 in the case of *H10-HIGH*. This is far lower than the rates observed in Figure 5-21.

One wonders why the current experiments produce outcomes that do not align with the findings of Ben-Elia *et al.* (2008). Perhaps they are not comparable directly. Certainly, whereas Ben-Elia *et al.* (2008) (and Avineri and Prashker (2006) as well) track the participants' responses over 100 simulated days, the current study limits the period to 20 days only. Perhaps if the number of simulated travel days were to be increased, an upward trend might still be observable. Certainly, in such *Info* conditions as *NO-INFO* (Figure 5-22) and *DYN-REL* and *DYN-UNREL* (Figure 5-26) in *H20-LOW*, one can see their maximisation rates still trending upwards moderately. There might be a possibility that the trends may continue beyond 20 days. However, this argument is tenuous at best because almost all of the remaining *Info* conditions exhibit a flat trend for a considerable number of days after the first few days, and there is no strong indication why more participants should decide to shift their choice to the maximising service subsequently. This is especially so in *NO-INFO*, *HDWAY* and *TTABLE* conditions in which the proportion of participants making changes to t_b decreases over time.

Even if it is decided that it is too much to expect the observations to be fully compatible with the findings of Ben-Elia *et al.* (2008), given the difference in context, one is still left with observations that do not fit intuition at the minimum and with questions why this is so. The first question is why a significant proportion of participants does not choose the maximising service when it can bring about an overall higher utility than other services, especially in lower headway scenarios in which only a very small minority does so. The second is why the provision of information does not induce significantly more participants to choose the maximising service than when information is not provided. This is counter to the common belief that information, especially if it is responsive and reliable, helps travellers make better decisions. The third is why do most of the participants who choose the non-maximising service initially do not learn through experience to switch their choice to the maximising service, i.e., exhibiting ‘stickiness’ in their choice. In fact, in some cases, the maximisation rate falls after the initial increase, indicating that some actually switch *away* from the maximising service after choosing it previously.

The participants’ behaviour appears much less consistent and intuitive than those that appear in Ben-Elia *et al.* (2008). It is already clear from the statistical tests on the hypotheses in Chapter 4 that the participants’ behaviour does not follow an intuitive, but shown eventually to be overly simplistic, descriptive scheme of learning under information in Chapter 2. Yet, from the preceding sections in this Chapter, the effects of information and learning are apparent in the variations in the mean and s.d. of t_b and the proportion of participants changing t_b (Section 5.1), as well as in the evolution of their choice of service in some of the scenarios (Section 5.2).

One possible explanation for the phenomenon observed is the payoff variability effect (Erev and Barron, 2005). One first re-examines Figures 5-22 and 5-23 that show the scenarios with *NO-INFO* and *HDWAY* with long headways (*H*20), where there are immediate feedback of outcome only. The proportion of participants choosing the maximising bus service (P_{best}) varies between 0.4 and 0.7, indicating close to random choices collectively. It may be argued that this is the effect of participants having to face the bundle of two sources of variability, the bus departure times, t_s, and in-vehicle time T_v, that result in highly variable outcomes (payoffs). Consequently, the collective behaviour of the participants tends towards random choices (of bus service).

The provision of dynamic information does not appear to increase the proportion of those choosing the maximising service, P_{best}. Figure 5-26 suggests that the choices become more random. It is suggested that the dynamic information, t_s^i, is an added source of variability itself. In fact, fully reliable t_s^i tracks the variable t_s, and does not reduce the variability faced by the participants.

As one moves to shorter headways (*H*10 and *H*5), one can observe that P_{best} trends downwards during the initial learning period and settles at less than 0.2. The majority of choices opt for the preceding service that provides a lower average payoff (in *Score*), but has a lower probability of adverse outcomes (of being late and a lower *Score*). This appears to be a manifestation of loss aversion, another effect that is postulated by Erev and Barron (2005) in scenarios with iterated tasks with immediate feedback,

It is also mentioned in Chapter 3 (Section 3.5.4) that there might be a concern of the incentive structure inducing the participants inadvertently to be more risk-seeking than they would be naturally. The evidence of this is that the case appears weak, given the conservative, loss aversion stance most participants took in selecting the services.

The endeavour to understand the participants' behaviour under learning and information provision can now take a different path. It is suggested that more useful insight can be obtained by venturing beyond the aggregate analytical approach used in Chapter 4 (and also in Ben-Elia *et al. (2008)* and Avineri and Prashker (2006)). Indeed, the heterogeneity in behavioural patterns discussed in the previous sections raises questions about the appropriateness of the aggregate approach described in this Chapter and in Chapter 4. It is very questionable if the mean values of the dependent variables, which are integral to these procedures, can be considered representative of the participants' behaviour under the various *Info* conditions. One should therefore proceed to a more disaggregate approach, one that examines how an individual participant responded on a daily basis and in terms of his choice of service and choice of bus stop arrival time in relation to his targeted service, to the feedback of the previous day's outcome and the current day's information content. This disaggregate approach is expected to be more challenging but should be more suitable for the current public transport scenario because of its relative complexity. The next section describes the investigation into the participants' decision-making patterns at a more disaggregate level

5.3 Behavioural Patterns in Choice of Service

The discussion returns to the *H20-LOW, NO-INFO* and *H20-LOW, HDWAY* scenarios to describe how the examination is carried out, see Figure 5-22. On the first day of the first scenario, most participants chose a non-maximising service. Although the maximization rate increased subsequently, the proportion of participants *not* choosing the maximizing service is still substantial. Even in the stable period (Day 5 onwards), these participants still formed a substantial minority, which is still quite stable. This observation suggests the likely presence of participants who had avoided selecting the maximizing service right from the first day, and persisted with this decision throughout the 20 days. The same can be described of the second scenario.

5.3.1 *Five Behavioural Types*

The investigation therefore looks at the choice decisions over 20 days of each individual participant. It begins by identifying the presence of a particular group of what one may deem expeditiously as “Fully Conservative” because this type of participant minimizes the risk of being late by targeting only a service departing earlier than the maximising service. It is found that 6 out of 21(29%) participants targeted only a non-maximising service over all 20 days in the session. Their presence is not unexpected. After all, participants have different risk profiles and it is inevitable that some of them would be disinclined to risk-taking. At the other extreme of the spectrum, there is also another group that targets the maximizing service only. Twenty-four percent (5 out of 21) belong to this group that will be labeled “Fully Maximising”. Again, the presence of a risk-seeking sub-group is not unanticipated, given that participants were heterogeneous in behaviour.

Given that both the “Fully Maximising” and “Fully Conservative” groups did not change the choice of service, they are of no further interest in terms of the evolution of choice behaviour. Nonetheless, the presence of these two groups set the range within which the maximisation rate varies. The proportion of “Fully Maximising” participants defines the lower limit of the range, and the corresponding proportion of “Fully Conservative”, the upper limit. The range defines the potential for the maximization rate to increase through the change in the choice of service by the remaining participants.

Among the remaining participants, some would have picked a non-maximizing service on the first day, and the rest, the maximising service. One of the necessary conditions for the maximization rate to increase is for those in the former sub-group to switch permanently to the maximizing service in the subsequent days. Hence, one can examine if there are some participants who have indeed behaved in such a manner. It is found that 5 (24%) participants did make this single switch. Four of them did the necessary change in service before the fifth day, i.e., within the initial period, with the lone ‘slow’ switcher doing so only on day 14. This group is classified “Maximising Switching”.

The remaining 5 started out with the initial choice of the maximizing service. If they were to maintain such a choice, the maximization rate would have been 71%. As one would have suspected, this is not the case. Figure 5-22 shows that the maximisation rate did not reach 70% at all, and for most of the session, it varied around the 60% level. One of the reasons is that 3 (14%) of the participants switched from the original choice of maximizing service to a non-maximising service. Such behaviour could be described as "Conservative Switching". Unlike the "Maximising Switching" sub-group, there is no clear pattern in terms of the timing of the switch; they made the change on Days 1, 8 and 12.

This leaves two final participants to be examined. Unlike the rest who made zero or one switch in the choice of service, they can be considered "Multiple Switching". In this scenario, both of them started off with a non-maximising service, and chose both the maximizing and non-maximising services on approximately an equal number of days (11 and 9 days respectively). However, one made only 2 switches, but the other made 5.

In summary, five behavioural patterns are identified among the participants with respect to the choice of service. They are: "Fully Conservative", "Conservative Switching", "Multiple Switching", "Maximising Switching" and "Fully Maximising". Table 5-6 shows that multiple switchers form the largest group, followed by those who are fully conservative, in all but one *Ops* condition. In the work of Avineri and Prashker (2006), five behavioural patterns are also discovered among the participants of the iterative route-choice experiments, and they are classified into such traveller types as "highly risk-averse", "risk-averse", "indecisive", "expected time minimisers" and "highly expected time minimisers". Although it is not the intention to demonstrate equivalence between the two sets of behavioural patterns (despite the same number of patterns), it is useful to note that one can draw certain analogies between them. Both sets attempt to describe the full spectrum of risk/reward seeking behaviour among the participants. To illustrate, a "fully conservative" participant in the current context chooses only the service(s) preceding the maximizing service such that the risk of being late appears to be minimised. This propensity to avoid risk is similarly exhibited by the "highly risk-averse" traveller of

Avineri and Prashker (2006), who chooses the less variable but slower route on most or all of the days. At the other end of the spectrum, both the "fully maximising" commuter and the "highly expected time minimiser" seek to maximise utility with the higher risk of incurring an outcome that is contrary to their intention.

Table 5-6 Distribution of Participants among Behavioural Groups

Ops	**Fully Conservative**	**Conservative Switching**	**Multiple Switching**	**Maximising Switching**	**Fully Maximising**
	Chose non-maximising service only	*Switched from maximising to non-maximising service*	*2 or more switches between maximising & non-maximising service*	*Switched from non-maximising to maximising service*	*Chose maximising service only*
H20-LOW	0.26	0.05	0.37	0.10	0.21
H20-HIGH	0.12	0.08	0.54	0.06	0.19
H10-LOW	0.50	0.11	0.37	0.02	0.00
H10-HIGH	0.39	0.12	0.46	0.00	0.04
H5-LOW	0.35	0.14	0.44	0.01	0.06
H5-HIGH	0.34	0.19	0.46	0.00	0.01
All	0.33	0.12	0.44	0.03	0.08

Before one explores the differences in the distribution of behavioural patterns across the *Info* and *Ops* combinations, it is useful to examine each type of behaviour in greater detail. Starting with that exhibited by "fully conservative" participants, because they chose only the service(s) preceding the maximising service, they had the lowest (but not zero) likelihood of arriving late at their workplace. As indicated in Table 5-5 earlier, if they were to catch their service preceding the maximising service every day, the outcome would be at most 2 late arrivals at the destination out of 20 days, or a late arrival rate of 10%, when the headways were 5 minutes (the two *H5* conditions), and no late arrivals in scenarios in which the service headways are 10 minutes or longer (the 4 *Ops* conditions of *H20* and *H10*). In the actual experiments, across all *Info* and *Ops* conditions, the mean rate is 11%,which is close to the expected rate. In 96% of these late arrivals, the participant missed her targeted service and caught the next service instead, i.e., the maximising service that happened to arrive at the workplace late. Table 5-7 summarises the choice outcomes and behavioural responses of the "fully conservative" participants.

Table 5-7 Distribution of Choice Outcomes and Responses of "Fully Conservative" Participants across all *Info* and *Ops* conditions

Outcome	Share	Failing to catch targeted service	Choice of Service following day		
			Later	No change	Earlier
Late	0.11	0.96	0.00	1.00	0.00
Not Late	0.89	0.35	0.00	1.00	0.00
Overall	1.00	0.41	0.00	1.00	0.00

At the other extreme end of the behavioural spectrum are the "fully maximising" participants. They are comparatively fewer in number, and are found primarily in the *H20* scenarios (see Table 5-6), with very few in the other *Ops* conditions. Because they chose the maximising service without exception, they would encounter a much higher risk of arriving late than the "fully conservative" participants. Again from Table 5-5, one can make some predictions about the outcomes in terms of late arrivals at the destination: out of 20 days, a "fully maximising" participant would be late on between 4 and 9 days (20% to 45%), depending on the *Ops* condition. Indeed, the outcome of 41% of the decisions made were late arrivals at the destinations across all scenarios, as shown in Table 5-8.

Table 5-8 Distribution of Choice Outcomes and Responses of "Fully Maximising" Participants across all *Info* and *Ops* conditions

Outcome	Share	Failing to catch targeted service	Choice of Service following day		
			Later	No change	Earlier
Late	0.41	0.15	0.00	1.00	0.00
Not Late	0.59	0.01	0.00	1.00	0.00
Overall	1.00	0.07	0.00	1.00	0.00

A quick comparison of the second columns of Tables 5-7 and 5-8 reveals that "fully maximising" participants appeared to be much more successful than their "fully conservative" counterparts in catching their targeted service. However, one should note that the departure times (t_s) of the services preceding the maximising service (chosen by "fully conservative" participants) were not more variable or unpredictable than those of the maximising service (targeted by "fully maximising" participants). One can surmise that this phenomenon is associated with what has been described earlier in Section 5.1, and illustrated unambiguously in Table 5-4, i.e., a larger safety margin in t_b was adopted consciously to reduce the chances of missing the targeted service when this service was the riskier (in terms of likelihood of being late) maximising service, whereas a smaller margin (and hence higher likelihood of failing to catch the service) was used if the targeted service was one that was earlier than the maximising service.

Located between the above two groups along the behavioural spectrum are the "switchers", who are classified into "conservative", "multiple" and "maximising" groups. Tables 5-9 and 5-10 present the same statistics as those shown earlier on the decision outcomes and responses in the choice of service, but for the groups of "conservative" and "maximising' switchers respectively. The major difference of these two groups from the earlier two is the presence of change in the choice of service. The "conservative" and "maximising" switchers made only one switch from the maximising service to an earlier service and from a non-maximising service to the maximising service, respectively.

Table 5-9 Distribution of Choice Outcomes and Responses of "Conservative Switching" Participants across all *Info* and *Ops* conditions

Outcome	Share	Failing to catch targeted service	Choice of Service following day		
			Later	No change	Earlier
Late	0.24	0.62	0.00	0.79	0.21
Not Late	0.76	0.31	0.00	0.99	0.01
Overall	1.00	0.38	0.00	0.95	0.05

Table 5-10 Distribution of Choice Outcomes and Responses of "Maximising Switching" Participants across all *Info* and *Ops* conditions

Outcome	Share	Failing to catch targeted service	Choice of Service following day		
			Later	No change	Earlier
Late	0.29	0.29	0.00	1.00	0.00
Not Late	0.71	0.17	0.07	0.93	0.00
Overall	1.00	0.20	0.05	0.95	0.00

The final group to be studied is the "multiple" switchers, who, as the label implies, made two or more switches between a non-maximising service and the maximising service. Their statistics are shown in Table 5-11.

Table 5-11 Distribution of Choice Outcomes and Responses of "Multiple Switching" Participants across all *Info* and *Ops* conditions

Outcome	Share	Failing to catch targeted service	Choice of Service following day		
			Later	No change	Earlier
Late	0.27	0.47	0.03	0.67	0.30
Not Late	0.73	0.27	0.15	0.79	0.05
Overall	1.00	0.33	0.12	0.76	0.12

Several noteworthy observations were made on these five groups of participants. First, there is a small but clearly discernible trend of ascending incidence of late arrivals as one progresses from the "fully conservative" group (0.11), to the "conservative switching" (0.24), then to "multiple switching" (0.27) and "maximising switching" (0.29) and finally to the "fully maximising" group (0.41). This trend is aligned to intuition: the order of these groups reflects the increasing degree to which the participants were willing to choose the riskier maximising service, and that in turn corresponds to the increasing likelihood of being late. Allied to this trend is the decreasing proportion of participants failing to catch their intended services as one moves along the same behavioural spectrum. The second trend can be explained by the fact that those who chose the maximising service were less likely to miss this service because of the safety margin adopted, and the proportion of those choosing this service increases in the order of "fully conservative" to "fully maximising".

The second observation is that, among these three groups of "switchers", the switches in the choice of service occurred in one of two fashions typically. First, a switch to an earlier non-maximising service took place mostly after a late arrival on the preceding day. Twenty-one percent of late arrivals encountered by "conservative" switchers were followed by such a switch, and 30% in the case of "multiple" switchers. A negligible 1% and 5% of late arrivals were followed by the same switch. Second, a forward switch to the maximising service was more associated with an early or on-time arrival the preceding day. This choice switch occurred the day after 7% and 15% of early or on-time arrivals for "conservative" and "multiple" switchers respectively. The statistics discussed earlier in this paragraph suggest the first is more likely to occur. Table 5-12 provides a more accurate picture of the propensity to change the choice of service, which can be obtained by analysing the decisions on the choice of service made from day 2 onwards by the "Conservative Switching", "Multiple Switching" and "Maximising Switching" participants together. (The decisions of the other two remaining groups were omitted from the analysis because they did not involve a change in the choice of service.) It shows that the overall likelihood of switching to a maximising service is about half that of switching to a service preceding it (14.5% versus 27.8%). More pertinently, it confirms that it is more likely for a switch from a maximising service to an earlier service to occur when the arrival at the destination was late on the previous day (39.6%) than for the opposite switch to take place when the arrival was early (15.6%). These observations are not surprising because it is intuitive that a traveller would opt for a less risky choice (of a non-maximising service) if the current choice (the maximising service) has resulted in an adverse outcome (late arrival). It is also expected that he would be more inclined to seek out a more rewarding but riskier choice if the previous choice produces no negative consequence.

Table 5-12 Switches in Choice of Service

	Phenomenon of Interest					
	Switch from Maximising Service to Earlier Non-Maximising Service			Switch from Earlier Non-Maximising Service to Maximising Service		
Outcome in Preceding Day	**Not Late**	**Late**	**Total**	**Not Late**	**Late**	**Total**
Total Outcomes (over 19 days)	1,383	1,332	2,715	4,069	626	4,695
Switches Made (as % of total outcomes)	227 (16.4%)	527 (39.6%)	754 (27.8%)	636 (15.6%)	44 (7.0%)	680 (14.5%)

What is however very clear from Table 5-12 is that a change in the choice of service occurs only in a minority of the daily decisions made by the participants. Even when the previous day's outcome is a late arrival, the probability of a shift to an earlier (non-maximising) service is no more than 40%. An even more cautious stance is adopted for switches to a later (maximising) service. Now, any increase or decrease in the proportion of participants choosing the maximising service (i.e., the maximisation rate) would have to be contributed by the three groups of "switchers". However, their choice of service was shown here to be 'sticky' or 'inelastic', and this observation explains why the maximisation rate did not increase substantially from the starting level over time (see Figure 5-22). Even where there was an increase in this rate due to a participant switching to a maximising service, it was offset by another who switched away from it. Indeed, the absolute number of 'forward' switches to the maximising service (680) is less than that of 'backward' switches away from it (754) (Table 5-12).

The 'stickiness' in the choice of service is not surprising for "conservative" and "maximising" switchers because, by definition, they made only one switch out of 20 days. What is somewhat more surprising is that it is true even among the "multiple" switchers, despite what the labels have suggested. Table 5-11 shows that more than three in four of their next-day responses involved no change in the service choice. Even when there was an adverse outcome the preceding day (being late), the majority of "multiple switchers" (0.67) did not switch either. Considering the two other groups of non-switching participants ("fully conservative" and "fully maximising"), maintaining the status quo in the choice of service is the predominant option for all participants.

With only a very small proportion of decisions involving a switch in the choice of service, it appears that framing the participants' responses to information and learning as switches in the choice of service and classifying them in the five behavioural groups based on such responses is neither rewarding nor insightful. In view of the observations described previously, it is doubtful if the participants were able to make explicit distinctions between services when making decisions on the time to arrive at bus stops. Recall that, in Chapter 2, it is hypothesised that the participants will maximise their utility, and to achieve this, they will learn to target the maximising service over time (in addition to minimising the wait time at the bus stop). It is further postulated that the type of information provided will influence the rate at which their utility is maximised, and the level of utility attained. The extensive but rather fruitless exploration described in this Chapter suggests that the approach of describing the participants' decision-making in terms of choice of service is fundamentally flawed. That Chapter 4 has also shown that there is insufficient evidence to show that participants maximised their choice of service lends further support to this conclusion.

If indeed the participants did not or were unable to make explicit distinctions between services and chose among these services, it may be more fruitful to return the investigation back to how they choose their arrival time at the bus stop (t_b). This is described in the following Chapter.

6 INVESTIGATING DAY-TO-DAY RESPONSES TO INFORMATION USING A DISAGGREGATE APPROACH

In Chapter 5, it was found that framing and analysing participants' responses in terms of the service they were assumed to be targeting was not a particularly fruitful approach. Analysis at the aggregate level is also shown to be less than satisfactory. This chapter returns to the analysis of the choice of arrival time at the bus stop (t_b) at the disaggregate level to elicit the factors that affect the decision making of the participants.

6.1 Investigating Day-to-Day Changes in Passenger Arrival Time at Bus Stop (t_b)

In Chapter 5, the propensity of the participant to change t_b was examined (Section 5.1). Most pertinent to the current discussion, it was found that there were substantially more instances of changes in t_b than there were in the choice of service. Across all scenarios, between 33% and 82% of the daily decisions involved a change in t_b, with scenarios with dynamic information associated with a higher propensity to change t_b than those with no or static information (Table 5-1). Such an observation indicates that the participants were not unresponsive by not changing their choice of service. They were indeed responding to the stimuli of either the previous day's outcomes or the information provided, or both, by changing their t_b. It is just that the changes in t_b had not been sufficiently large on most days to result in a change in the choice of service under the previous analytical approach.

The following sections provide an alternative descriptive scheme on the participants' behaviour to the one on which the original hypotheses were formulated in Chapter 2, and examine whether the actual observations support such a description. As is shown in this chapter, this scheme is conceptually simpler, and does not assume the concept of choice of service that has since been deemed inadequate.

6.1.1 Non-Dynamic Information Scenarios

6.1.1.1 No Information (*NO-INFO*) Scenario

The description for a case in which information is absent is presented first. It postulates that the traveller chooses an initial t_b that he assesses would enable him to catch a service to bring him to the destination on or before the *PAT*, without making reference to any particular service. He would engage in some exploratory behaviour in the first few days to locate the t_b he is comfortable with, a process similarly postulated in the original descriptive scheme. His responses in terms of changing t_b would follow the intuition similar to that used in the earlier analytical approach: that he would opt for a less risky choice of an earlier t_b if the previous choice has resulted in an adverse outcome (i.e., a late arrival in which $t_l < 0$), and seek a more rewarding but riskier choice of a later t_b if the previous choice produces no negative consequence (of an early arrival in which $t_l \geq 0$).

Obviously, it is unrealistic to expect the traveller to adhere to the above behavioural rule for long. He is likely to apply some form of assessment to weigh the expected reward of changing the t_b in the direction as described against the risk of doing so. For example, if he were to be late at the destination by a mere minute or two after catching his desired service, he is unlikely to shift t_b back on the next day if the preceding service is a long headway, say 20 minutes. The benefit of being assured of not being late is outweighed by the cost of being excessively early. Similarly, if he catches the bus just on time ($T_w = 0$) and arrives early at the destination within an acceptable period before the *PAT*, he is not likely to choose a later t_b the next day because that decision will possibly result in him missing the bus. When such outcomes occur, the traveller will not adjust his choice of t_b on the following day. At most, he would vary the t_b around the value he has settled with, and within a small range. It can be argued that the prevalence of such outcomes marks the end of the exploratory period and the onset of the stable period, as described in Chapter 4.

The above descriptive scheme is examined using observations of the *NO-INFO* scenarios, in which no information is provided. First is an examination of the *Ops* condition in which the headway is 20 minutes and the variability of service departure time (t_s) is low (*H20-LOW*). Particular attention is paid to two aspects, namely, the presence of the exploratory behaviour and the reactions to the previous day's outcome.

Figure 6-1 presents how one of the participants (Subject 101) responded (through changing t_b) to the outcome of the preceding day (t_l). It is shown that his response is in line with intuition broadly: for all days except one on which he arrived late at the destination ($t_l < 0$), he adjusted t_b backwards the following day (days 3, 8, 9, 12, 15 and 19). For example, on day 7, the participant arrived late at his destination by 9 minutes (represented by the white bar), and he responded by shifting t_b backwards by three minutes on day 8 (represented by the blue bar). For days immediately following an early arrival at the destination ($t_l \geq 0$), he made either forward shifts in t_b (days 2, 4, 5, 6, 7, 10 and 18), or no change in t_b (days 13, 14, 16, 17 and 20).

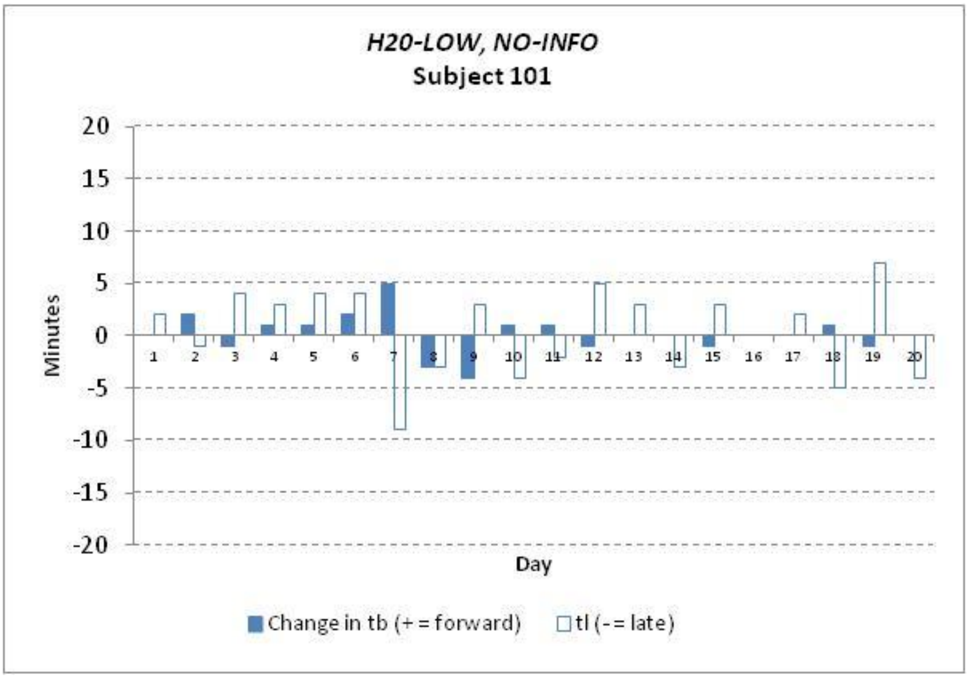


Figure 6-1 Plot of Change in t_b and Arrival Time at Destination (t_l) by Day under No Information condition (Subject 101)

The participant's exploratory behaviour in the initial period is not apparent from the magnitude of t_b changes, but from the frequency of adjustments. There is a higher number of adjustments in t_b in the first half of the session, during which he made changes in t_b every day until day 12.His t_b choices in the first 10 days indicate an exploratory behaviour. In line with the descriptive scheme, he kept moving t_b forward on days 4, 5, 6 and 7 as the corresponding responses to his early arrivals on days 3, 4, 5 and 6. Once he arrived late on two consecutive days on days 7 and 8, he moved t_b back as expected. In the second half, changes in t_b become less frequent (5 out of 10 days) and in smaller magnitudes (all are ±1 minute), reflecting a cessation of his exploratory behaviour and stabilisation in his choice-making.

The same plot for another participant (Subject 106) reveals exploratory behaviour that is more pronounced. See Figure 6-2. He shifted t_b forward for 6 consecutive days, the first 3 of which see shifts of large magnitudes (10 minutes or more). Apparently, he had chosen t_b that was excessively early on the first day (in contrast to subject 101 who was early by just 2 minutes on the first day upon his initial choice of t_b), and had to make successive large forward adjustments to t_b to rectify it. His forward shifts in t_b ended on day 7 when he encountered a late arrival at his destination, to which he responded with a backward shift. As with Subject 101, the second half of the session generally sees adjustments of smaller magnitudes, indicating that he has located a range of t_b he is comfortable with. The t_b shifts in response to previous days' outcomes are also mostly in the directions expected.

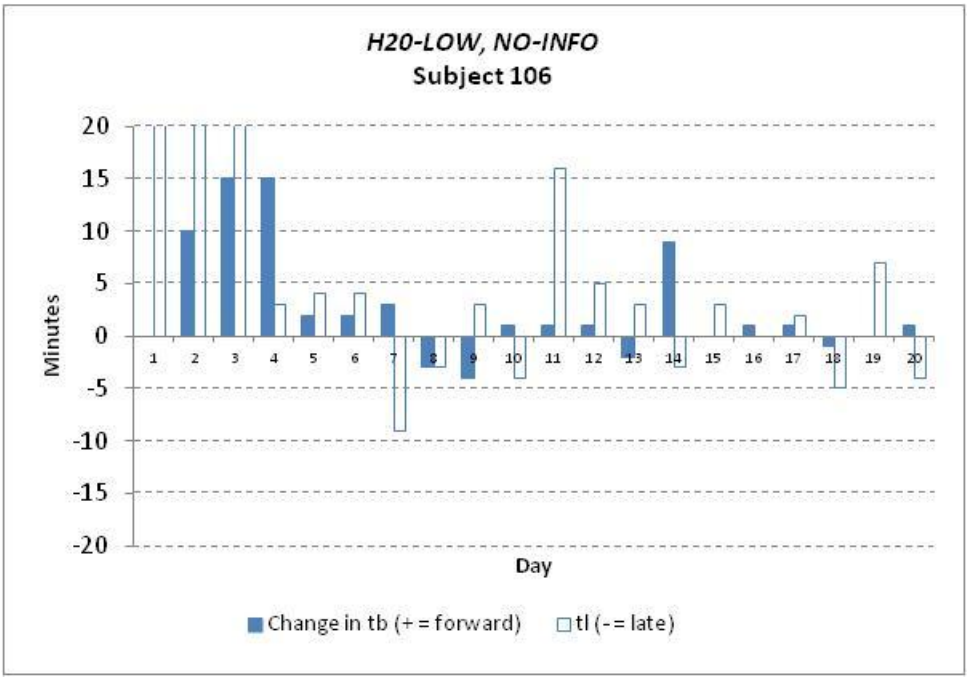


Figure 6-2 Plot of Change in t_b and Arrival Time at Destination (t_l) by Day under No Information condition (Subject 106)

Figure 6-3 shows the choice behaviour of a third participant (Subject 105) who also exhibited an observable exploratory phase in the first few days. This participant made a forward shift in t_b of 20 minutes, or exactly the service headway, on day 2 after he was early for a substantial 17 minutes. He made another three consecutive adjustments to t_b within the next 5 days. However, his exploratory behaviour ceases far more abruptly than the preceding two participants (Subjects 101 and 106), with only one small t_b shift for the rest of the 20 days. In the second half of the session, he did not respond to the decision outcomes even though he was late for 5 out of 10 days. This is as predicted by the descriptive scheme for the stable period in which the participant has a very low likelihood of changing t_b. During this period, all except one of the deviations of t_l from the PAT were no more than 5 minutes, the magnitudes of which were small relative to the headway of 20 minutes. Therefore, he found it not worth his while to catch a bus 20 minutes earlier or later in order to avoid a few minutes of being late or early respectively.

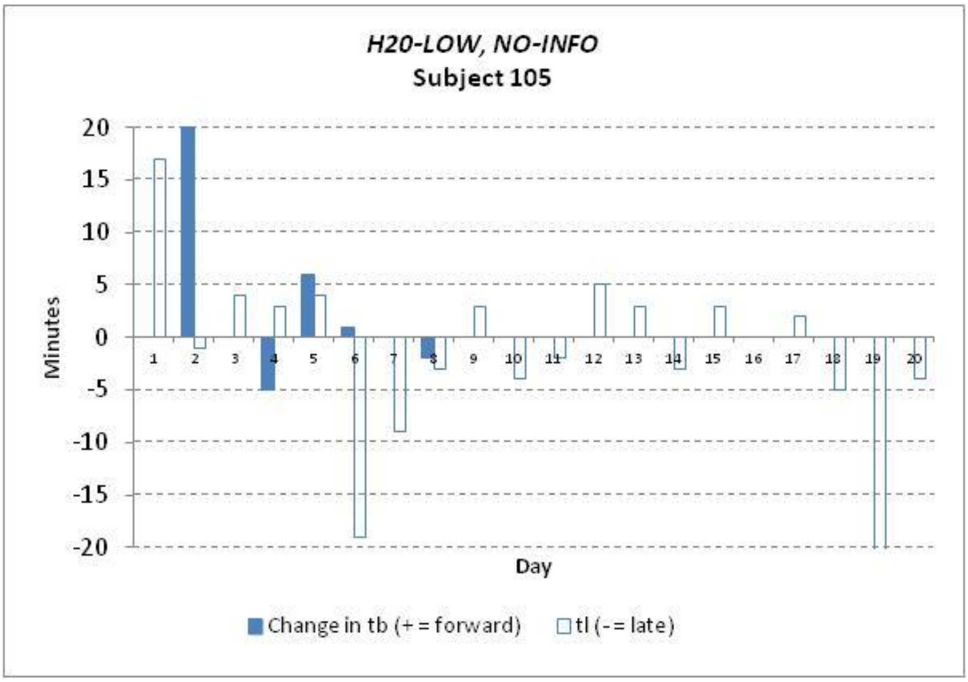


Figure 6-3 Plot of Change in t_b and Arrival Time at Destination (t_l) by Day under No Information condition (Subject 105)

The last participant to be described (Subject 111) showed no apparent sign of an exploratory behaviour. See Figure 6-4. He made daily t_b adjustments, mostly of ±1 minute and no more than 3, right from the first day to the last.

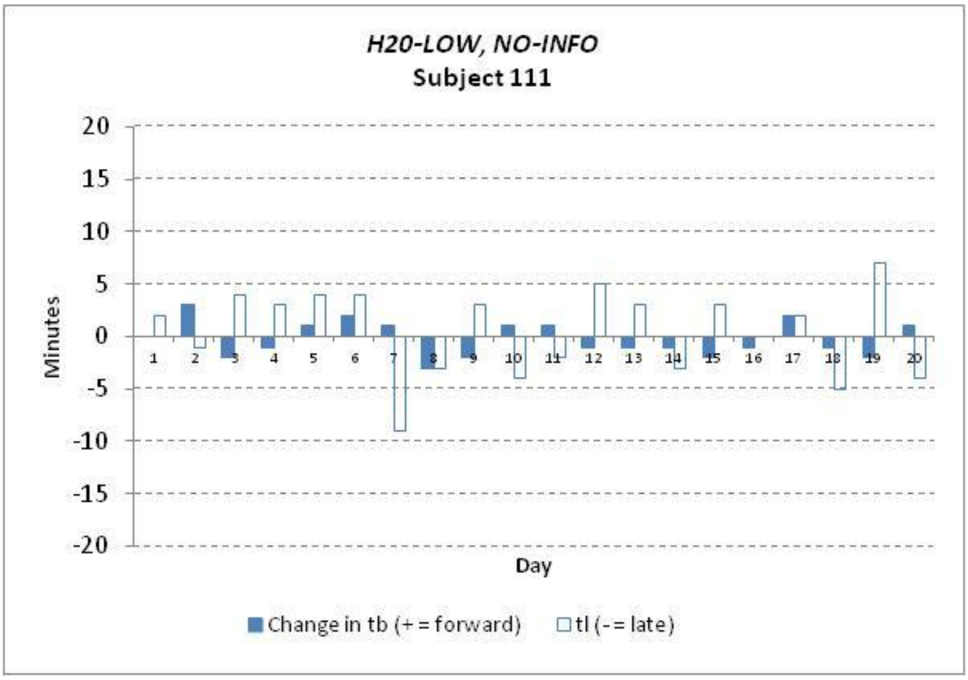


Figure 6-4 Plot of Change in t_b and Arrival Time at Destination (t_l) by Day under No Information condition (Subject 111)

The behavioural patterns of the four participants described above cover broadly those in the same scenario. The rest of the plots for this *H20, NO-INFO* treatment combination are presented in the Appendix 6. Three main observations can be made. First, the adjustments in t_b are in the directions as postulated in the descriptive scheme. For the participant in this treatment combination, the change in t_b between day d and $d - 1$ $(\Delta t_b)_d$, is positively correlated with the outcome on the previous day $(t_l)_{d-1}$ ($\rho = +0.444$, $p = 0.000$).

Second, exploratory behaviour in the form of large shifts in t_b in the initial period need not occur as postulated (as shown by Subjects 101 and 111, Figures 6-1 and 6-4). Although some predictably make large shifts in t_b when the initial choices of t_b have resulted in exceedingly early or late arrivals; others prefer to settle simply around the range of the t_b on the first day, as long as this choice does not result in late arrivals or extremely early arrivals. For those who made the shifts, the exploratory behaviour ceases mostly within five days. Hence, one can confidently define the exploratory period as the first five days.

Third, once the participant has located the t_b within the range with which he is comfortable, his decision-making stabilises. During the stable period, there is either no adjustment in t_b or small adjustments of mostly ±1 minute, and no more than ±5 minutes, that are well within the headway (H = 20 minutes). The change in behaviour between the initial exploratory period (first 5 days) and the subsequent stable period is significant across various attributes at α = 0.05, as shown in Table 6-1.

Table 6-1 Differences in Behaviour in Initial and Stable Periods in *H20-LOW, NO-INFO* scenario

Attribute	**Day 1 to 5 (Initial Period)**	**Day 6 to 20 (Stable Period)**	**Sig. (*p*)**
Proportion of days with t_b change	0.69	0.54	0.013*
Average absolute change in t_b	3.48	0.94	0.000*

* significant at α = 0.05

The above describes the observations made under the *Ops* condition of *H20-LOW*. Examination of the five other *Ops* conditions with the same *NO-INFO* condition reveals similar patterns. In the absence of information, the participants do not appear to differ in behaviour across different service headways or service reliability. The similarity in behaviour across all six *Ops* conditions is shown in Table 6-2 and 6-3.

Table 6-2 Correlations between Change in t_b and Outcome of Previous Day across all *Ops* conditions under *NO-INFO* condition

***Ops* Condition**	**Correlation between $(\Delta t_b)_d$ and $(t_l)_{d-1}$**	**Sig. (p)**
H20-LOW	+0.444	0.000*
H20-HIGH	+0.495	0.000*
H10-LOW	+0.389	0.000*
H10-HIGH	+0.328	0.000*
H5-LOW	+0.523	0.000*
H5-HIGH	+0.383	0.000*

* significant at $\alpha = 0.05$

Table 6-3 Differences in Behaviour in Initial and Stable Periods across all *Ops* conditions under *NO-INFO* condition

***Ops* Condition**	**Attribute**	**Initial Period**	**Stable Period**	**Sig. (p)**
H20-LOW	Proportion of days with t_b change	0.69	0.54	0.013*
	Average absolute change in t_b	3.48	0.94	0.000*
H20-HIGH	Proportion of days with t_b change	0.81	0.67	0.015*
	Average absolute change in t_b	3.17	1.63	0.000*
H10-LOW	Proportion of days with t_b change	0.64	0.49	0.018*
	Average absolute change in t_b	2.58	1.05	0.000*
H10-HIGH	Proportion of days with t_b change	0.62	0.34	0.000*
	Average absolute change in t_b	3.26	0.59	0.000*
H5-LOW	Proportion of days with t_b change	0.65	0.35	0.000*
	Average absolute change in t_b	3.20	0.63	0.000*
H5-HIGH	Proportion of days with t_b change	0.64	0.53	0.039*
	Average absolute change in t_b	2.46	0.82	0.000*

* significant at $\alpha = 0.05$

6.1.1.2 Headway (*HDWAY*) Scenario

It is postulated that when the traveller is given headway information, his behaviour will be no different from when he is provided with no information. This is because information on the scheduled intervals between successive services does not inform on when the services are expected to depart (t_s), and therefore he is not able to use this information to locate his t_b with reference to t_s. He therefore still requires the previous day's outcome to identify the range within which t_b is best located, which is no different from the situation under the no information scenario. Indeed, without presenting the plots here, the same plots for the *HDWAY* scenarios contained in the Appendix 6 show that the behavioural patterns are broadly similar to those under the *NO-INFO* scenarios. Tables 6-4 and 6-5 also show that the overall behaviour exhibited in *HDWAY* mirrors that largely described for *NO-INFO* in the preceding section.

Table 6-4 Correlations between Change in t_b and Outcome of Previous Day across all *Ops* conditions under *HDWAY* condition

***Ops* Condition**	**Correlation between $(\Delta t_b)_d$ and $(t_l)_{d-1}$**	**Sig. (p)**
H20-LOW	+0.456	0.000*
H20-HIGH	+0.354	0.000*
H10-LOW	+0.385	0.000*
H10-HIGH	+0.345	0.000*
H5-LOW	+0.553	0.000*
H5-HIGH	+0.614	0.000*

* significant at α = 0.05

Table 6-5 Differences in Behaviour in Initial and Stable Periods across all *Ops* conditions under *HDWAY* condition

***Ops* Condition**	**Attribute**	**Initial Period**	**Stable Period**	**Sig. (*p*)**
H20-LOW	Proportion of days with t_b change	0.57	0.42	0.013*
	Average absolute change in t_b	1.95	0.98	0.033*
H20-HIGH	Proportion of days with t_b change	0.43	0.31	0.026*
	Average absolute change in t_b	3.02	1.30	0.000*
H10-LOW	Proportion of days with t_b change	0.70	0.55	0.012*
	Average absolute change in t_b	2.92	1.62	0.000*
H10-HIGH	Proportion of days with t_b change	0.54	0.39	0.006*
	Average absolute change in t_b	2.58	0.63	0.000*
H5-LOW	Proportion of days with t_b change	0.67	0.42	0.000*
	Average absolute change in t_b	1.90	0.73	0.000*
H5-HIGH	Proportion of days with t_b change	0.58	0.46	0.051
	Average absolute change in t_b	2.00	0.96	0.000*

* significant at $\alpha = 0.05$

6.1.1.3 Time Table (*TTABLE*) Scenario

In Chapter 5, it is found that there is no significant difference in the choice behaviour between *NO-INFO*, *HDWAY* and *TTABLE* conditions with respect to t_b at the aggregate level. One would therefore expect the behaviour in *TTABLE* to be similar to *NO-INFO* and *HDWAY*, and characterised by small adjustments in t_b.

Observations of the plots in *TTABLE* reveal that indeed most participants exhibit the behavioural characteristics of their counterparts in *NO-INFO* and *HDWAY* under the same *H20-LOW* condition. Most of the adjustments in t_b are small in magnitude (≤5 minutes), and in the directions expected, except in the exploratory period during which larger shifts are observed in some of the participants, as characterised by Subject 1321 (Figure 6-5).

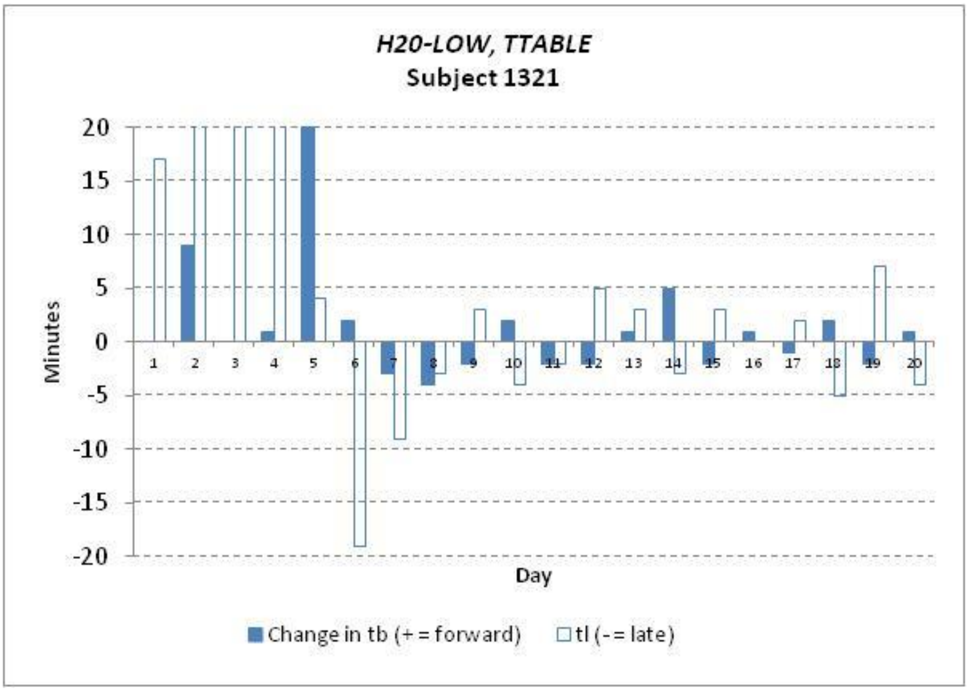


Figure 6-5 Plot of Change in t_b and Arrival Time at Destination (t_l) by Day under Time Table condition (Subject 1321)

Again, the similarity in behaviour observed in the three *Info* conditions discussed thus far can be seen by comparing Tables 6-6 and 6-7 with Tables 6-2 to 6-5.

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Table 6-6 Correlations between Change in t_b and Outcome of Previous Day across all *Ops* conditions under *TTABLE* condition

***Ops* Condition**	**Correlation between $(\Delta t_b)_d$ and $(t_l)_{d-1}$**	**Sig. (p)**
H20-LOW	+0.451	0.000*
H20-HIGH	+0.562	0.000*
H10-LOW	+0.428	0.000*
H10-HIGH	+0.556	0.000*
H5-LOW	+0.576	0.000*
H5-HIGH	+0.467	0.000*

* significant at $\alpha = 0.05$

Table 6-7 Differences in Behaviour in Initial and Stable Periods across all *Ops* conditions under *TTABLE* condition

***Ops* Condition**	**Attribute**	**Initial Period**	**Stable Period**	**Sig. (*p*)**
H20-LOW	Proportion of days with t_b change	0.57	0.49	0.197
	Average absolute change in t_b	4.86	1.75	0.000*
H20-HIGH	Proportion of days with t_b change	0.70	0.49	0.000*
	Average absolute change in t_b	6.74	1.24	0.000*
H10-LOW	Proportion of days with t_b change	0.63	0.46	0.004*
	Average absolute change in t_b	3.32	1.36	0.000*
H10-HIGH	Proportion of days with t_b change	0.57	0.41	0.009*
	Average absolute change in t_b	2.05	0.60	0.000*
H5-LOW	Proportion of days with t_b change	0.71	0.46	0.000*
	Average absolute change in t_b	2.42	0.86	0.000*
H5-HIGH	Proportion of days with t_b change	0.60	0.43	0.003*
	Average absolute change in t_b	1.90	0.91	0.000*

* significant at $\alpha = 0.05$.

There is one distinct difference, however. There is a subset of participants who make larger than expected adjustments in t_b *after* the exploratory period. Among them is Subject 1306, whose behaviour is presented in Figure 6-6. While the large swings in the choice of t_b on days 2, 3 and 4 can be attributed to his exploratory behaviour, those between days 9 and 13 cannot be explained so. One would expect his behaviour to stabilise after approximately day 5, and any adjustments to be small, as exhibited by most of his counterparts and all the other participants in *NO-INFO* and *HDWAY* conditions.

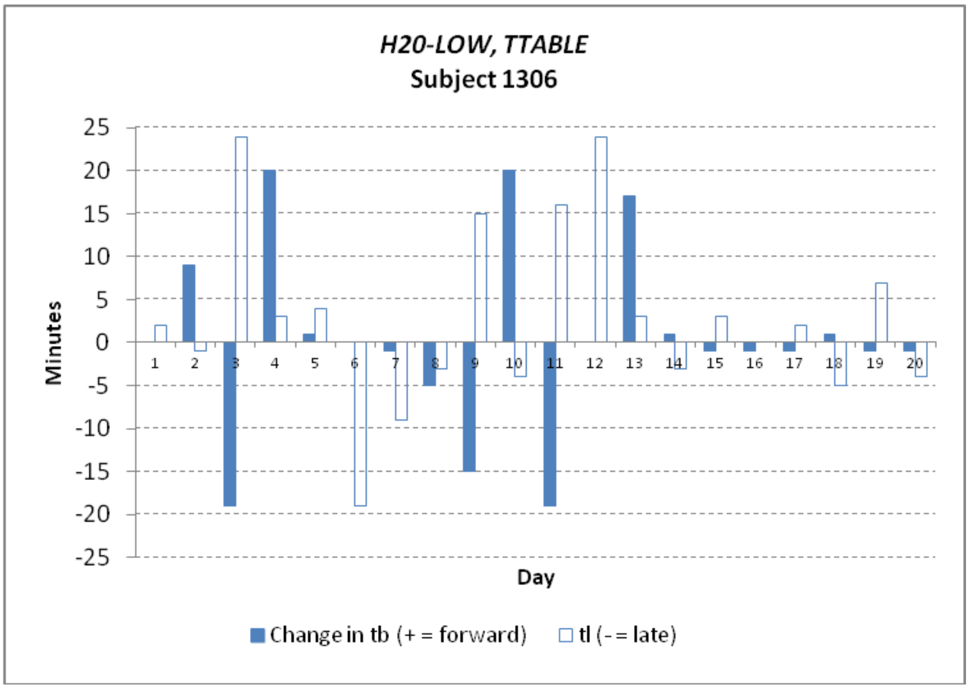

Figure 6-6 Plot of Change in t_b and Arrival Time at Destination (t_l) by Day under Time Table condition (Subject 1306)

That these t_b changes are of a magnitude close to the headway (H = 20) and appear only in the *TTABLE* condition thus far leads one naturally to consider if such a behaviour is associated with the provision of timetable information. After all, in *HDWAY* condition, the headway H = 20 is given explicitly, but similarly large t_b changes are not observed outside of the exploratory period. To examine if this is so, a different plot is generated to examine the relationship between t_b and t_s^i, the scheduled service departure time listed on the timetable. Figure 6-7 shows the t_b chosen by the same participant, Subject 1306, on each day in relation to the published scheduled service times. The lines marked "tsi" refer to the scheduled service departure times given to the participant and are horizontal because such time estimates are static in the timetable. (The 'tsi 6' and 'tsi 7' refer to the 6th and 7th scheduled departure time out of the 10 presented).

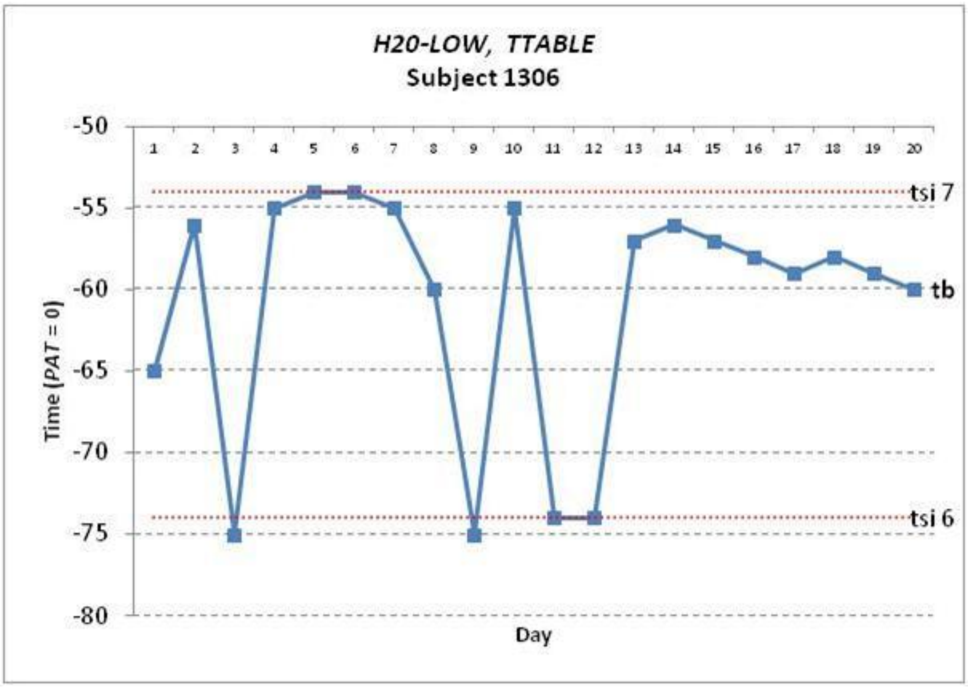

Figure 6-7 Plot of t_b and Scheduled Service Departure Time (t_s^i) by Day under Time Table condition (Subject 1306)

It appears that the timetable has enabled the participant to take reference from the t_s^i when locating a t_b that is far from the current one. The absence of such t_s^i in *NO-INFO* results in a much lesser propensity to make large switches in t_b. Even in *HDWAY* in which the participant is informed that the service departure times are approximately 20 minutes apart, the lack of such "anchors" makes it less likely for him to make large changes in t_b.

For Subject 1306, it appears that the timetable does have an effect on his behaviour. However, as mentioned earlier, he belongs to only a minority sub-group apart from the rest of the participants in the same scenario who have not responded as he has. To understand the extent to which timetable information has an influence, other participants who exhibit behaviour similar to Subject 1306 were identified. Obviously, there will be no other participant whose behaviour will be identical to his, and a rule of thumb, however subjective, will be necessary. For example, one can deem a participant to have used the timetable information if he has selected a t_b that is at or within close proximity to a t_s^i, as was done by Subject 1306 on days 3 to 7, and 9 to 12 (See Figure 6-7). However, this will not be sufficient to deem the participant to have been influenced by the timetable. This is because another participant in *NO-INFO* and *HDWAY* could have similarly selected t_b that are approximately the same as his, through learning and inference. Take Subject 105, whose behaviour is discussed in Section 6.1.1 and plotted in Figure 6-8, as an illustration. After a period of exploration, he has chosen t_b that are within the vicinity of 'tsi7' (t = -54) even though he is not given the actual t_s^i values in the *NO-INFO* scenario. Therefore, another criterion other than close proximity of t_b relative to t_s^i is needed.

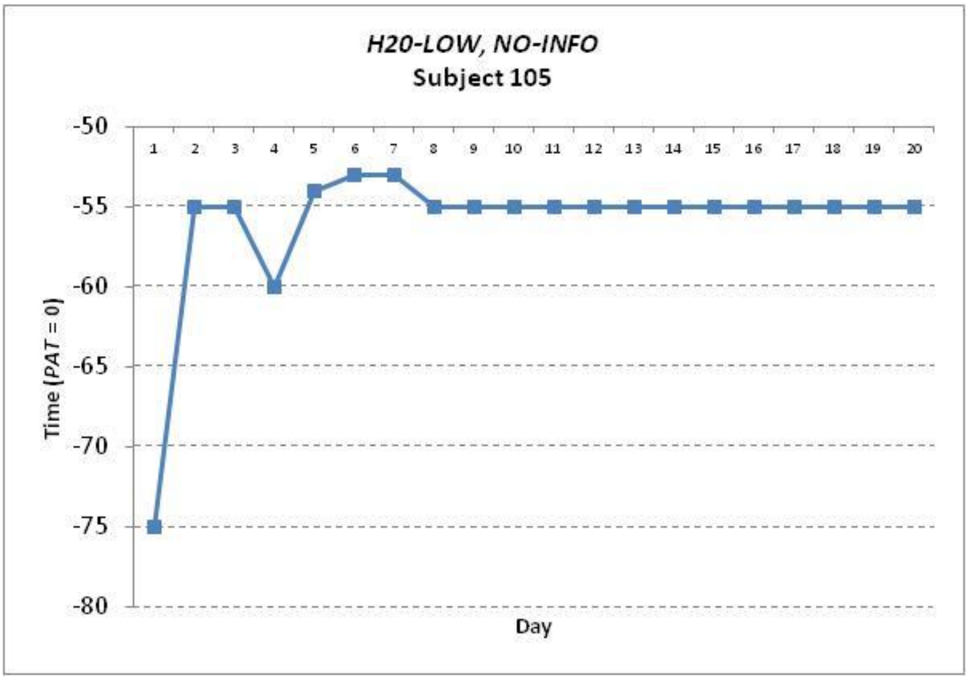

Figure 6-8 Plot of t_b under No Information condition (Subject 105)

Returning to the earlier description of large swings in t_b that set Subject 1306 apart from most of his peers, one can easily determine the second criterion: that in selecting a t_b that is in close proximity to t_s^i, the participant would have made at least one shift in t_b that is of a magnitude equal or close to the headway H. Both conditions need to be met in order for one to infer that the participant has used the timetable information. Referring to Figure 6-7, the t_b choices of Subject 1306 on days 4, 9, 10, 11 and 13 meet both of these criteria. However, it cannot be determined using these criteria if he uses the timetable information on the remaining days when he makes smaller changes in t_b (or none at all).

Using this rule of thumb, it is found that 8 out of the 21 participants in the *Ops* condition of *H20-LOW*, including the said Subject 1306, respond to t_s^i on at least one day. The same exercise is applied to the remaining 5 *Ops* conditions to ascertain the overall degree to which timetable information has an effect on behaviour across all operating circumstances. As shown in Table 6-8, the influence of timetable information is indeed limited to a minority of the participants.

It should be noted that the criteria do not allow one to determine if the participant uses the timetable every single day. In cases where a participant chooses on consecutive days the same t_b that is at or close to a t_s^i, as Subject 1306 has done on days 5 and 6, and days 11 and 12, as shown in Figure 6-7, one cannot ascertain if he does so by adhering to the static t_s^i value, or just due to inertia. Hence, in Table 6-8, one can only classify those who meet the rule of thumb as responding to t_s^i partially.

Table 6-8 Number and Proportion of Participants Responding to Timetable Information by *Ops* condition

***Ops* condition**	**Partially responds to t_s^i**	**Ignores t_s^i**
H20-LOW	8	13
	(0.38)	(0.62)
H20-HIGH	10	11
	(0.48)	(0.52)
H10-LOW	6	18
	(0.25)	(0.75)
H10-HIGH	3	19
	(0.14)	(0.86)
H5-LOW	7	14
	(0.33)	(0.67)
H5-HIGH	8	14
	(0.36)	(0.64)

The findings show that the provision of a timetable, in the form of static t_s^i, has limited effect on traveller's behaviour in terms of t_b. In all six *Ops* conditions, participants who respond to the timetable information are the minority, ranging from 14% to 48%. Across all six *Ops* conditions, there is no significant difference in the proportion of such non-responsive participants ("Ignore Estimates") ($p = 0.231$ at $\alpha = 0.05$).

Nonetheless, its effect on this minority of participants is apparent, compared to that of headway information. Table 6-9 reproduces Table 6-7, but lists the attribute values after removing data from participants who responded partially to timetable information (those in the second column of Table 6-8) in addition. Although there appear no substantial differences in the proportion of days with t_b change (first data row for each *Ops* condition) compared to those in Table 6-8 (second data row), there are observable decreases in the average absolute change in t_b in *H20* and *H10* scenarios. These findings indicate that those who made use of the timetable made larger changes in t_b because they have t_s^i estimates from which to take reference.

Such an effect among a minority of participants is not observed when examining the aggregate t_b described in Chapter 5, and the value of a disaggregate approach in revealing the heterogeneity in the behaviour has been brought forth clearly in this analysis. This leads one to wonder if the disaggregate approach can also reveal greater effects of dynamic information, as commonly expected. The next section examines this.

Table 6-9 Behaviour in Initial and Stable Periods across all *Ops* conditions under *TTABLE* condition for Participants who did not respond to Timetable Information

***Ops* Condition**	**Attribute**	**Initial Period**	**Stable Period**
H20-LOW	Proportion of days with t_b change	0.58 (0.57)	0.47 (0.49)
	Average absolute change in t_b	3.21 (4.86)	0.94 (1.75)
H20-HIGH	Proportion of days with t_b change	0.70 (0.70)	0.51 (0.49)
	Average absolute change in t_b	2.41 (6.74)	0.88 (1.24)
H10-LOW	Proportion of days with t_b change	0.60 (0.63)	0.42 (0.46)
	Average absolute change in t_b	2.18 (3.32)	1.07 (1.36)
H10-HIGH	Proportion of days with t_b change	0.53 (0.57)	0.37 (0.41)
	Average absolute change in t_b	1.74 (2.05)	0.53 (0.60)
H5-LOW	Proportion of days with t_b change	0.75 (0.71)	0.51 (0.46)
	Average absolute change in t_b	2.07 (2.42)	0.92 (0.86)
H5-HIGH	Proportion of days with t_b change	0.63 (0.60)	0.49 (0.43)
	Average absolute change in t_b	1.80 (1.90)	0.75 (0.91)

Figures in parentheses are for all participants, and are reproduced from Table 6-8.

6.1.2 *Dynamic Information Scenarios*

The behaviour of participants who are given dynamic information, both unreliable and reliable (*DYN-UNREL* and *DYN-REL*) is assessed in the same manner as for those provided with no or static information. Given the earlier findings in Chapters 4 and 5, one can expect the behaviour under dynamic information scenarios to differ substantially from the static ones (*NO-INFO*, *HDWAY* and *TTABLE*). Specifically, there is no clear indication of the cessation of large variations in t_b after the initial period. This is borne out in Tables 6-10 and 6-11 that show that, out of the 10 *Ops* conditions over the two dynamic information conditions, 8 see no statistically significant reduction (at 5% level) in the proportion of days with t_b changes after the initial period.

Table 6-10 Differences in Behaviour in Initial and Stable Periods across all *Ops* conditions under *DYN-UNREL* condition

***Ops* Condition**	**Attribute**	**Initial Period**	**Stable Period**	**Sig. (*p*)**
H20-LOW	Proportion of days with t_b change	0.73	0.81	0.092
	Average absolute change in t_b	7.66	4.01	0.000*
H20-HIGH	Proportion of days with t_b change	0.77	0.77	0.963
	Average absolute change in t_b	5.07	4.06	0.139
H10-LOW	Proportion of days with t_b change	0.87	0.81	0.158
	Average absolute change in t_b	4.01	2.61	0.000*
H10-HIGH	Proportion of days with t_b change	0.73	0.70	0.582
	Average absolute change in t_b	5.13	2.89	0.001*
H5-LOW	Proportion of days with t_b change	0.85	0.75	0.051
	Average absolute change in t_b	3.45	2.72	0.018*
H5-HIGH	Proportion of days with t_b change	0.61	0.71	0.059
	Average absolute change in t_b	2.61	2.38	0.519

* significant at $\alpha = 0.05$

Table 6-11 Differences in Behaviour in Initial and Stable Periods across all *Ops* conditions under *DYN-REL* condition

***Ops* Condition**	**Attribute**	**Initial Period**	**Stable Period**	**Sig. (*p*)**
H20-LOW	Proportion of days with t_b change	0.77	0.68	0.109
	Average absolute change in t_b	4.68	5.57	0.312
H20-HIGH	Proportion of days with t_b change	0.84	0.79	0.303
	Average absolute change in t_b	7.09	5.15	0.013*
H10-LOW	Proportion of days with t_b change	0.87	0.72	0.003*
	Average absolute change in t_b	5.57	3.07	0.000*
H10-HIGH	Proportion of days with t_b change	0.84	0.75	0.077
	Average absolute change in t_b	5.25	2.79	0.000*
H5-LOW	Proportion of days with t_b change	0.76	0.63	0.026*
	Average absolute change in t_b	2.90	1.60	0.000*
H5-HIGH	Proportion of days with t_b change	0.63	0.62	1.000
	Average absolute change in t_b	2.07	1.65	0.094

* significant at $\alpha = 0.05$

To examine the phenomenon at the disaggregate level, the plots of the day-to-day change in t_b are generated for each participant across all *Ops* conditions. As the average t_b value at the aggregate level, under *DYN-UNREL* and *DYN-REL* scenarios varies much more than in *NO-INFO*, *HDWAY* and *TTABLE*, one can expect the plots to show more day-to-day changes in t_b.

This expectation is borne out by many of the plots, one of which is shown in Figure 6-9. It shows that, for Subject 401 who is given unreliable dynamic information when faced with a long headway service with low variability (*H20-LOW, DYN-UNREL*), there are more instances of t_b changes, a significant proportion of which are of large magnitudes. Such a behavioural pattern bears greater resemblance to the minority of participants in *TTABLE* who respond to timetable information (Figure 6-6) than to those in *NO-INFO* and *HDWAY* (Figures 6-1 to 6-4). Intuitively, one can surmise that participants with such behaviour are also likely to make decisions with reference to t_s^i, but ones that are dynamic rather than static in this case. A cursory scan of the plots from *DYN-UNREL* and *DYN-REL* scenarios also reveals that there are a higher proportion of such patterns than is found in *TTABLE* scenarios.

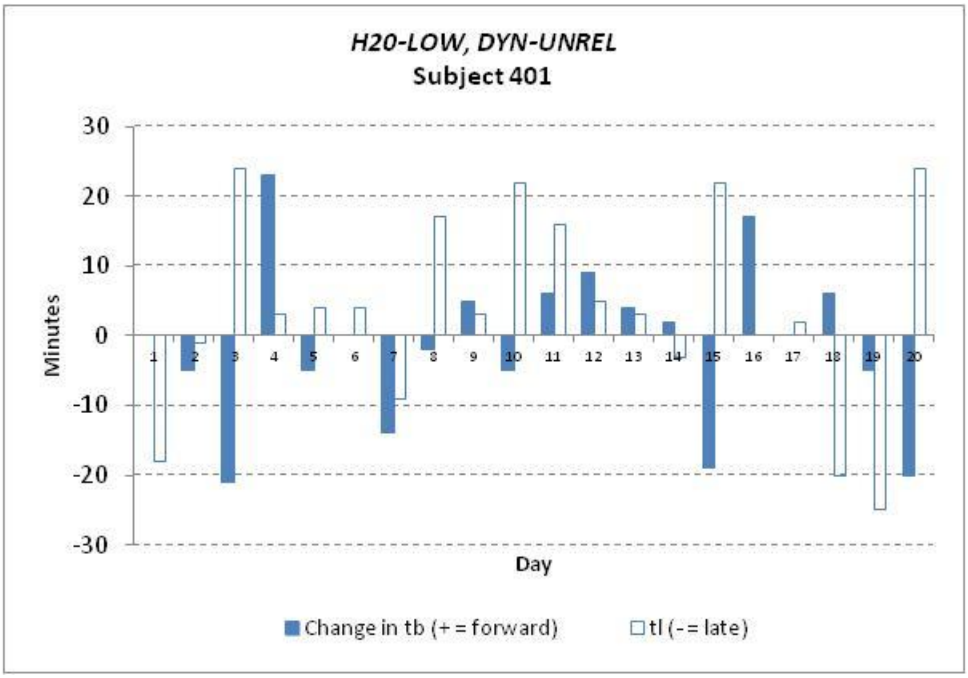

Figure 6-9 Plot of Change in t_b and Arrival Time at Destination (t_l) by Day under Unreliable Dynamic Information condition (Subject 401)

It was decided that a meaningful way to present the behavioural patterns of participants with dynamic information was to plot the relationship between t_b and t_s^i, as is done in Figure 6-7. The choice behaviour of Subject 401 in relation to t_s^i is presented in Figure 6-10. Unlike the horizontal lines representing the scheduled service departure times in *TTABLE*, the 'tsi' lines here fluctuate daily, reflecting the dynamic t_s^i in *DYN-UNREL*.

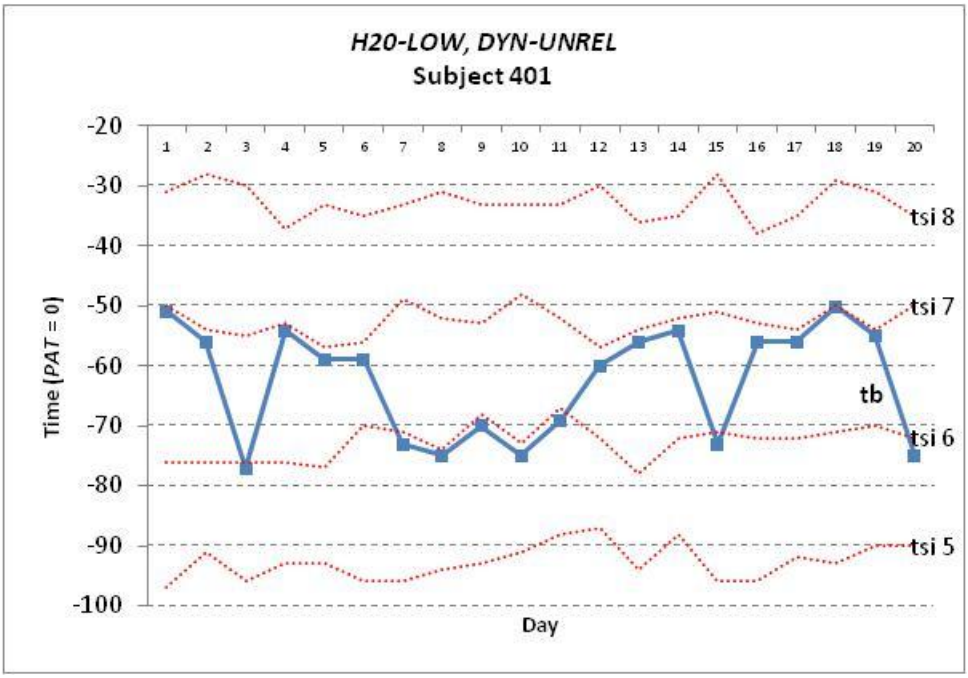

Figure 6-10 Plot of t_b and Scheduled Service Departure Time (t_s^i) by Day under Unreliable Dynamic Information condition (Subject 401)

The t_b choices of Subject 401 and how they track the t_s^i closely are laid out very clearly in Figure 6-10. Each of the t_b is located at or marginally before t_s^i associated with either the 6th or 7th service. As in *TTABLE*, the presence of dynamic information appears to lead to greater confidence to make large switches in t_b, from the t_s^i (or within its proximity) of one service to another of the adjacent service. Even where there is no apparent change in the service he intends to catch, Subject 401 changes his t_b in accordance with the variations of t_s^i. For him, every t_b choice is anchored to a t_s^i.

Although Subject 401 appears to take reference from the dynamic information in every episode of decision-making, the influence of the same information is less pronounced on another of the participants. Figures 6-11 and 6-12 present the same plots of t_b and t_s^i for Subject 422. It suggests that he takes reference from t_s^i intermittently: when he selects the initial t_b (day 1), makes his first large shift in t_b to catch a later service (day 5) and for a period between days 12 and 16. On the remaining days, he makes small adjustments in t_b similar to many in the static information scenarios. Unlike Subject 401, he has not aligned his decisions fully on the dynamic estimates.

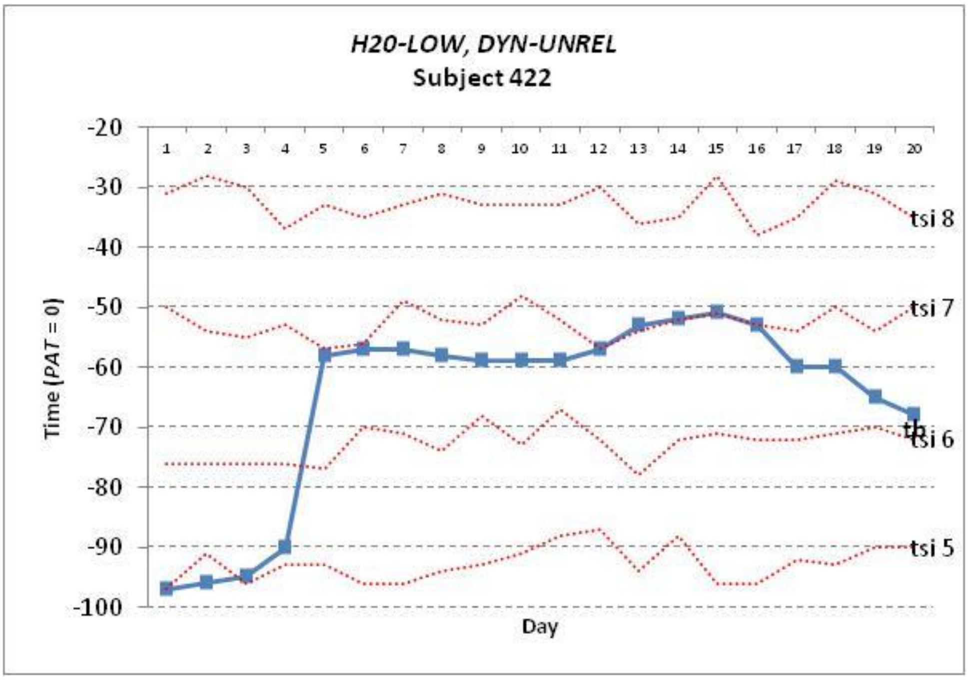

Figure 6-11 Plot of t_b and Scheduled Service Departure Time (t_s^i) by Day under Unreliable Dynamic Information condition (Subject 422)

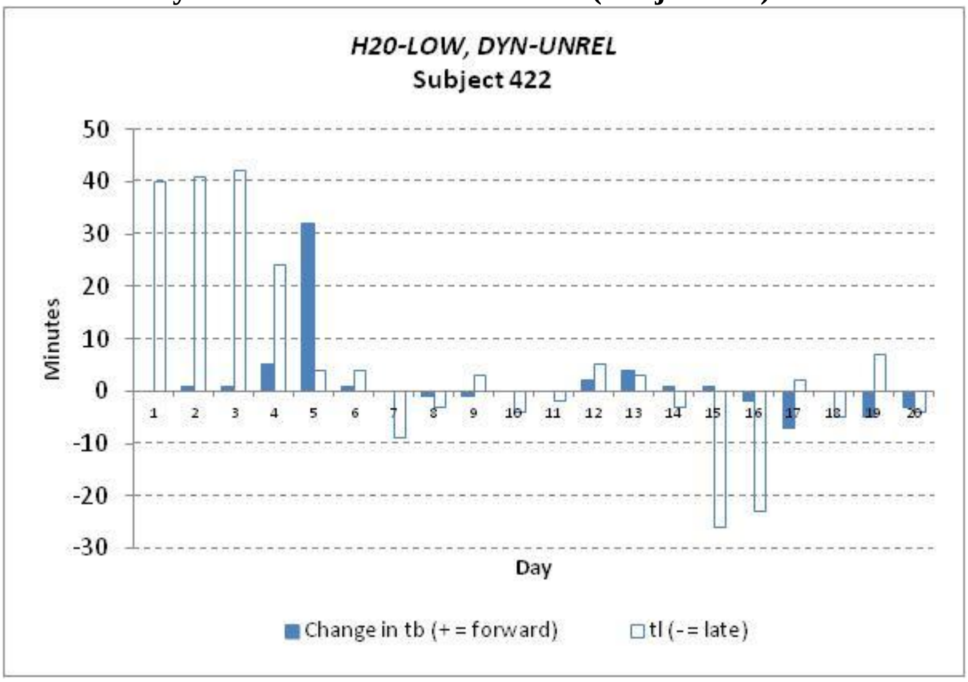

Figure 6-12 Plot of Change in t_b and Arrival Time at Destination (t_l) by Day under Unreliable Dynamic Information condition (Subject 422)

At the other end of the behavioural spectrum to Subject 401, one can find Subject 413 whose t_b choices are observed not to be associated with t_s^i at all, as shown in Figure 6-13. Although there are a number of days on which t_b are located with t_s^i, one can argue that such occurrences are merely coincidental given the general lack of association between t_b and t_s^i on preceding and succeeding days. His overall behaviour resembles those found in *NO-INFO* and *HDWAY*, or the majority in *TTABLE*.

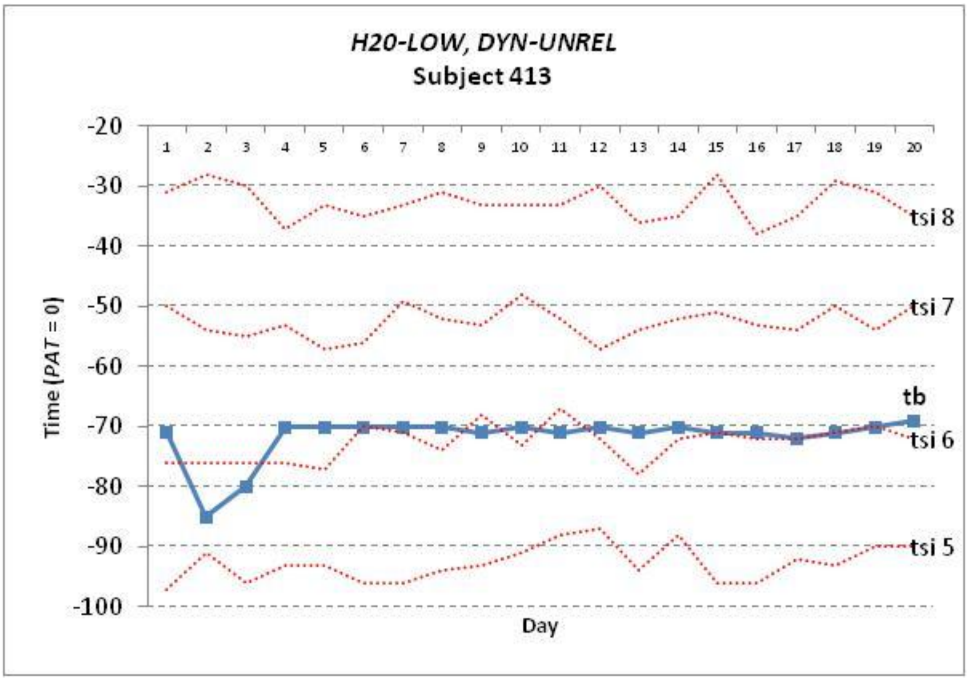

Figure 6-13 Plot of t_b and Scheduled Service Departure Time (t_s^i) by Day under Unreliable Dynamic Information condition (Subject 413)

Hence, there is heterogeneity in the responses to the provision of dynamic information. Based on the above description, there are three broad behavioural patterns. While there are those who adhere strictly to t_s^i, there are also others who appear to ignore them totally, with the remainder referring to the estimates partially and intermittently. To get a fuller picture of the distribution of these behavioural patterns, all the participants in the scenario are examined individually and classified into the respective patterns. As with *TTABLE* scenarios, a rule of thumb is required. However, the rule needed here is more straightforward than in *TTABLE*: the number of days on which t_b is co-located, or in close proximity, with t_s^i. The higher the number, the more responsive to the dynamic information the participant is deemed to be. Obviously, a certain degree of subjective judgement has to be exercised further to distinguish such cases as Subject 422, who is partially responsive (Figure 6-11) from those like Subject

413 who is clearly unresponsive (Figure 6-13), when both of them have approximately the same number of days on which $t_b = t_s^i$. Further visual examination of the t_b trend in each plot is needed to identify its association with t_s^i. With this rule of thumb described above, there is less ambiguity in terms of the degree to which the participants respond to the information, given the non-static nature of t_s^i. While one can only assess a participant to be *partially* responsive at most in *TTABLE* scenarios, it is possible to identify those who are fully responsive because their t_b track the varying t_s^i on almost all days.

This assessment and classification process is applied to all *Ops* conditions under both *DYN-UNREL* and *DYN-REL* conditions. The findings are produced in Table 6-12 that shows the proportion of participants responding fully and partially to dynamic information. The pertinent data from Table 6-8 relating to timetable information are appended in the last two columns for comparison.

Higher proportions of participants respond to dynamic information than to timetable information. Across all *DYN-UNREL* and *DYN-REL* scenarios, between 31% and 78% respond to the information at least partially, compared to between 14% and 48% in *TTABLE* scenarios. Whereas those who respond to the information form a minority in all *TTABLE* scenarios, in 8 out of 10 *DYN-UNREL* and *DYN-REL* scenarios, those who respond to the information at least partially outnumber those who do not. Among those who respond to the dynamic information, a clear majority do so fully, i.e., their t_b choices adhere to t_s^i on almost all days.

Table 6-12 Proportion and Number of Participants Responding to Dynamic and Timetable Information by *Ops* condition

Ops	***Info***							
	DYN-UNREL			***DYN-REL***			***TTABLE***	
	Responds to estimates	**Partially responds to estimates**	**Ignores estimates**	**Responds to estimates**	**Partially responds to estimates**	**Ignores estimates**	**Partially responds to estimates**	**Ignores estimates**
H20-LOW	.39 (9)	.22 (5)	.39 (9)	.64 (14)	.05 (1)	.32 (7)	.38 (8)	.62 (13)
H20-HIGH	.38 (8)	.19 (4)	.43 (9)	.35 (8)	.35 (8)	.30 (7)	.48 (10)	.52 (11)
H10-LOW	.38 (10)	.15 (4)	.46 (12)	.39 (9)	.17 (4)	.43 (10)	.25 (6)	.75 (18)
H10-HIGH	.43 (9)	.19 (4)	.38 (8)	.41 (9)	.14 (3)	.45 (10)	.14 (3)	.86 (19)
H5-LOW	.55 (12)	.23 (5)	.23 (5)	.24 (5)	.19 (4)	.57 (12)	.33 (7)	.67 (14)
H5-HIGH	.24 (5)	.29 (6)	.48 (10)	.29 (7)	.04 (1)	.67 (16)	.36 (8)	.64 (14)
Overall	.40 (53)	.21 (28)	.40 (53)	.39 (52)	.16 (21)	.46 (62)	.33 (42)	.66 (87)

There is one exception though. Only under *H5-HIGH*, the proportion of participants who ignore the information is higher when the information is reliable and dynamic (*DYN-REL*) than when it is static (*TTABLE*). It is unclear why this is so. One could attribute it to the common observation that a frequent service tends to result in random passenger arrivals at the bus stop, and is hence associated with non-usage of information. However, this same behaviour is not observed when the dynamic information is unreliable (*DYN-UNREL*), given that the proportion of those who ignore the information is not exceptionally high, and comparable to those in *H20-HIGH* and *H10-LOW*.

Across all *Ops* conditions in every *Info* condition, a substantial proportion of participants is observed who ignore the information, be it static or dynamic. The ratio of such non-responsive participants relative to responsive ones is not significantly different across the *Ops* condition within each of the three *Info* conditions (*DYN-UNREL*, $p = 0.583$, *DYN-REL* $p = 0.099$, and *TTABLE* $p = 0.231$, all at $\alpha = 0.05$). Hence, one can focus on comparing the behaviour across the *Info* conditions using the aggregate proportions (last row of Table 6-12). At the aggregate level, it is indeed found that there is a significantly higher proportion of participants who respond to dynamic information (*DYN-UNREL* and *DYN-REL*) than to timetable information (TTABLE) ($p = 0.000$).

The effect of dynamic information on the majority of participants is therefore quite apparent. Less apparent is the influence of the level of reliability on the propensity to use the information. Here, one compares the behaviour between *DYN-UNREL* and *DYN-REL*. Aggregated across all *Ops* conditions, there is no substantial difference in the proportion of those who respond to the information fully or partially between *DYN-UNREL* and *DYN-REL* ($p = 0.291$ at $\alpha = 0.05$). Each of the two *Info* conditions has a higher proportion of those who respond at least partially to the information than the other condition in 3 out of 6 *Ops* conditions. Three possible explanations are offered. First, the difference in t_s^i variability between the two *INFO* conditions may be insufficiently large for the participants to distinguish between the two. Second, it is argued that, even if they were so, 20 experimental days may be not be long enough for the participants under *DYN-UNREL* to experience sufficient episodes of inaccurate t_s^i estimates that they would eventually conclude that it is not worthwhile to follow the estimates. The third, and more plausible, explanation is that participants have the preconception that dynamic information is accurate inherently, and make little or no effort to ascertain that. That those participants who responded to the information did so right from day 1 supports this explanation.

The apparent inability to distinguish the different levels of reliability in the dynamic information is also reflected in how the participants perceive this attribute in their respective *Info* conditions. The reader may recall from Chapter 3 that participants were asked to rate four scenario- and information-related attributes at the end of each of the four 20-day sessions. One of these attributes is the accuracy of the estimates by the dynamic information service. Table 6-13 lists the mean rating scores for the perceived accuracy for each *Ops* condition under *DYN-UNREL* and *DYN-REL*. The scores are given on a scale from 1 to 7, with 1 indicating the lowest level of perceived accuracy, and 7 the highest. While no tests are conducted on the statistical significance of the differences, the mean scores between *DYN-UNREL* and *DYN-REL*, in consideration of the associated standard deviations, do not appear to show substantial differences at the aggregate level. *DYN-UNREL* and *DYN-REL* each have higher scores in half of the *Ops* conditions. Such observations are consistent with the notion that participants are not able to distinguish the two levels of reliability in dynamic information.

Table 6-13 Rating Scores on Reliability of Information by Information Condition

Ops	***Info***					
	DYN-UNREL			***DYN-REL***		
	Mean	**Standard Deviation**	**Number**	**Mean**	**Standard Deviation**	**Number**
H20-LOW	3.57	1.532	23	4.18	1.651	22
H20-HIGH	3.86	1.108	21	3.96	1.186	23
H10-LOW	4.23	1.177	26	4.00	1.477	23
H10-HIGH	4.05	1.532	21	4.32	1.492	22
H5-LOW	5.00	1.234	22	4.81	1.123	21
H5-HIGH	5.05	1.024	21	4.67	0.963	24
Overall	4.28	1.374	134	4.32	1.347	135

The findings in the preceding section reveal that static types of information have limited effect on the participants' decisions. Their t_b choice behaviours when given headway information (*HDWAY*) do not appear different from those in the absence of information. Timetable information (*TTABLE*) influences the behaviour of a proportion of participants, but one can at most infer that the effect on this minority is partial. The effects of dynamic information (*DYN-UNREL* and *DYN-REL*) are more apparent. A substantially higher proportion of participants respond to the dynamic information, and for these in the majority group, most chose their t_b in close accordance with the dynamic estimates t_s^i. However, reliability does not appear to affect the propensity of most of the participants to use the dynamic information.

These findings are in line with the expectations discussed previously. To determine further if the above interpretation is reasonable, one makes another digression in discussion to the rating scores provided by the participant. Table 6-13 presents the rating scores given by the participants for the attribute of dynamic information. The same participants were also asked to rate the usefulness of the types of information they were given in the sessions. Table 6-14 shows that they perceived the timetable information as less useful than dynamic information in all the *Ops* conditions.

Based on the average scores, it is not conclusive if the participants perceive a meaningful difference between *DYN-UNREL* and *DYN-REL*. The former has a higher score in 2 *Ops* conditions, the latter in 3, with the last one being almost a tie. This should not be unexpected because, as discussed earlier, the participants are unlikely to be able to distinguish between these two *Info* conditions.

Table 6-14 Rating Scores on Usefulness of Information by Information Condition

Ops	*Info*								
	DYN-UNREL			***DYN-REL***			***TTABLE***		
	Mean	**Std Dev.**	**No.**	**Mean**	**Std Dev.**	**No.**	**Mean**	**Std Dev.**	**No.**
H20-LOW	4.78	1.536	23	5.59	1.368	22	4.38	1.802	21
H20-HIGH	5.05	1.774	21	5.17	1.302	23	3.67	1.798	21
H10-LOW	4.69	1.594	26	4.83	1.614	23	4.50	1.445	24
H10-HIGH	5.43	1.886	21	5.09	1.688	22	4.23	1.510	22
H5-LOW	5.32	1.323	22	5.33	1.683	21	4.90	1.411	21
H5-HIGH	5.81	1.289	21	5.33	1.049	24	4.73	1.549	22
Overall	5.16	1.598	134	5.22	1.454	135	4.40	1.607	131

6.1.2.1 Non-Responses to Dynamic Information

As described in the preceding section, dynamic information has the greatest effect on the t_b choice behaviour of the participants. Nonetheless, there is a significant proportion of participants in every *Ops* condition who do not respond to the estimates at all. This sub-group of participants reflects the lower limit to which dynamic information can be expected to have an effect on travel behaviour at the aggregate level. One wonders why these participants remain unaffected by the dynamic information.

One possible factor behind this phenomenon is that experience in similar, but not identical, travel settings may influence the current propensity to use information. For example, one may postulate that a traveller is less likely to use the travel information provided if the travel environment he is encountering is similar to what he has encountered previously. Instead, he may prefer to rely on his experience or learning in making the travel decisions. He is likely to be confident in his own decisions such that he perceives no need to consult the information provided. In the real world, this behaviour is likely to be exhibited by habitual travellers.

In this experimental context, the operating and information conditions a participant encounters previously in earlier decision episodes (which can be either previous days or sessions) can affect how he perceives and responds to the information given in succeeding ones. Specifically, he may be less likely to use the dynamic information in the later experimental sessions because he may have decided to use heuristics developed in earlier sessions or rely solely on experience for his decision-making. Conversely, he may be more inclined to trust and use the dynamic information (if his first session involves dynamic information) because of his lack of experience in the given experimental settings.

For such a line of investigation, the obvious approach is to determine the *Ops* and *Info* conditions experienced by individual participants prior to the dynamic information scenario, and examine how the propensity to use dynamic information differs between these individuals based on the previous conditions experienced by them. However, a more expedient approach is decided upon. Instead of comparing across sessions, the investigation is narrowed to two *Info* conditions that simulate a change from timetable information (in the first 10 days) to a dynamic one (in the last 10 days), "*TTABLE then DYN-UNREL*" and "*TTABLE then DYN-REL*" (Table 3-2 in Chapter 3). These two specific *Info* conditions allow one to examine the response of a participant to dynamic information immediately after a period (of 10 days) of learning about the hypothetical bus service (and the timetable information) within the same session. The behavioural responses of each participant to dynamic information in the last 10 days in these two *Info* conditions are classified using the same approach described in preceding section. Table 6-15 shows the proportion of participants responding fully, partially and not at all to dynamic information in the last 10 days.

Table 6-15 Proportion and Number of Participants Responding to Dynamic Information After Being Provided Timetable Information, by *Ops* condition

Ops	***Info***											
	TTABLE THEN DYN-UNREL						***TTABLE THEN DYN-REL***					
	Responds to estimates		**Partially responds to estimates**		**Ignores estimates**		**Responds to estimates**		**Partially responds to estimates**		**Ignores estimates**	
H20-LOW	0.48	(10)	0.05	(1)	0.48	(10)	0.68	(15)	0.09	(2)	0.23	(5)
H20-HIGH	0.28	(7)	0.16	(4)	0.56	(14)	0.23	(5)	0.18	(4)	0.59	(13)
H10-LOW	0.14	(3)	0.24	(5)	0.62	(13)	0.39	(9)	0.09	(2)	0.52	(12)
H10-HIGH	0.59	(13)	0.09	(2)	0.32	(7)	0.29	(6)	0.10	(2)	0.62	(13)
H5-LOW	0.43	(10)	0.04	(1)	0.52	(12)	0.14	(3)	0.09	(2)	0.77	(17)
H5-HIGH	0.36	(8)	0.18	(4)	0.45	(10)	0.14	(3)	0.09	(2)	0.77	(17)
Overall	.38	(51)	.13	(17)	.49	(66)	.31	(41)	.10	(14)	.57	(77)
	DYN-UNREL						***DYN-REL***					
Overall	.40	(53)	.21	(28)	.40	(53)	.39	(52)	.16	(21)	.46	(62)

Aggregated across the *Ops* conditions, the proportions of participants who respond to dynamic information fully and partially after gaining experience of the bus service (Table 6-15) are significantly lower than those in scenarios in which dynamic information is given right from the outset (Table 6-12), (0.38 and 0.13 compared to 0.40 and 0.21 for *DYN-UNREL* [p = 0.029], and 0.31 and 0.10 compared to 0.39 and 0.16 for *DYN-REL* [p = 0.038]). In 9 out of 12 scenarios listed, the proportions of those who ignore the dynamic information completely after gaining prior experience of the bus service operating characteristics are also higher than those who were given dynamic information right from the beginning. This observation is consistent with the view that a participant who has learnt over time may be less inclined to respond to new information. This finding illustrates the limits to which the introduction of Advanced Traveller Information Systems (ATIS) can induce behavioural changes in habitual travellers such as commuters to work.

6.2 Summary of Findings

In summary, the effect of information depends on the type of information. The information effect is manifested in a higher propensity to make day-to-day changes in t_b. The choices of t_b when such switches are made are located at or in close proximity to the service departure time t_s^i. It shows that those influenced by the information will 'anchor' their decisions to the t_s^i. Such 'anchors' also appear to result in a greater likelihood of participants making an attempt to catch another service earlier or later than the one he has taken the previous day after the initial exploratory period. Hence the more frequent occurrences of t_b changes of large magnitude that are equal or close to the headway.

Such an effect is negligible in the case of headway information because of the absence of specific time estimates in the information. It is moderate for static timetable as only a minority exhibit such switching behaviour. It is most pronounced when the information provided is dynamic, regardless of reliability. This is in line with expectations and intuition certainly, but one that has not surfaced clearly using the aggregate approach described in Chapters 4 and 5. This demonstrates the utility of the disaggregate approach in the examination of heterogeneous responses to the various types of information.

7 CONCLUSION

This Chapter concludes the thesis by setting out the main research findings and proposes future research that will build on the current work. It first summarises the main findings in the preceding chapters and discusses the implications of these findings. It then sets out some of the limitations before suggesting possible refinements to address these limitations as well as future lines of investigation.

7.1 Summary of Findings

This thesis examines the behavioural responses of travellers to travel information over time. There are two phenomena of interest being investigated, namely the effect of information on travel decisions, and the effect of learning. The first effect concerns the difference in behavioural responses to various types of travel information. In this study, the travel information is classified into static and dynamic, with the absence of information as the base case. The second effect involves learning by the traveller as he embarks on the same trip repeatedly. As he experiences both the outcomes and the characteristics of the travel information service in successive trips, he adjusts his perceptions and decisions in subsequent trips. This study explores both effects individually and their interaction.

A set of five hypotheses was developed to explore the interplay between learning, the type of information, and the information reliability. It is postulated that, first, in the absence of information, the traveller will attain better decision outcomes over time through learning. When given information, he will be able to reinforce the learning process and attain better decision outcomes overall. It has been hypothesised further that dynamic information has a greater reinforcement effect than static information. When dynamic information is applied, the higher its reliability, the more the learning effect is reinforced. In addition, the traveller is also more likely to adjust his perception to align to the information if the information is reliable. The key assumption underpinning the above hypotheses is that the traveller seeks to maximise his utility.

To test the hypotheses, a hypothetical scenario using a public transport travel setting is constructed. In this scenario, the traveller makes repeated home-based work trips by public bus. He is to decide on each day (*d*) his arrival time at the bus stop $(t_b)_d$ to catch the desired bus service, out of the ten available, that will bring him to his workplace at his preferred arrival time (*PAT*). However, he has to contend with the day-to-day variability of the departure time of the service (t_s) and the in-vehicle trip time he spends on it (T_v). To assist him in decision-making in the face of such uncertainty, he may be given information on the estimated departure time t_s^i of each service arriving at the bus stop, as well as the estimated range of in-vehicle time T_v. The information on t_s (*INFO*) can be static and given in the format of the scheduled headway (*HDWAY*) or timetable (*TTABLE*). It can also be dynamic, with t_s^i values that vary daily. The variance of the t_s^i distribution defines the reliability of this dynamic information, with two levels of reliability (*DYN-UNREL* and *DYN-REL*) incorporated in the scenarios. The operating characteristics (*Ops*) of the bus service are also varied by headway and departure time variability.

In the context of the experiments, the attainment of ‘better outcomes’ described in the hypotheses are to be manifested in the traveller increasing his likelihood over time of (a) choosing the bus service that is most likely to bring him to the destination closest to, but not later than the *PAT*, (Svc_{best}) and (b) reducing the wait time for that service (T_w). This is premised on the assumption that the traveller wants to maximise his travel utility by keeping his total travel time as short as possible. Aggregated across all experimental participants (travellers), the improvement of outcomes is observed in the increase in the proportion of travellers choosing Svc_{best} , P_{best}, and the decrease in the average T_w over time. The degree and rate at which P_{best} is increased and average T_w decreased vary with the type of information provided and the amount of experience the participants gain. In general, it is postulated that the rate of change of both variables is the fastest under reliable dynamic information (*DYN-REL*), followed by less reliable dynamic information (*DYN-UNREL*), timetable information and lastly, headway and no information (*HDWAY* and *NO-INFO*). The participants are also likely to acquire *DYN-REL* than *DYN-UNREL*, such that the information margin $T^i = |t_b - t_s^i|$ under *DYN-REL* is smaller and reduces at a faster rate than *DYN-UNREL*.

Tests reveal that the hypothesised relationships on the three variables of P_{best}, T_w and T^i are not statistically significant, regardless of the *Info* or *Ops* condition involved. However, this does not mean that the effects of learning and information are absent; they have not manifested themselves in the manner postulated at the aggregate level. Subsequent analyses at the aggregate level reveal that most of the decisions are inferred to be conservative in that services that arrive before Svc_{best} appeared to be chosen, rather than Svc_{best} itself. For most participants, once the choice of service is settled upon, only a very small proportion of subsequent decisions involve a switch in the choice of service. This suggests that the basic premise that the participants seek to maximise their utility is not necessarily valid.

The analyses were then carried out at the disaggregate level. Specifically, the day-to-day choices of t_b of each participant were examined, and this approach appears to provide more useful insights into the effects of information. The first important finding is that the choice of t_b relates significantly to the outcome of the previous day. If the previous day sees an adverse outcome (i.e., a late arrival at the destination), the participant is likely to choose an earlier t_b; if the previous day sees no adverse consequence (an early or on-time arrival), he is likely to seek a more rewarding but riskier choice of a later t_b. This applies to all *Info* and *Ops* conditions.

However, the frequency and magnitude of day-to-day changes in t_b is found to be affected by type of information. Under conditions where the information source does not provide specific estimates, t_s^i is absent, as in *NO-INFO* and *HDWAY*, t_b changes are infrequent and in amounts that are smaller than the service headway. The few large t_b changes that take place occur in the initial few days primarily, during which the participant engages in exploratory behaviour to locate his intended service. These observations are made across all *Ops* conditions.

The presence of specific service departure time estimates t_s^i in a static timetable (*TTABLE*) sees the participants' t_b choices 'anchoring' at or near t_s^i. It also results in a moderately higher likelihood among a significant proportion of participants to change t_b than in *NO-INFO* and *HDWAY*. These t_b changes are usually equal or close to the headway, and are from the proximity of one t_s^i to the vicinity of another, indicating that the participants are using t_s^i to attempt to catch a service that is earlier or later than the one he chose the previous day.

The choices of t_b when such switches are made are located at or in close proximity to the service departure time t_s^i. It shows that those influenced by the information will 'anchor' their decisions to the t_s^i. Such 'anchors' also appear to result in a greater likelihood of participants making an attempt to catch another service earlier or later than the one he has taken the previous day after the initial exploratory period. Hence the more frequent occurrences of t_b changes of large magnitude that are equal or close to the headway.

The effect described above is most pronounced when the information provided is dynamic. For a substantial proportion of participants, their t_b choices adhere closely and vary in close tandem with the t_s^i, resulting in a much higher frequency of t_b changes compared to the static information types. One interesting finding is that the strict adherence to t_s^i occurs regardless of how well the dynamic information predicts the service departure times. This indicates that the propensity to acquire the information for their decision-making is influenced more by the type of information (in this case, they are likely to acquire the information for their decision-making) than its reliability. This finding appears to be aligned with those of Ben-Elia *et al*. (2013) that discover the influence of dynamic (but prescriptive) information on traveller's choice is sustained when the information accuracy is reduced, suggesting similar preferences to anchor their choices to what the information service provides, regardless of its accuracy.

While the above description applies to the behaviour of many participants across all *Ops* conditions, a significant number of their counterparts exhibit a different behaviour altogether. The latter group makes few, if any, changes to the t_b they have chosen. This indicates heterogeneity in the responses to information.

7.2 Discussion

The findings from the experiment offer some useful and interesting implications about how behaviour under travel information is modelled, as well as about real-life applications of ATIS. The following sections discuss three pertinent issues.

7.2.1 Non-maximising behaviour

The hypotheses that are first formulated in Chapter 2 on the learning and the effect of information are premised on the traveller being utility-maximising (or disutility-minimising). That there is insufficient evidence to support these hypotheses empirically suggests that such utility maximisation may not be the main driver of a traveller's behaviour. While the utility maximisation paradigm is commonly used in the travel behaviour literature because of its simplicity and ease of formulation, its limitations are well documented. This finding is consistent with the already substantial body of evidence on its limitations.

There is stronger evidence from the findings pertaining to the day-to-day responses, described in Chapter 6, that travellers may instead rely on certain heuristics, or simple rules of thumb. In the face of multiple sources of uncertainty in t_s, and T_v, a significant proportion of the experiment participants in the *NO-INFO*, *HDWAY* and *TTABLE* decides on t_b based primarily on the previous day's outcome: an earlier t_b if outcome is adverse (late arrival at destination); and a later one if favourable (early or on-time arrival). In the presence of dynamic information (*DYN-UNREL* and *DYN-REL*), the use of an even simpler, rule of thumb becomes apparent among many of the participants. The decision is simply to follow the information source, i.e., $t_b = t_s^i$.

One wonders why the use of a rule of thumb is favoured even when it does not lead to the best outcomes that maximise the utility (minimise the disutility). Perhaps for some, the motivation is not one of maximising utility, even though the experiment has attempted to link the financial rewards to the participants' score performance. Another possible reason is that, given the multiple sources of uncertainty (in the varying t_s, and T_v, and in the case of dynamic information, t_s^i), and outcomes (the arrival time at destination, t_l and the wait time, T_w), to acquire, process and assimilate all of these decision inputs every day imposes too high a cost. In such circumstances, it is highly improbable that the traveller will engage in integrating the full probability distribution of outcomes and the payoffs of each outcome, a process that is assumed in the utility maximisation paradigm. This is especially true in real life when the payout of a utility-maximising outcome is just travel-time savings of a few minutes.

In contrast, heuristics or rules of thumb offer a more viable, lower-cost decision-making approach. If this is the predominant decision-making behaviour of travellers, there will be implications on how travel behaviour should be modelled. It could mean that more caution should be exercised in the use of utility-based models, because while popular for their simplicity and tractability, they may not be descriptive of the decision-making behaviour of travellers.

The suggestion that travellers may place a greater reliance on heuristics for decision-making, instead of maximising utility, will have implications to the wider contexts of such repetitive travel behaviour as the daily commute. In studies in which the traveller considers primarily a single variable travel attribute, typically travel times by car along routes, the choice behaviour already exhibits robust departures from utility maximisation (e.g., Avineri and Prashker, 2005, Jou *et al*, 2008, Ben-Elia *et al*., 2013). In the much less studied, but clearly more complex decision-making scenario of a public transport journey, the traveller has to contend with multiple travel attributes and sources of variability (waiting times, service departure times, in-vehicle times, transfer times, etc.) over multiple legs (train and bus). Therefore, the likelihood of the public transport user relying on heuristics, or simply habit is high, given the overwhelming cognitive burden on decision-making.

7.2.2 Effect of ATIS

This research also suggests that there is a higher propensity for travellers to use dynamic information (represented by *DYN-UNREL* and *DYN-REL* in the experiment) over static information (*HDWAY* and *TTABLE*). This higher likelihood to acquire dynamic information is evident during the first few days in which the information is provided, and also for a significant number of days subsequently. This suggests that if an Advanced Traveller Information System (ATIS) is implemented, its (dynamic) information is highly likely to be acquired by both ad-hoc users who may encounter the ATIS for the first or second time, and by regular ones who make repeated trips and are exposed to it on an almost daily basis. The high and sustained rate of utilisation could provide one of the justifications for the provision of an ATIS.

However, it should be noted that a high rate of utilisation does not necessarily lead to outcomes that maximise utility, as discussed in the previous section. Therefore, claims or assumptions of travel-time savings that are used to compute the quantifiable benefits of an ATIS project should be scrutinised carefully, or at the minimum, accepted with a high degree of caution. On the other hand, a high level of responsiveness to ATIS that is sustained over time suggests travellers may find sources of utility other than travel-time savings, e.g., reduction in perceived uncertainty in service arrival times, such that a higher level of satisfaction with the transport service is attained. Such utility may be non-quantifiable.

The research further suggests that the travellers' propensity to acquire and use the dynamic information is not affected by its reliability. Nor do the travellers appear to be able to differentiate the different levels of reliability. One may surmise that there may be no compelling reason for an ATIS operator to invest to improve reliability, especially if the improvement is marginal and the cost, substantial, if his objective is to attract a higher rate of utilisation. The counter-argument is that reliability improvements should still bring benefits in the form of better outcomes perceived by the current users, even if the more reliable information service results in no new users. Of course, one would then consider the earlier finding that such outcomes may not be utility maximising in nature, but those that are less quantifiable, such as "positive psychological factors" and greater satisfaction with the transport service (Dziekan and Kottenhoff, 2007). The benefits could also be further circumscribed by the heterogeneity of the responses to the information service, as is discussed in the following section.

Although the finding that the travellers are likely to acquire dynamic information regardless of reliability appears encouraging to proponents of ATIS, one should also take heed of another finding that may be of practical, but less promising, implication. This study finds that the provision of dynamic information does not appear to increase the proportion of travellers choosing the maximising option. In fact, the collective behaviour of the experimental participants tends towards random choice, which is a manifestation of the payoff variability effect (Avineri and Prashker, 2005, Erev and Barron, 2005). One could argue that the traveller who has a high propensity to acquire dynamic information is effectively introducing an additional source of variability (of the dynamic t_s^i) to those of the travel attributes with which he is contending in the first place (the service departure time, t_s, and in-vehicle time, T_v). The bundle of multiple sources of variability could have led to highly variable outcomes or payoffs. The resultant shift towards random choice from the payoff variability effect can thus lead to the outcome being not substantially better than one where no provision of travel information is provided. In fact, the more dynamic and responsive the ATIS is, the higher the likelihood that the payoff variability effect can be exacerbated.

The above discussion pertains to the provision of descriptive information on individual travel attributes (e.g., estimates of service departure times). In contrast, prescriptive information provides suggestions on the choice to be made, such as the specific service to catch and when to depart home. To lessen the traveller's cognitive burden of assimilating different sources of variability, especially in the more complex decision-making environment of a public transport journey, prescriptive information can be considered. One can draw lessons from the findings of Ben-Elia *et al*. (2013) that suggest it can have more effects behaviourally than descriptive information. However, whether its effect persists is debatable, especially if the travel outcome from following the prescriptive information turns out to be less favourable than previous outcomes. This is particularly so considering the findings of Verplanken *et al*. (1997) that suggests travellers with strong habits tend towards acquiring less information, and even if amenable to acquire information initially, are likely to be subject to chronic habit effects in subsequent repeated trips.

7.2.3 Heterogeneity of Responses to ATIS

Another important finding is that there is clearly heterogeneity in the responses to information. Whether the information is static or dynamic, there is always present a group of travellers that may not respond to information. The experimental findings suggest the proportion of travellers who may not respond to ATIS (dynamic information) averages 43%, which is not an insignificant minority. It is higher at 66% for static information. Another 18% on average may respond to ATIS on some of the trips. Only the remaining 40% can be classified as those who respond fully.

This finding clearly deviates substantially from the assumption of many studies on travel information that travellers are a homogeneous group that respond fully to information. Although such an assumption simplifies the analysis substantially, one should recognise that it provides a less-than-realistic depiction. A more refined approach that recognises such heterogeneity, e.g., model the effect of information on different traveller groups of varying propensity to use the information, is therefore recommended. Otherwise, if the analysis is used to estimate the effect of travel information, the homogeneity assumption runs the risk of grossly over-estimating the effect of travel information. If it is additionally used to justify investment in ATIS, it will be necessary to discount the purported benefits correspondingly.

7.3 Suggested Improvements and Further Research

This thesis has provided some contributions to the body of research on travellers' responses to different types of travel information over time. Nonetheless, more useful insights should be gained if one improves on the current work and builds on it to explore new lines of investigation. Three areas for improvement and research are proposed.

7.3.1 Examining Information Acquisition Behaviour

The experiment was designed to elicit responses to different types of information (*INFO*) and the outcomes in the form of actual arrival time (t_s) of the service the participant 'boards', the arrival time at which he reaches the destination (t_l) (and whether he is late), and the score for the day. All these are revealed on the experimental screen immediately after each decision taken.

Inherent in such an experimental design is the assumption that the participant indeed acquires what is displayed on screen. (Whether he assimilates and utilises it in the decision-making for the next or subsequent trips is a different matter). This appears reasonable for the participant to acquire the revealed outcomes, as in real life, in which the traveller would very likely notice when his bus arrives and when he arrives at the workplace. At the minimum, the real-life traveller would have taken note, however cursorily, of whether he is late, or whether he has waited exceptionally long for his bus. This is supported by the findings that the change in the choice of passenger arrival time at the bus stop (t_b) is significantly correlated with the arrival time at the destination (t_l) across all experimental scenarios. The same cannot be assumed for the acquisition of information. The finding that a significant proportion of participants do not, or at most only partially, respond to the dynamic information suggests many may have foregone this process of information acquisition. One could counter-argue that the acquisition and utilisation of information are two distinct processes, and these participants do acquire the information, but decide against utilising it.

The experimental design is limited in providing an unambiguous resolution as to which is the likelier case. Instead, as described in Chapter 3, a set of rules has been devised to *infer* the service departure time (t_s^i) from which the participant is taking reference in his decision-making (with another set to infer the service he is catching). Such inference rules rely on simplistic assumptions whose validity is somewhat questionable, as is discussed in Chapter 3. Among them is an implicit one that assumes the information is acquired automatically every single day.

A more satisfactory approach is presented in Chorus *et al*. (2008b). Its experimental design requires the participant to make a deliberate and explicit request for travel information. He would need to click a button to reveal the hidden travel information and make a payment from a pre-determined travel budget for this information. This replicates the deliberate act of acquiring information and offers a more realistic representation of the behaviour of a real-life traveller. For example, to obtain the published bus arrival times, a commuter would need to make a deliberate step towards the published timetable at the bus stop pole, collect the timetable from an information kiosk, or read it off an internet website. Likewise, dynamic information has to be accessed consciously from mobile devices or information panels.

While the experimental design of Chorus *et al*. (2008) differs from this research in that it is designed to elicit the willingness to pay for travel information among others, emulating it in the current experiment will enrich the findings. Doing so would enable one to ascertain if the participant acquires the information (though not using it necessarily) on a particular day, and whether the propensity to do so changes over the entire experimental session. This would be an improvement of the current unsatisfactory state of assuming every participant acquires the information at all times and making the tedious attempt to infer how he does so.

It is discussed briefly in Chapter 1 (Section 1.3) that contextual information has a role to play in traveller's learning and information acquisition. Future research can therefore also extend to examining how different forms of presenting the same content can influence decision making. Such additional explanatory variables as colour, default choices and semantics, can be included to explore the effects of contextual information.

7.3.2 Modelling Choice Behaviour under Information Acquisition

This study involves aggregate analysis, followed by further exploration of behaviour at the disaggregate level. Moving on from the present stage of research, this study should benefit from more in-depth analysis of the association between the choices made by the participants (in t_b), and the types and reliability of information provided. To this end, discrete choice analysis should serve as a fruitful approach, given that it is commonly used to investigate travel behaviour, and has been applied in similar contexts.

Formulating and applying a discrete choice model will enrich the findings by not only providing estimates of the various hypothesised effects, but also by accounting for such participant-specific attributes as age, education, and income that could have influence on the participants' propensity to acquire information. Data on such socio-demographic characteristics are collected in this study, but are not tested as explanatory factors and examined for greater insights. The model could also capture the effects of such attributes as risk attitudes and travel habits.

In this study's context, t_b is a discrete choice, and such a model will express the utility of choosing t_b, over all other possible times t (in one-minute intervals) in day d by participant i as a function of a series of explanatory factors, whose coefficients are to be estimated and tested for statistical significance. These factors would conceivably be such experimental variables as estimates of service departure times, t_s^i, and decision outcomes of previous day(s) like wait time T_w or *Score*, and participant-specific attributes. Data for all of these factors are already obtained through the experiment. Risk attitudes and habits could also be incorporated, although data on these attributes would have to be collected additionally through carefully designed questionnaires, while ensuring that the burden on the participants is not increased excessively.

7.3.3 Examining Effect of “Learning by Analogy” Experience

In this research, participants attempted 4 consecutive experimental sessions. Each session contained different information (*Info*) and operating (*Ops*) conditions not repeated from the preceding ones. Such experimental parameters as work start time (*PAT*) and scheduled in-vehicle and access times (T_v, T_a and T_e) were varied across the sessions. Survey questions to obtain the participants’ perceptions of the preceding session and their sociodemographic characteristics and travel experience were also inserted between sessions. Within a group of participants with the same set of scenarios, the sequence of presentation of scenarios was “counter-balanced” to ensure that each scenario appeared in the first, second, third and fourth sessions approximately an equal number of times within the group. Such intentional interventions were to provide hints to the participant that the sessions were unrelated to each other, thus minimising association of scenarios of successive sessions and reducing carryover effects. This is so that the effects of different types of information that are manifest across the sessions can be isolated for analysis.

Such deliberate attempts to suppress the carryover effects are premised on the paradigm that such effects are undesirable in the quest to understand the effect of travel information on learning. However, it stands to reason that the traveller in real life does not treat different episodes of his travel in isolation and does “carry over” the perceptions from past travel events that have characteristics similar, though not necessarily identical, to the current.

For example, if a traveller perceives the bus service he takes regularly from home to be somewhat unreliable, he would factor in some buffer in the wait time when he starts taking another service at the same bus stop, because he is likely to view the latter service to be similarly unreliable. Another traveller who makes use of the ATIS often to decide on his departure time on his commute trips is more likely to do the same for his ad-hoc trips. This is described by Chorus *et al*. (2006a) as “learning by analogy”.

Hence, the “learning by analogy” effect should be a phenomenon of research interest itself, and it can be argued that analysis on how experience of the experiment participant in one session affects his perceptions and behaviour in subsequent sessions should be conducted. One can, for instance, assign one group of participants to attempt two consecutive sessions with dynamic information (*DYN*), and another group to do a session under a static or no information scenario (*TTABLE*, *HDWAY* or *NO-INFO*) before the *DYN* scenario. Even with the work start time (*PAT*), scheduled in-vehicle and access times (T_v, T_a and T_e) in the consecutive sessions assigned different values, one can argue that the “learning by analogy” effect, if present, can be observed across similar, but not necessarily identical, scenarios. In real life, the traveller will encounter travel episodes that are similar to past events, but can never be their complete replicates.

Such factors as the propensity to acquire information in the second common *DYN* session can then be examined between the two groups to elicit the effect of carryover experience. Within the current experimental design, it is possible to identify sub-groups of participants that have participated in the sessions in the order described. However, because they are an outcome of randomised assignment and not of deliberate design, their sub-groups are too small ($n \approx 5$) for analysis and comparison. To be able to conduct such contrasts, it is necessary to incorporate such assignments in the experimental design from the start.

7.3.4 Studying Behavioural Mechanisms

This research has examined the effects of information over time by analysing the traveller’s decisions that are manifest in his choice of departure time in an experimental setting. What is absent is the lack of investigation into the behavioural mechanisms through which such decisions are developed. Chapter 1 has described this gap in research briefly. It also provides the theoretical framework proposed by Chorus *et al*. (2006a) that seeks to address this shortcoming.

A future line of research could, therefore, integrate the current empirical approach with the theoretical framework of Chorus *et al*. (2006a) that sets out the behavioural mechanisms explicitly. The current empirical approach can be used to collect data to test the iterative decision scheme (Figure 1-1) and the assumptions behind it, and thus provide useful insights into the behavioural processes a traveller undergoes. This scheme describes individual behavioural processes of perception updating, information acquisition, and choice. One could therefore formulate individual behavioural models for each of these processes, and carry out the estimation of these models using empirical data obtained from experiments

Preliminary work has been done by the researcher to this end, and could be considered for future research. Without going into detail here, the behavioural models are formulated on the basis that the traveller's perceptions of the trip attributes t_s (service departure time) and T_v (in-vehicle time) can be described by probability distributions, in which the mean of the distribution represents his best guess of the attribute, and the standard deviation, the confidence he has with this best guess. The characteristics of the dynamic information and the traveller's perceptions of these characteristics are likewise represented by probability distributions. The models describe the five individual processes of perception, information acquisition, choice evaluation, learning, and information perception updating. Each of them uses transformations of distributions to represent its respective process of perception changing. The models are inter-related with each other, such that the output of each model becomes the input of another in a realistic representation of how the traveller perceives, decides and learns in an iterative manner in the real life context of repeated trips.

Although an extensive body of empirical data has been obtained in the current work, it is not able to support such a line of analysis. This is because the large number of free parameters (up to ten) to be estimated for the entire set of models demands a much larger dataset than is provided by the current experiment. A different experimental design that can yield a substantially larger number of data points and a larger sample size is required. This could be the subject of a separate study that can be structured to contribute to the body of empirical knowledge on the behavioural mechanisms of information acquisition, an area that Chorus *et al.* (2006a) identify as one that warrants greater emphasis.

7.3.5 Feasibility of Field Experiments

The natural progression from a laboratory-based study is to examine the posited effects in real life. It would be useful to consider field experiments to validate the observations from the laboratory experiment. Commuters who travel from home to work daily by public transport could be recruited, and given different types of travel information. Their travel behaviour can then be observed via travel diaries and questionnaires.

It is conceivable that such field experiments involving public transport travel are much more complex to carry out, as compared to those pertaining to car trips that are more commonly studied, such as that by Jou *et al*. (2008). This is because the latter requires observations that are relatively straightforward for the commuter to report, such as departure and arrival times or route choice. In contrast, sampled commuters in a public transport context will need to contend with a more complex travel situation. In addition to his travel decisions (e.g., departure time from home), he will also be required to report observations on the public transport service itself, such as the wait, service departure, in-vehicle and between-service transfer times.

To relieve the excessive burden the experiment participant may have to bear in such field experiments, the researcher may exploit a range of information-communications technology applications that are increasingly prevalent. For example, the fare payment card will be able to provide accurate data on boarding and alighting times. An application can also be specially developed and installed on the participant's personal mobile device to facilitate the collection of experiment data (e.g., departure time from home) in real-time. Trip- or participant-specific questionnaires may also be launched by the application on the go to increase the salience of the questions to the on-going trip. More importantly, it serves as a means to deliver experimental stimuli (e.g., static or dynamic estimates of service departure times) that would otherwise be almost impossible to provide.

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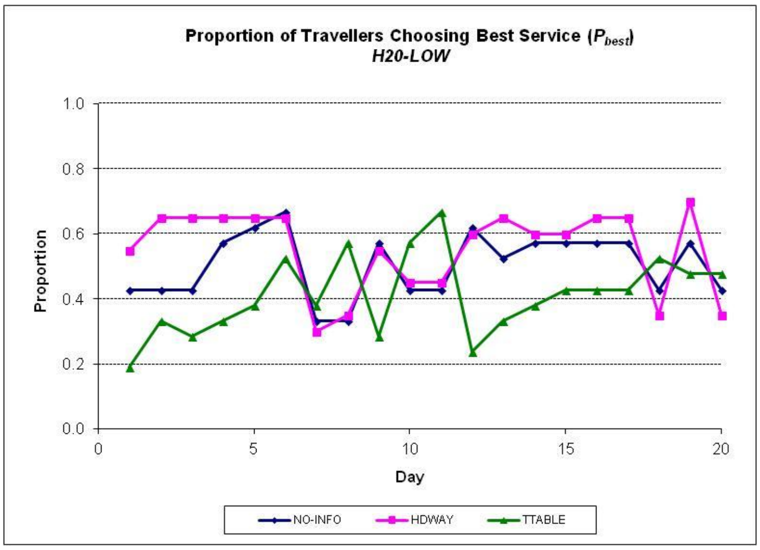
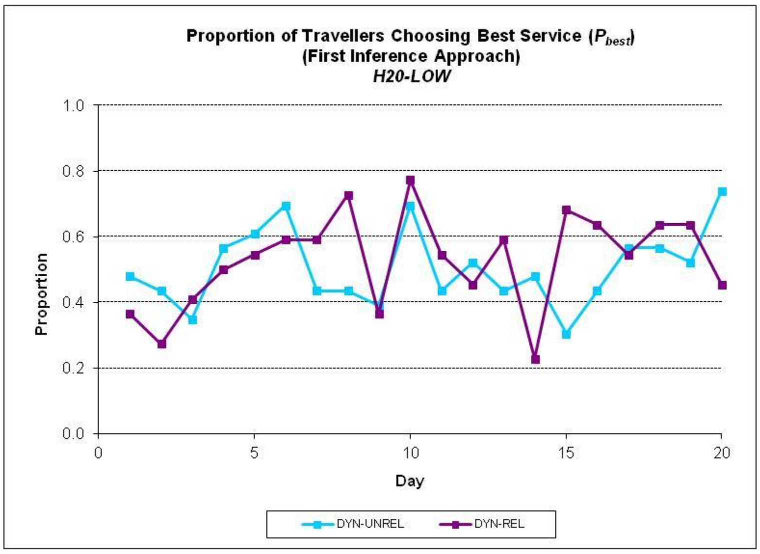
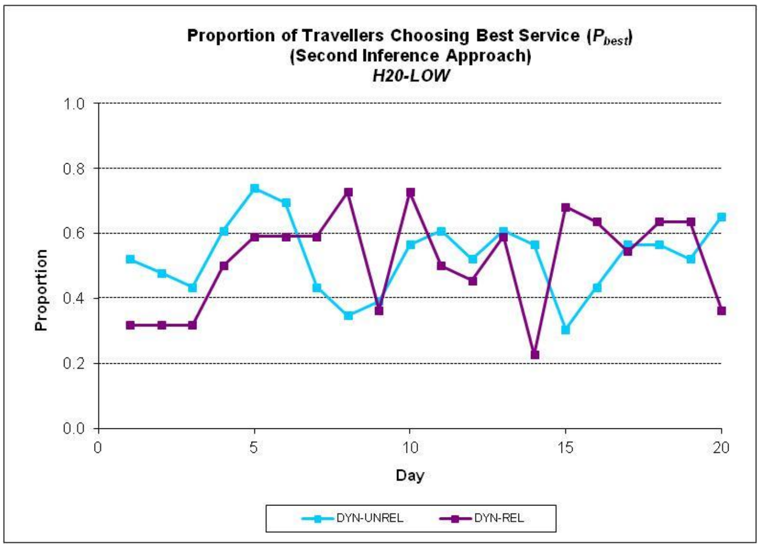
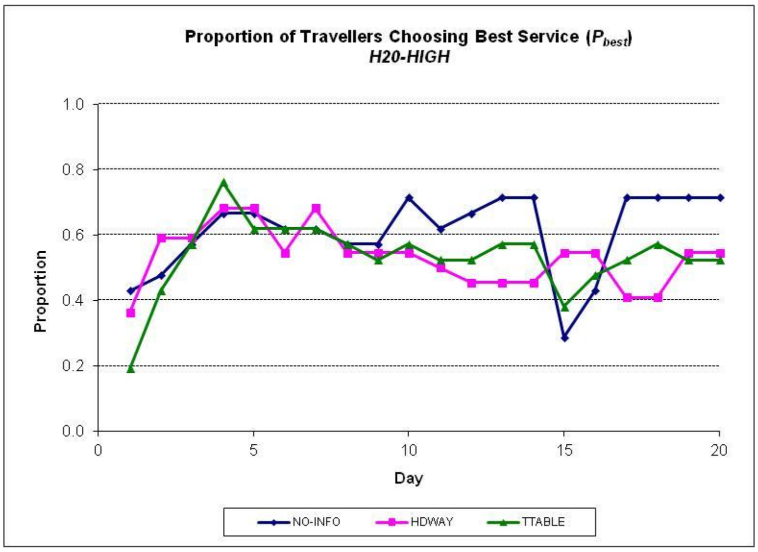
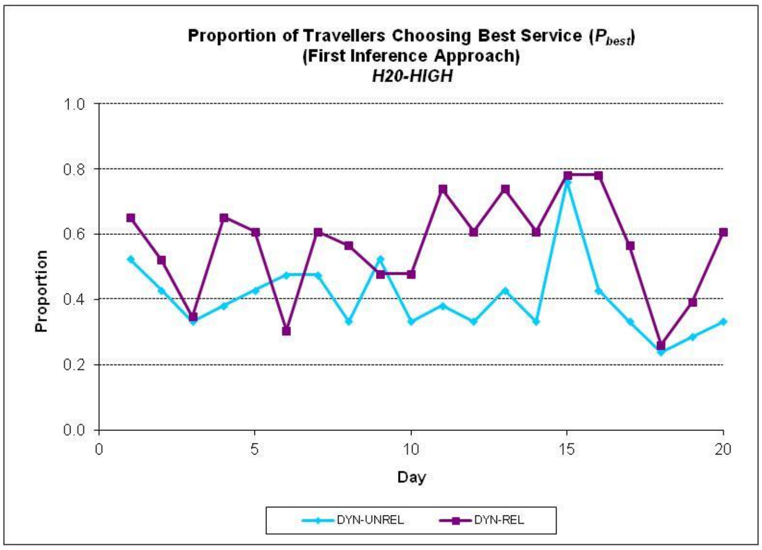
APPENDIX 1: PLOTS OF TRAVELLERS CHOOSING BEST SERVICE, P_{best}, BY SCENARIO

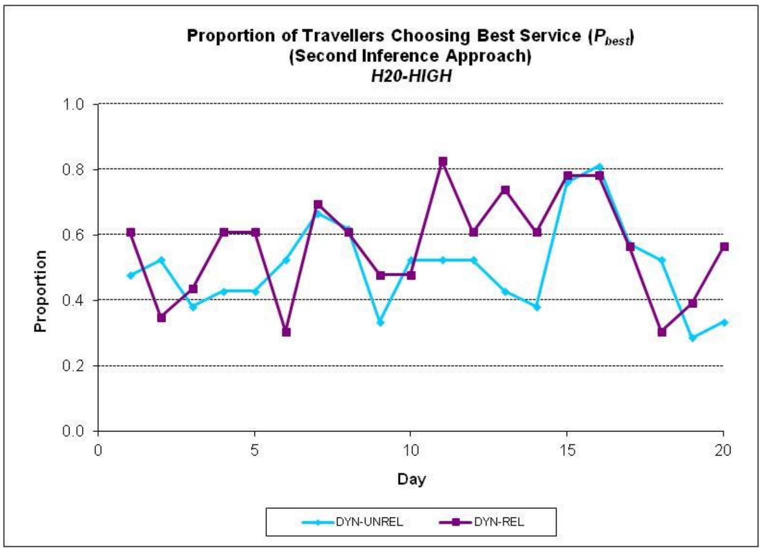


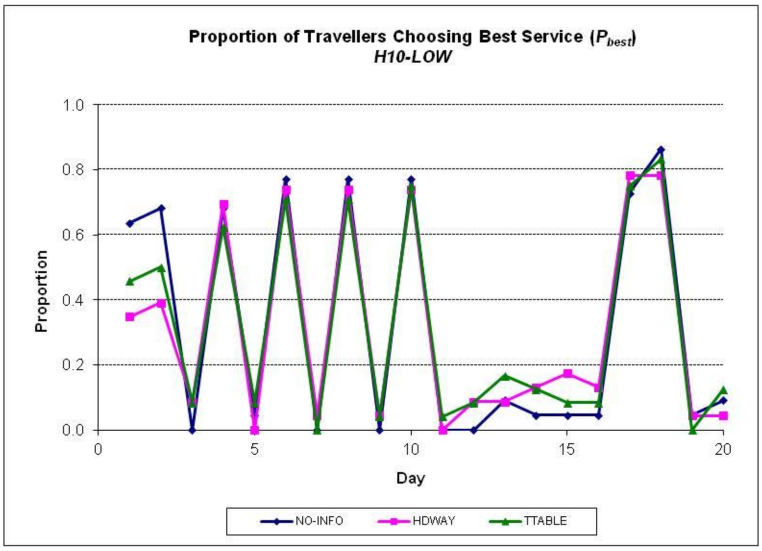


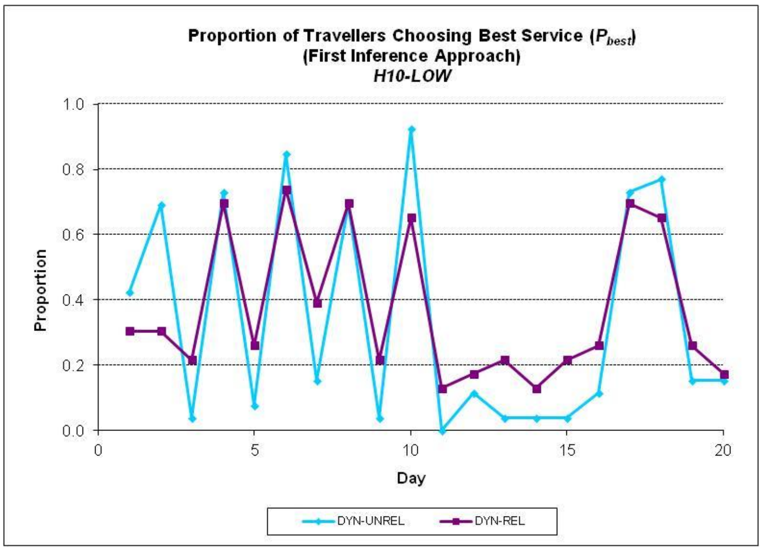


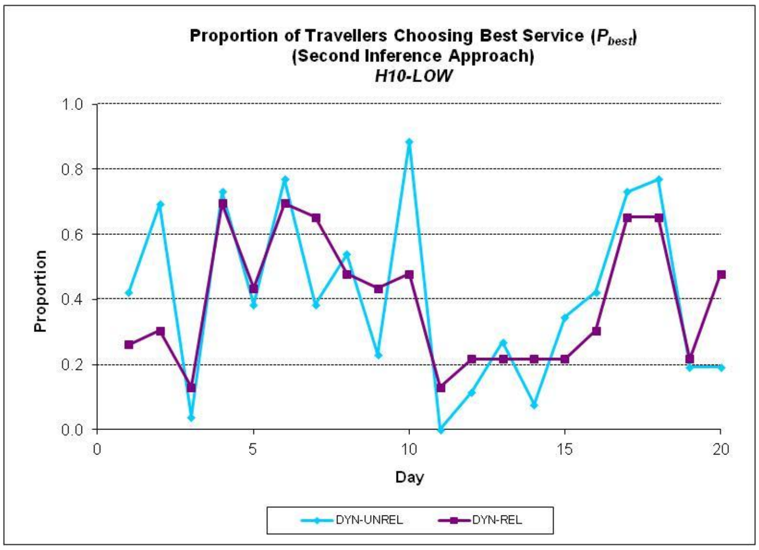

Proportion of Travellers Choosing Best Service (P_{best})
H20-HIGH
Proportion
Day
NO-INFO
HDWAY
TTABLE

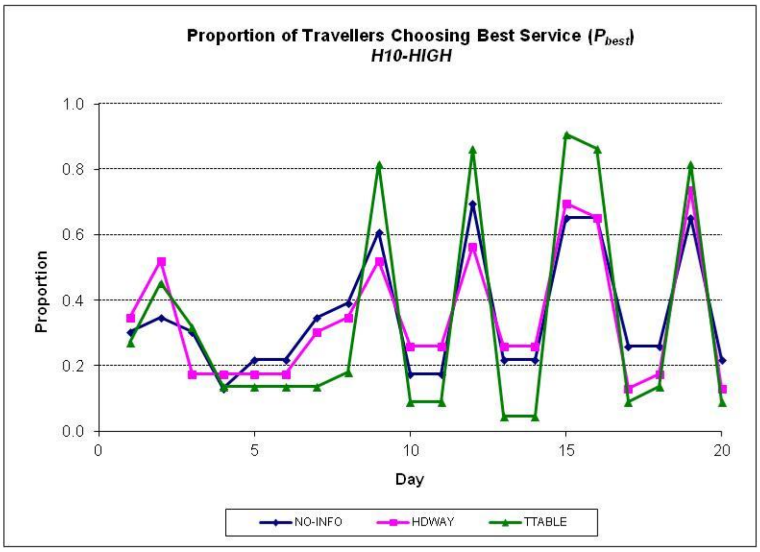

Proportion of Travellers Choosing Best Service (P_{best})
(First Inference Approach)
H20-HIGH
Proportion
Day
DYN-UNREL
DYN-REL

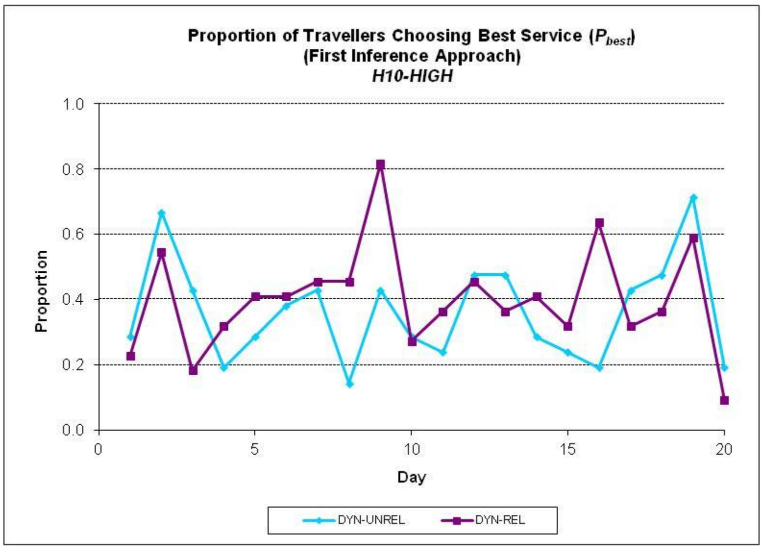

Proportion of Travellers Choosing Best Service (P_{best})
(Second Inference Approach)
H20-HIGH
Proportion
Day
DYN-UNREL
DYN-REL

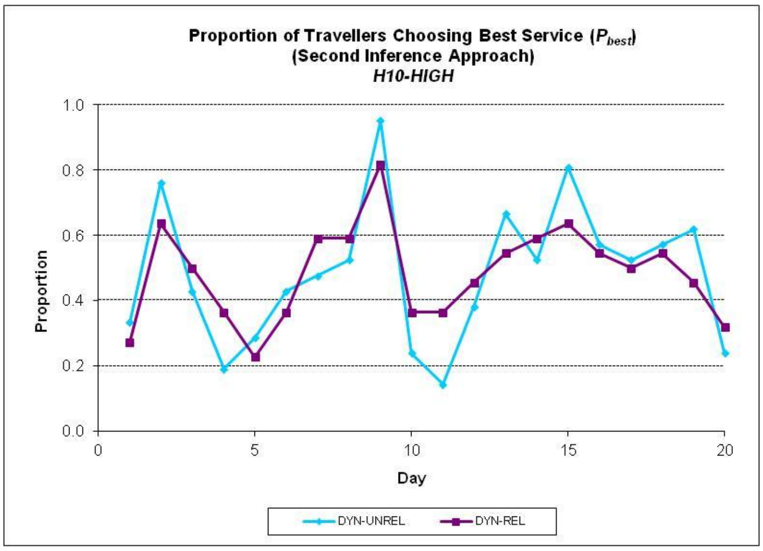

Proportion of Travellers Choosing Best Service (P_{best})
H10-LOW
Proportion
Day
NO-INFO
HDWAY
TTABLE

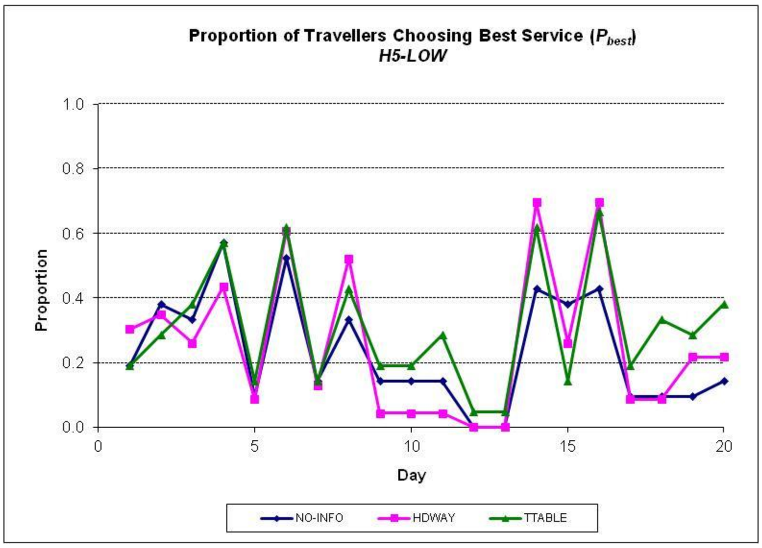

Proportion of Travellers Choosing Best Service (P_{best})
(First Inference Approach)
H10-LOW
Proportion
Day
DYN-UNREL
DYN-REL

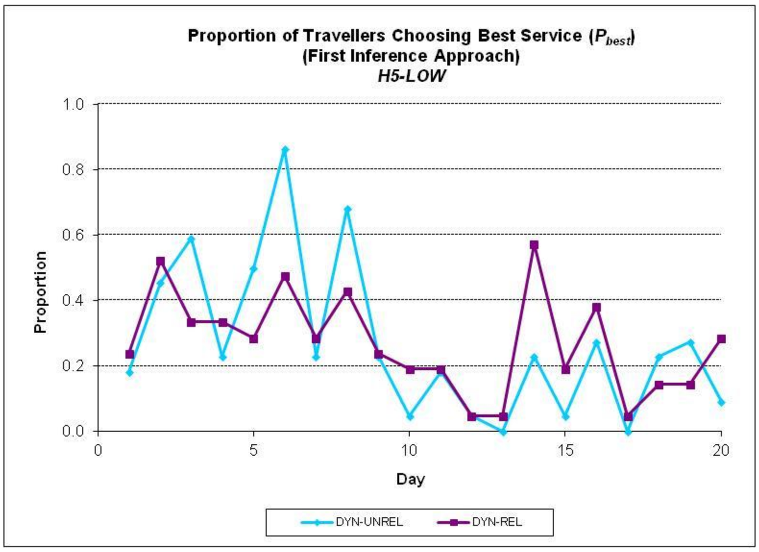

Proportion of Travellers Choosing Best Service (P_{best})
(Second Inference Approach)
H10-LOW
Proportion
Day
DYN-UNREL
DYN-REL

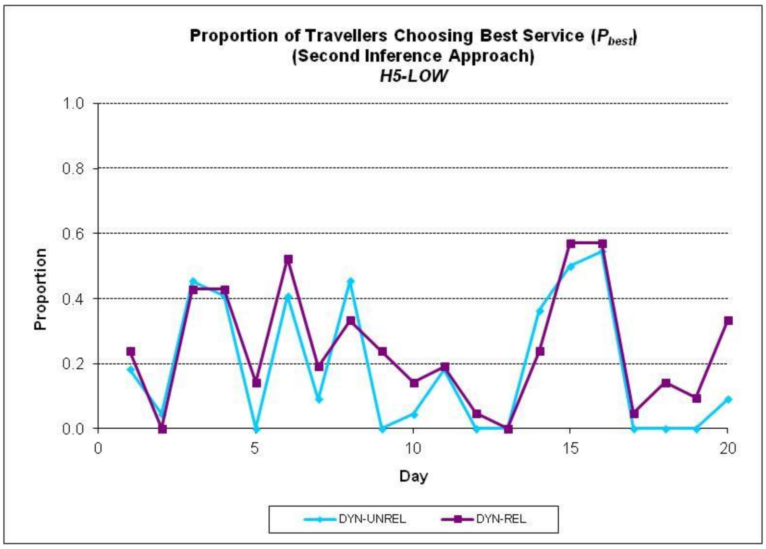

Proportion of Travellers Choosing Best Service (P_{best})
H10-HIGH
1.0
0.8
0.6
0.4
0.2
0.0
Proportion
0
5
10
15
20
Day
NO-INFO
HDWAY
TTABLE

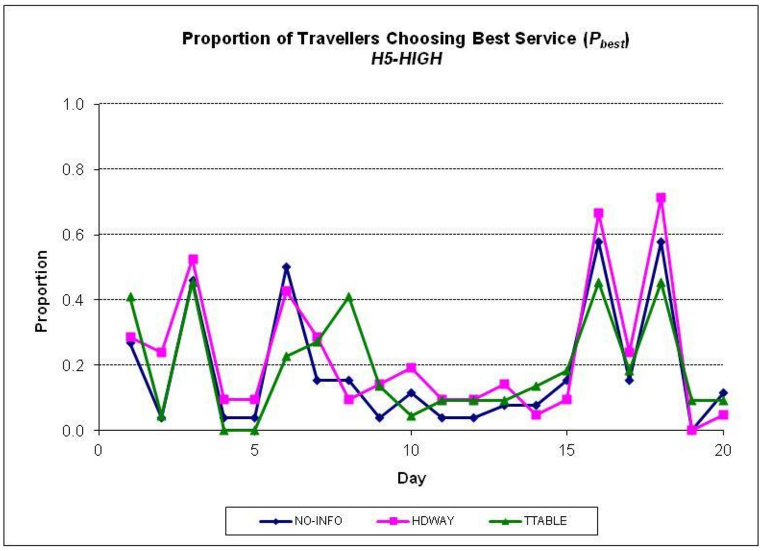

Proportion of Travellers Choosing Best Service (P_{best})
(First Inference Approach)
H10-HIGH
1.0
0.8
0.6
0.4
0.2
0.0
Proportion
0
5
10
15
20
Day
DYN-UNREL
DYN-REL

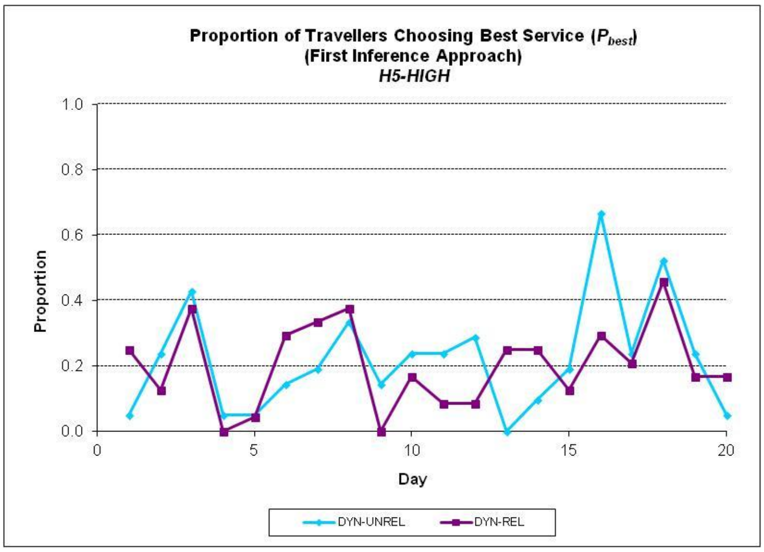

Proportion of Travellers Choosing Best Service (P_{best})
(Second Inference Approach)
H10-HIGH
1.0
0.8
0.6
0.4
0.2
0.0
Proportion
0
5
10
15
20
Day
DYN-UNREL
DYN-REL

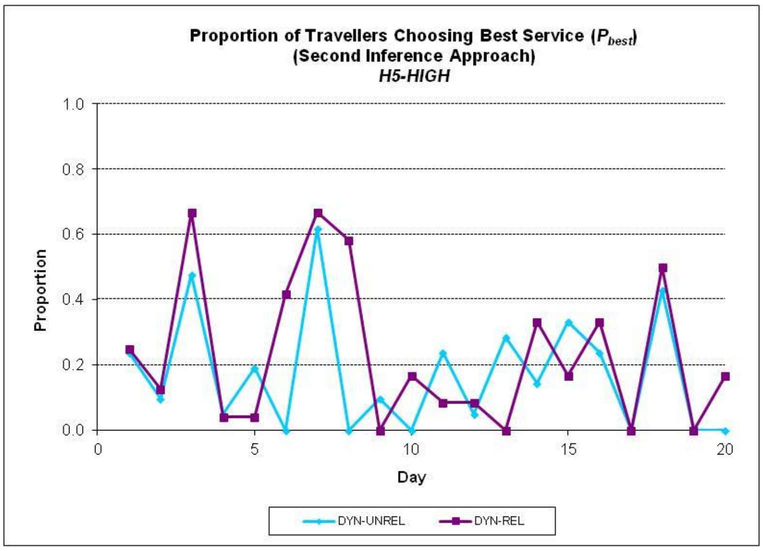

Proportion of Travellers Choosing Best Service (P_{best})
H5-LOW
Proportion
Day
NO-INFO
HDWAY
TTABLE


Proportion of Travellers Choosing Best Service (P_{best})
(First Inference Approach)
H5-LOW
Proportion
Day
DYN-UNREL
DYN-REL

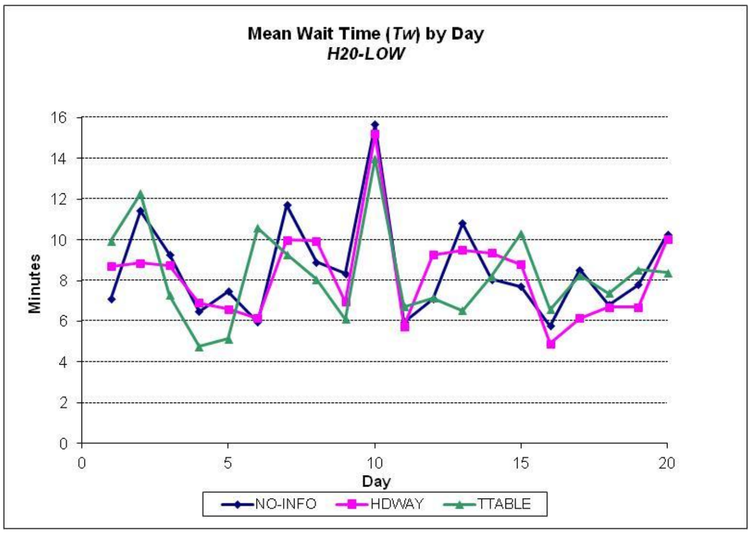

Proportion of Travellers Choosing Best Service (P_{best})
(Second Inference Approach)
H5-LOW
Proportion
Day
DYN-UNREL
DYN-REL

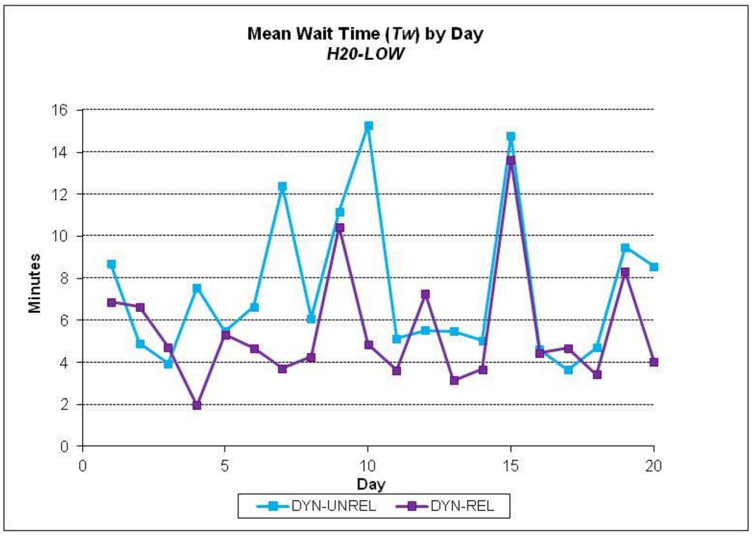

Proportion of Travellers Choosing Best Service (P_{best})
H5-HIGH
Proportion
Day
NO-INFO
HDWAY
TTABLE

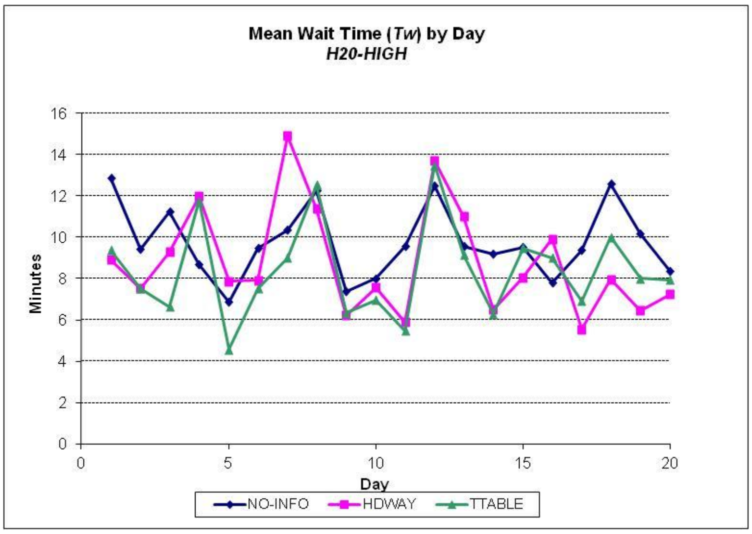

Proportion of Travellers Choosing Best Service (P_{best})
(First Inference Approach)
H5-HIGH
Proportion
Day
DYN-UNREL
DYN-REL


Proportion of Travellers Choosing Best Service (P_{best})
(Second Inference Approach)
H5-HIGH
Proportion
Day
DYN-UNREL
DYN-REL

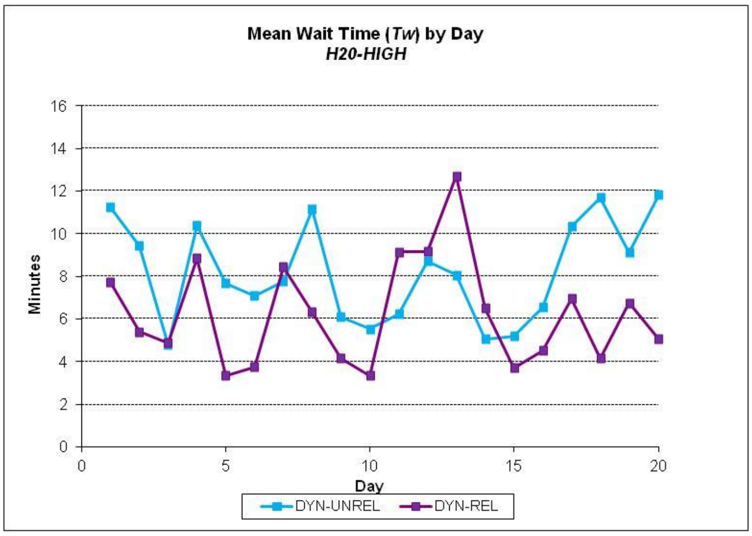
APPENDIX 2: PLOTS OF MEAN WAIT TIME, *Tw*, BY DAY BY SCENARIO



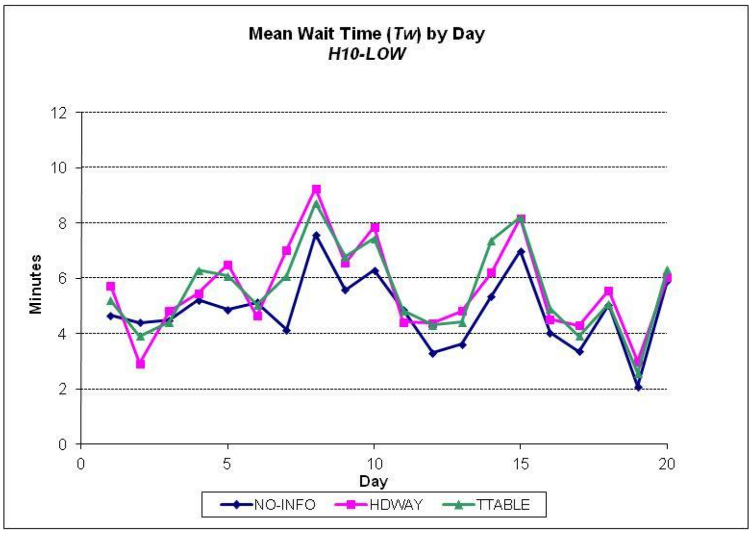


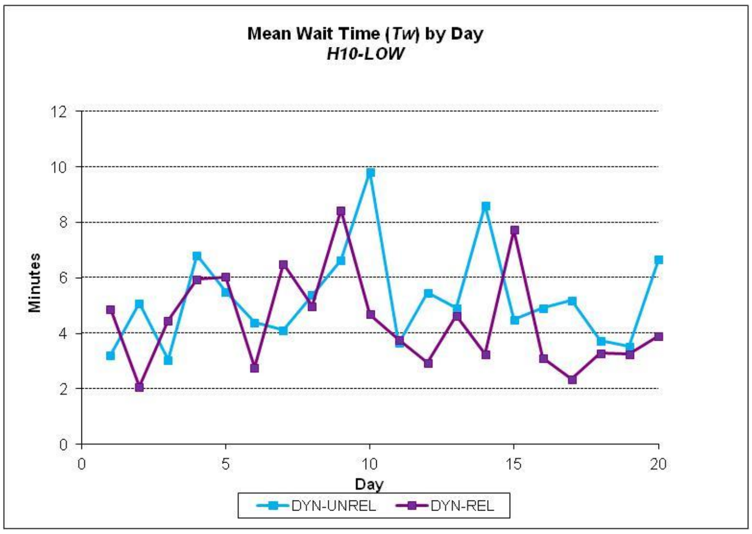


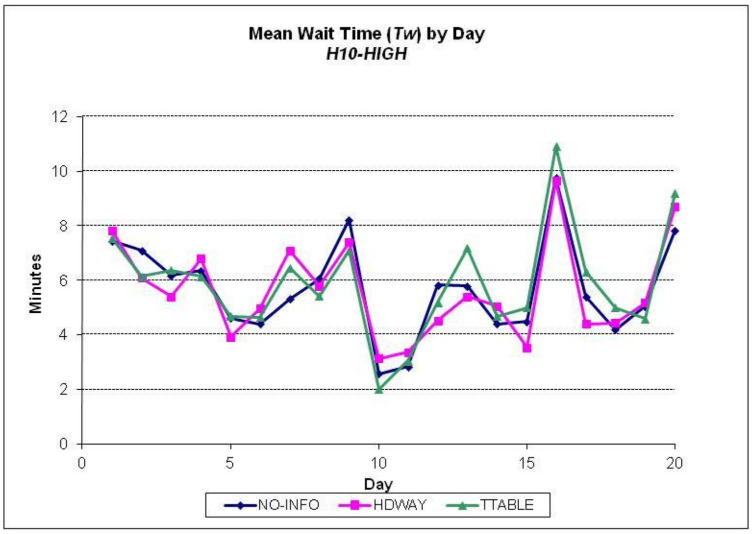
Mean Wait Time (*Tw*) by Day
H20-HIGH
Minutes
Day
0
2
4
6
8
10
12
14
16
0
5
10
15
20
NO-INFO
HDWAY
TTABLE



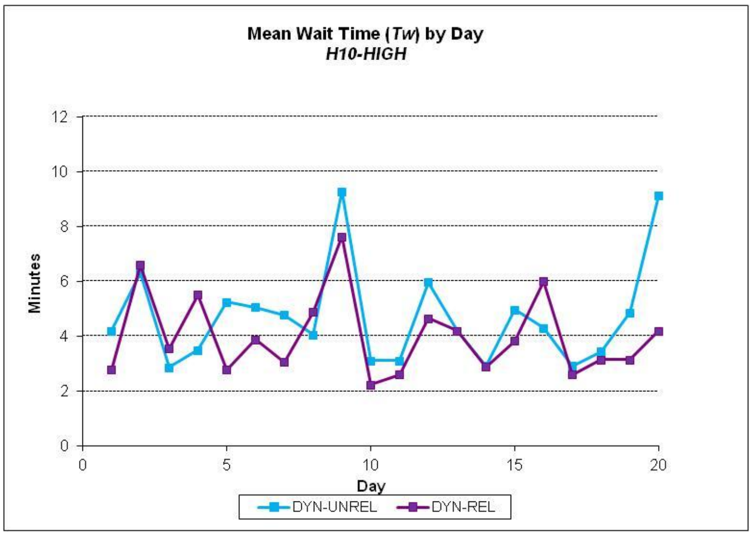
Mean Wait Time (*Tw*) by Day
H20-HIGH
Minutes
Day
0
2
4
6
8
10
12
14
16
0
5
10
15
20
DYN-UNREL
DYN-REL


Mean Wait Time (*Tw*) by Day
H10-LOW
Minutes
Day
0
2
4
6
8
10
12
0
5
10
15
20
NO-INFO
HDWAY
TTABLE

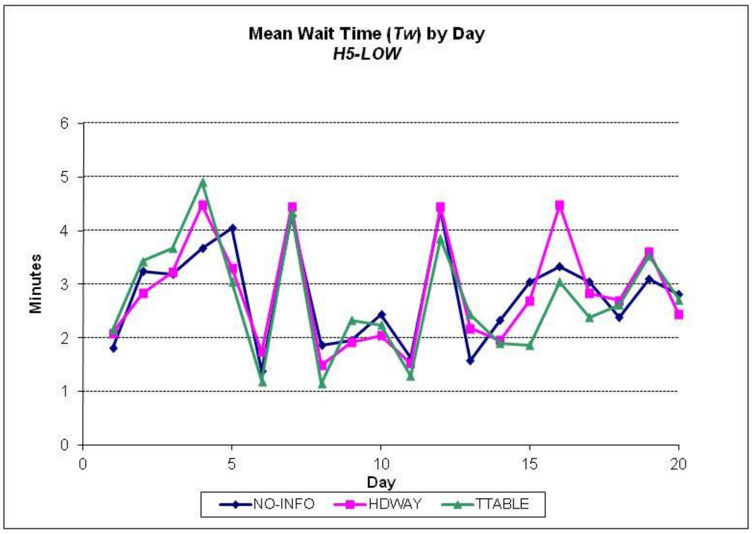

Mean Wait Time (*Tw*) by Day
H10-LOW
Minutes
Day
0
2
4
6
8
10
12
0
5
10
15
20
DYN-UNREL
DYN-REL

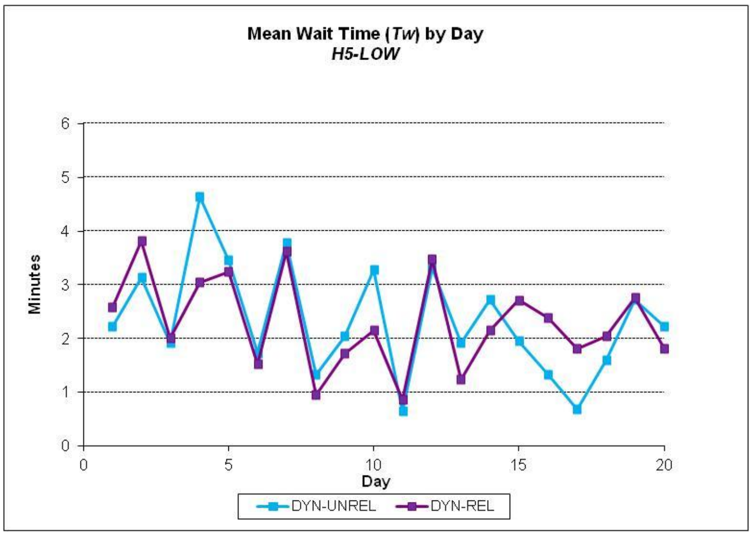


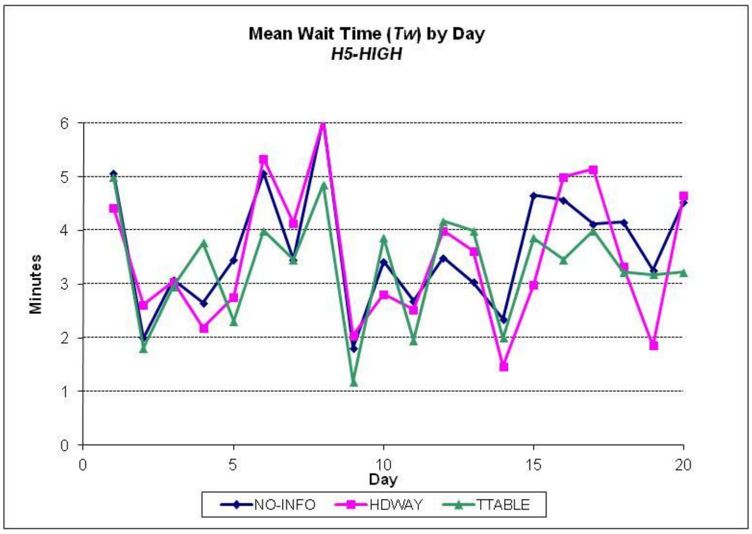
Mean Wait Time (*Tw*) by Day
H10-HIGH
Minutes
Day
0
2
4
6
8
10
12
0
5
10
15
20
NO-INFO
HDWAY
TTABLE



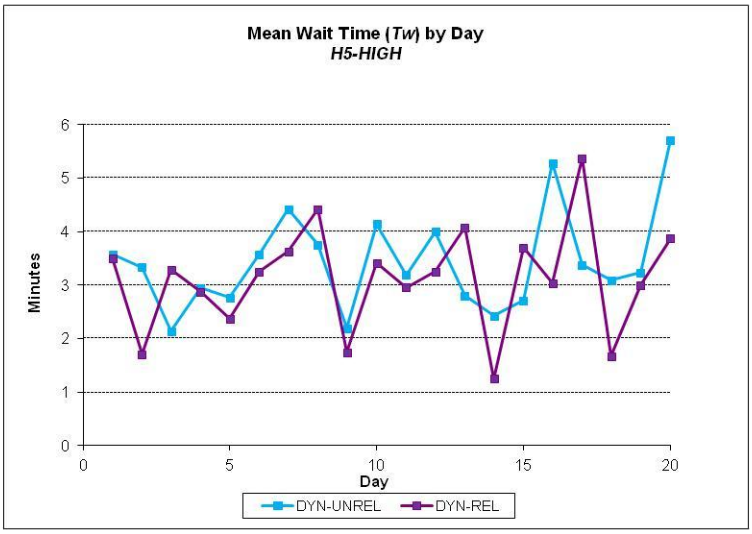
Mean Wait Time (*Tw*) by Day
H10-HIGH
Minutes
Day
0
2
4
6
8
10
12
0
5
10
15
20
DYN-UNREL
DYN-REL


Mean Wait Time (Tw) by Day
H5-LOW
Minutes
Day
NO-INFO
HDWAY
TTABLE


Mean Wait Time (Tw) by Day
H5-LOW
Minutes
Day
DYN-UNREL
DYN-REL

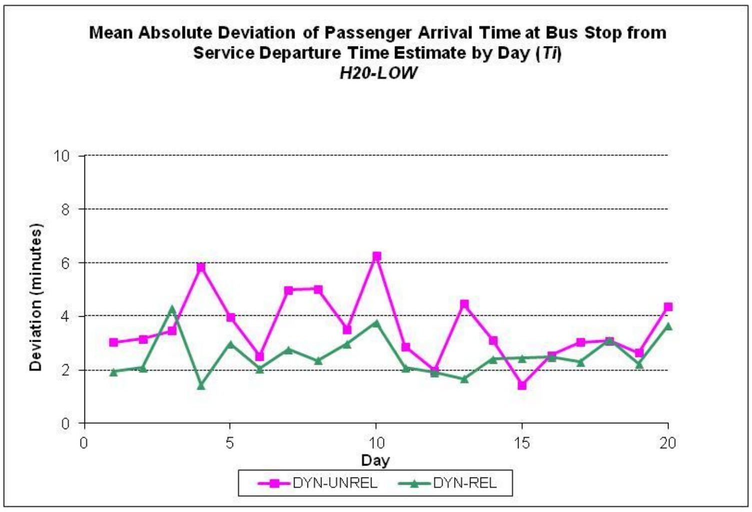


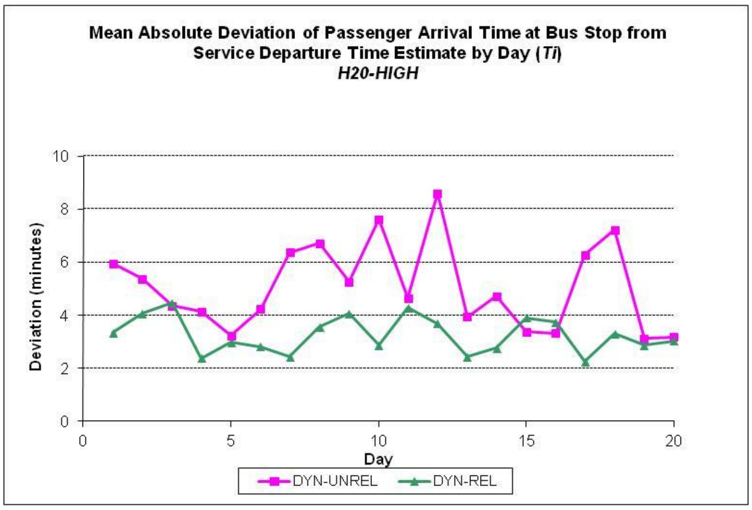
Mean Wait Time (Tw) by Day
H5-HIGH
Minutes
Day
0
1
2
3
4
5
6
0
5
10
15
20
NO-INFO
HDWAY
TTABLE

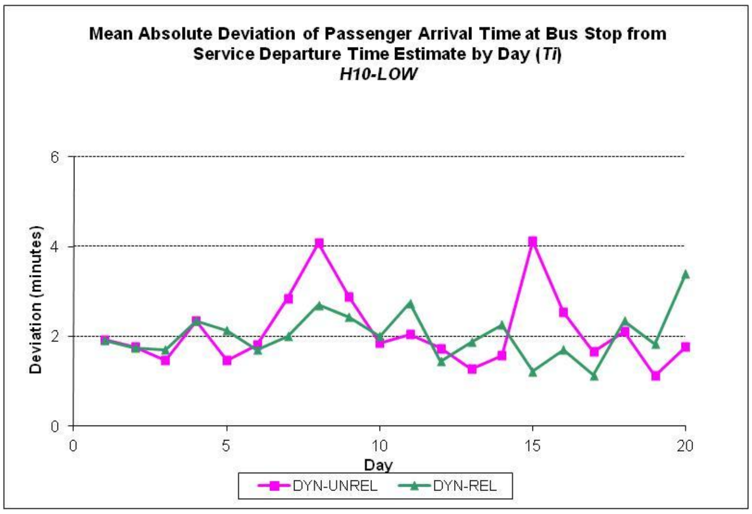


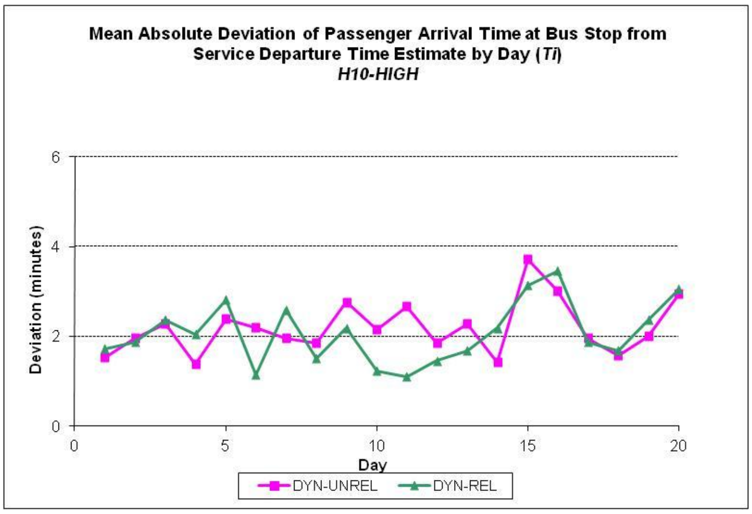
Mean Wait Time (Tw) by Day
H5-HIGH
Minutes
Day
0
1
2
3
4
5
6
0
5
10
15
20
DYN-UNREL
DYN-REL

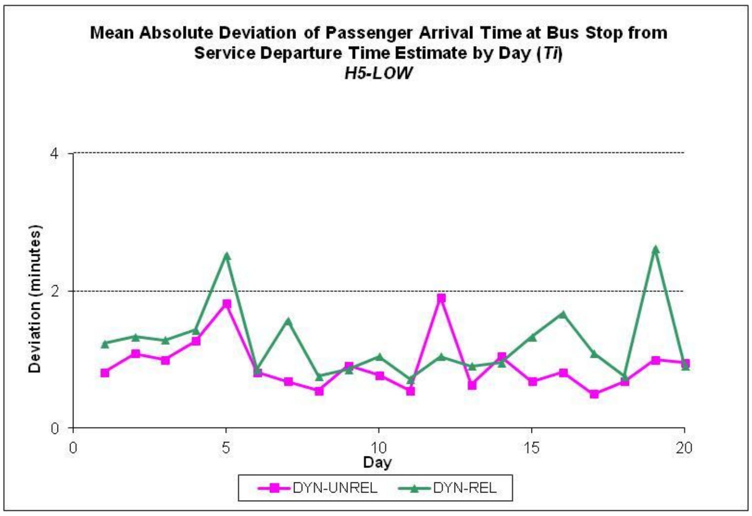
APPENDIX 3: PLOTS OF MEAN ABSOLUTE DEVIATION OF PASSENGER ARRIVAL TIME FROM SERVICE DEPARTURE TIME ESTIMTE, T^i, BY SCENARIO

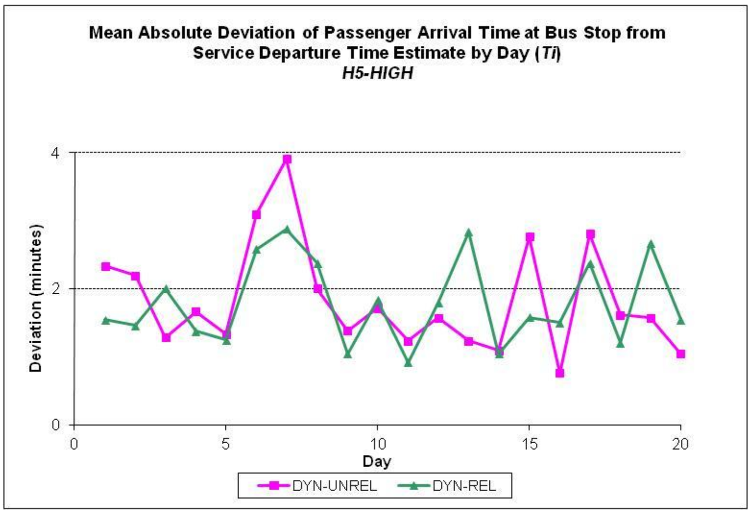




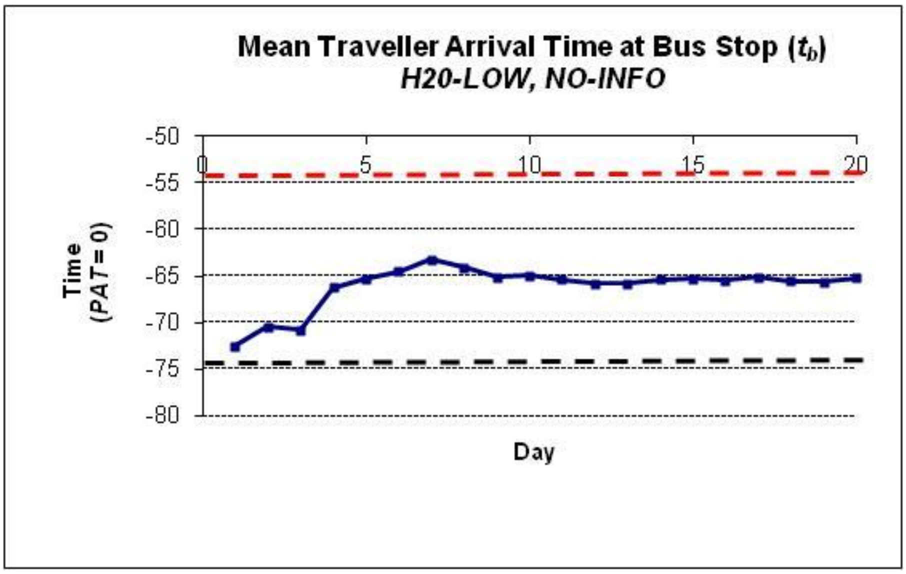


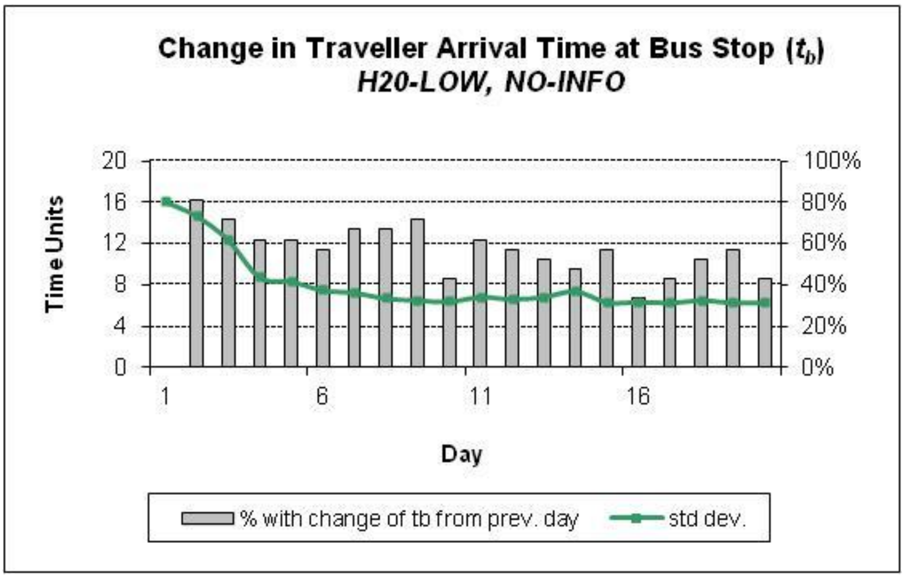

Mean Absolute Deviation of Passenger Arrival Time at Bus Stop from
Service Departure Time Estimate by Day (Ti)
H10-HIGH
Deviation (minutes)
6
4
2
0
0
5
10
15
20
Day
DYN-UNREL
DYN-REL

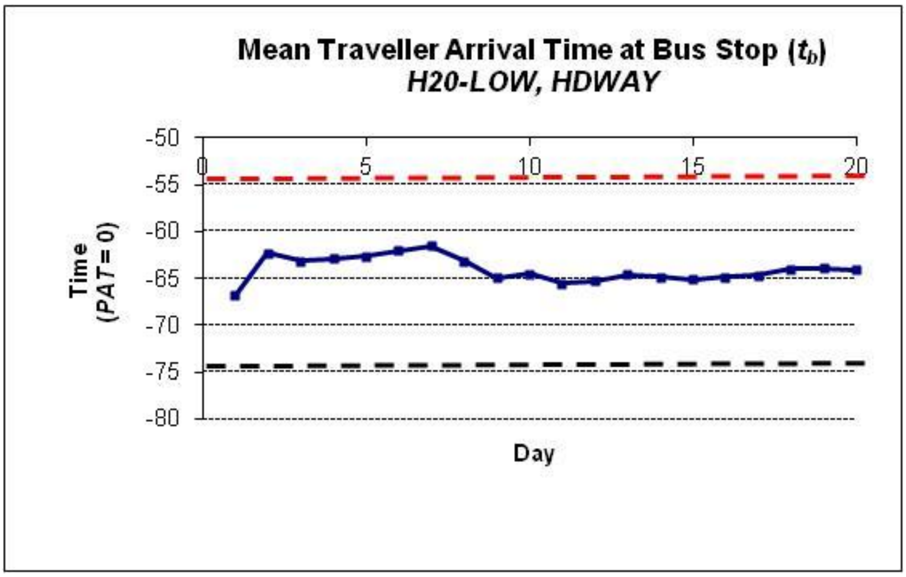

Mean Absolute Deviation of Passenger Arrival Time at Bus Stop from
Service Departure Time Estimate by Day (Ti)
H5-LOW
Deviation (minutes)
4
2
0
0
5
10
15
20
Day
DYN-UNREL
DYN-REL

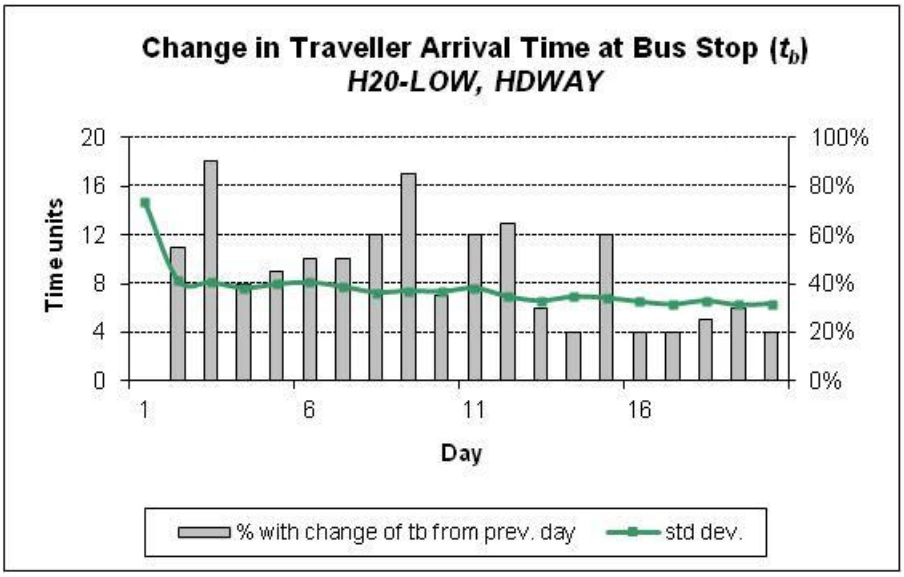

Mean Absolute Deviation of Passenger Arrival Time at Bus Stop from
Service Departure Time Estimate by Day (Ti)
H5-HIGH
Deviation (minutes)
4
2
0
0
5
10
15
20
Day
DYN-UNREL
DYN-REL

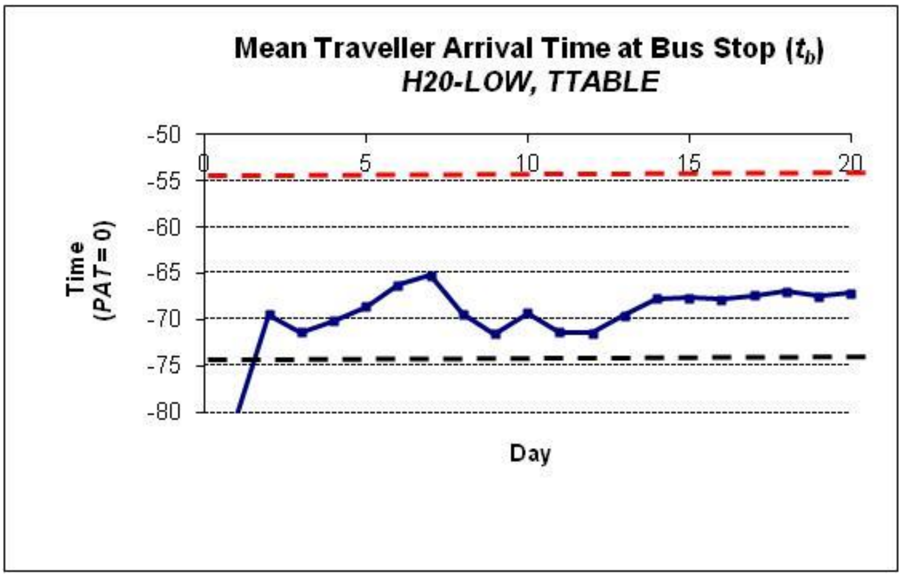
APPENDIX 4: PLOTS OF MEAN TRAVELLER ARRIVAL TIME AT BUS STOP (t_b) BY SCENARIO



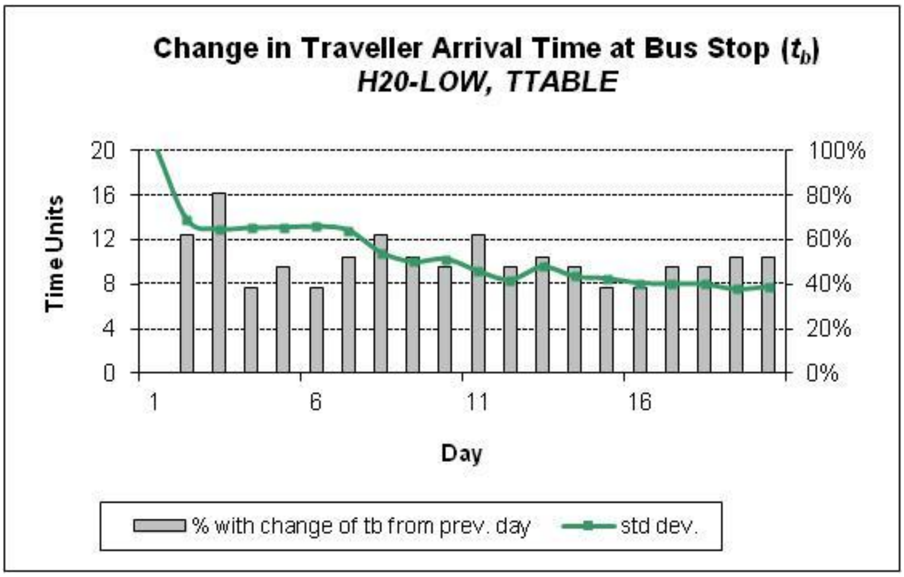



Mean Traveller Arrival Time at Bus Stop (t_b)
H20-LOW, HDWAY
Time
(PAT=0)
-50
-55
-60
-65
-70
-75
-80
0
5
10
15
20
Day

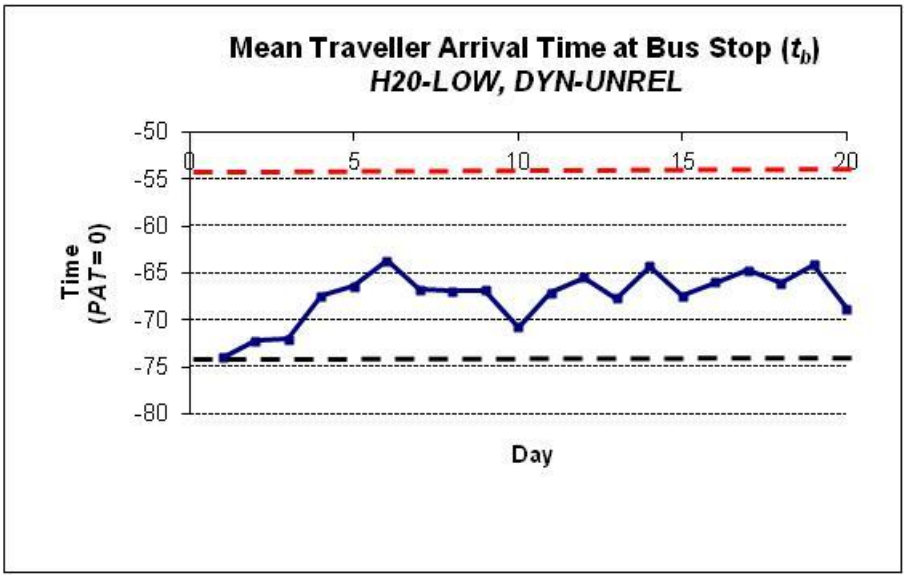

Change in Traveller Arrival Time at Bus Stop (t_b)
H20-LOW, HDWAY
Time units
20
16
12
8
4
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Day
% with change of tb from prev. day
std dev.

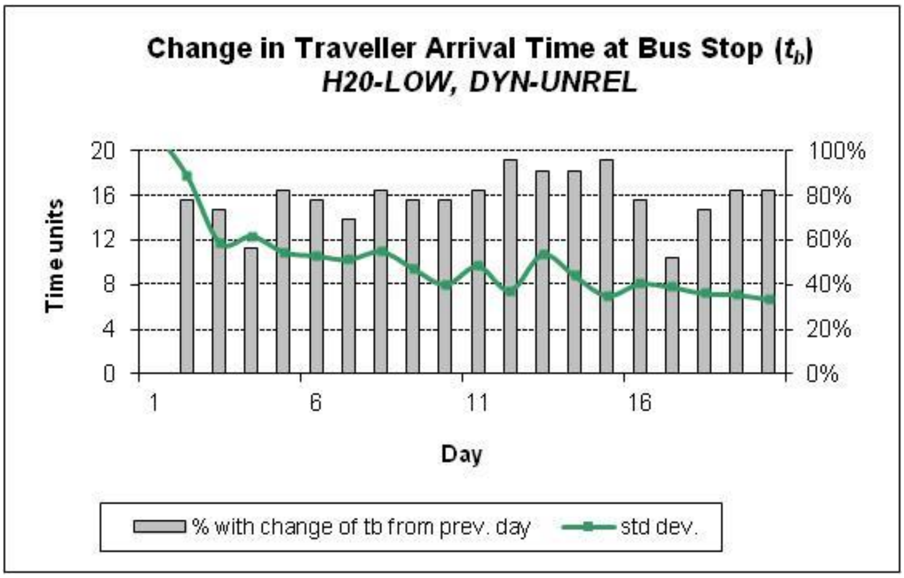


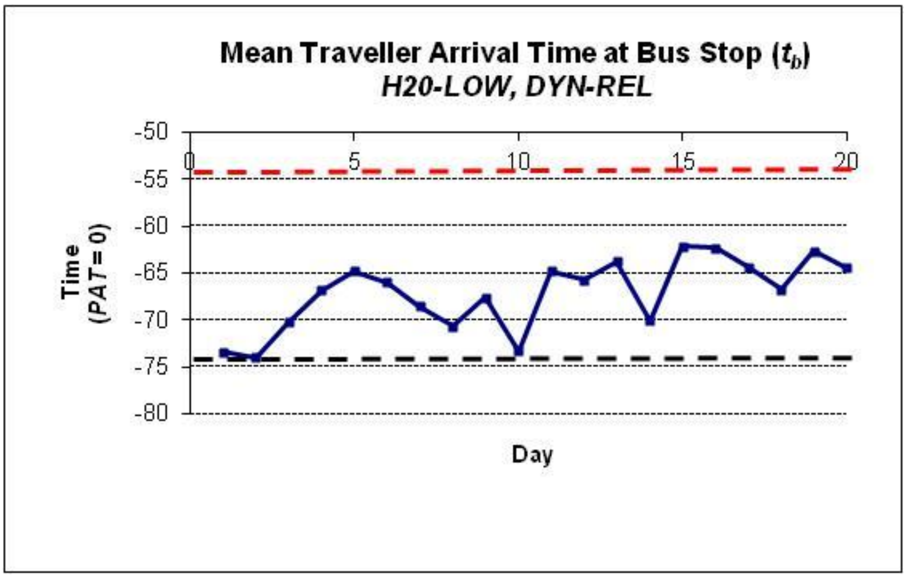
Mean Traveller Arrival Time at Bus Stop (t_b)
H20-LOW, TTABLE
Time (PAT=0)
-50
-55
-60
-65
-70
-75
-80
0
5
10
15
20
Day

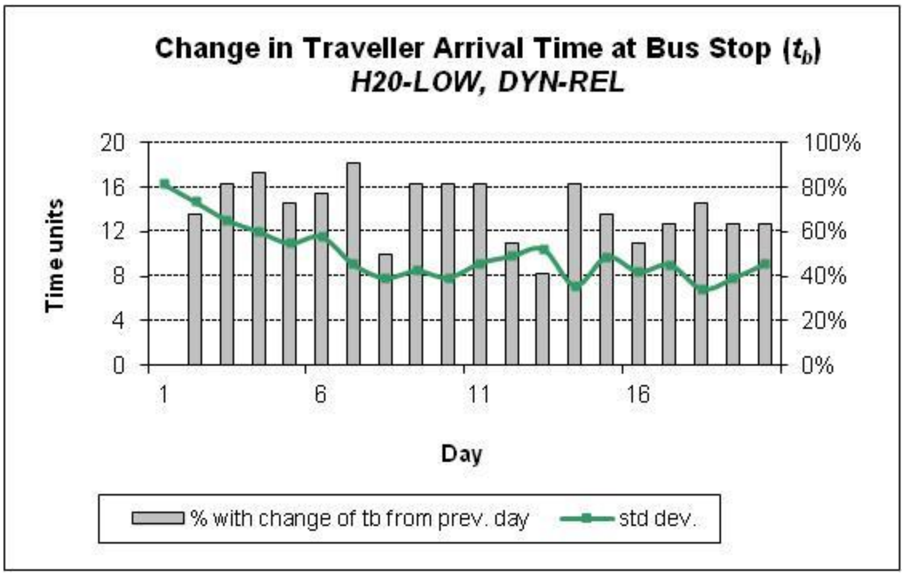


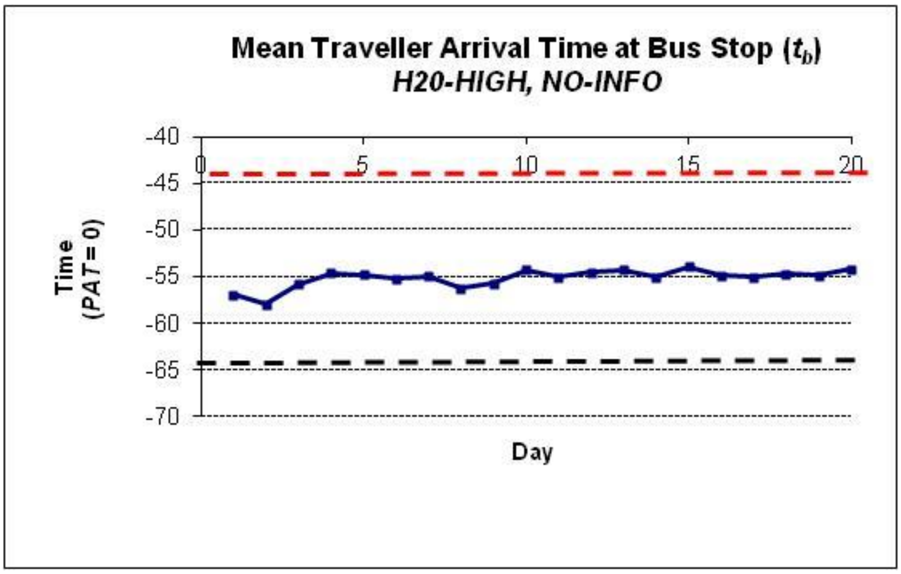
Change in Traveller Arrival Time at Bus Stop (t_b)
H20-LOW, TTABLE
Time Units
20
16
12
8
4
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Day
% with change of tb from prev. day
std dev.

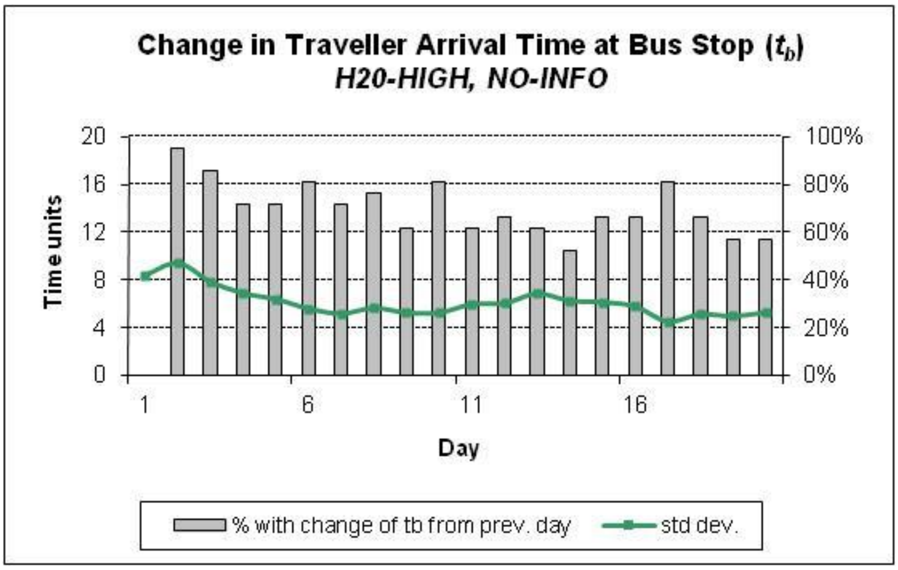

Mean Traveller Arrival Time at Bus Stop (t_b)
H20-LOW, DYN-UNREL
Time
(PAT = 0)
-50
-55
-60
-65
-70
-75
-80
0
5
10
15
20
Day

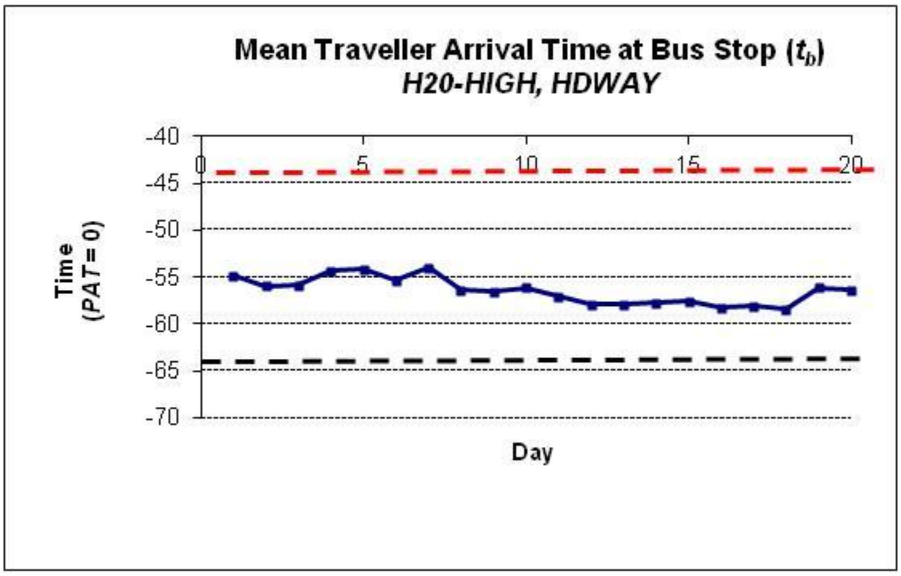

Change in Traveller Arrival Time at Bus Stop (t_b)
H20-LOW, DYN-UNREL
Time units
20
16
12
8
4
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Day
% with change of tb from prev. day
std dev.

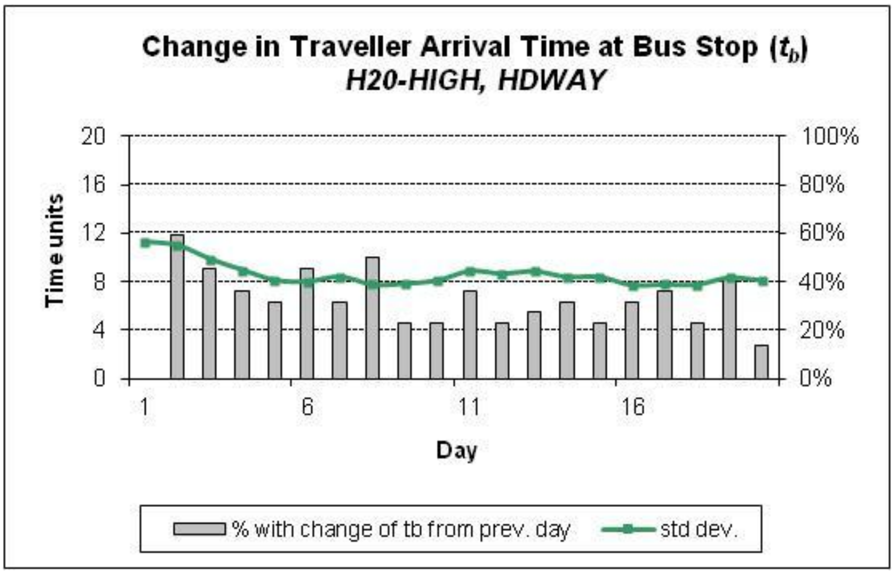

Mean Traveller Arrival Time at Bus Stop (t_b)
H20-LOW, DYN-REL
Time (PAT = 0)
Day
-50
-55
-60
-65
-70
-75
-80
0
5
10
15
20

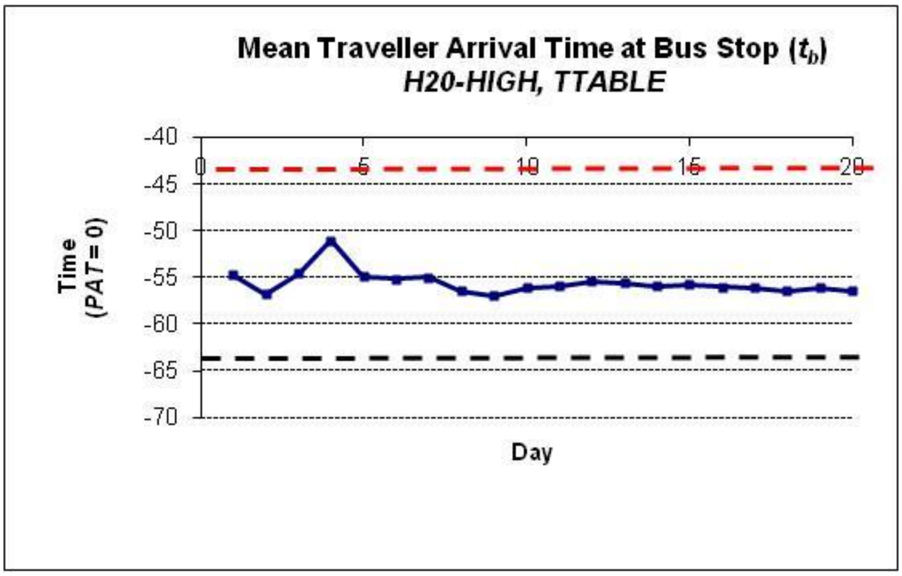

Change in Traveller Arrival Time at Bus Stop (t_b)
H20-LOW, DYN-REL
Time units
Day
20
16
12
8
4
0
100%
80%
60%
40%
20%
0%
1
6
11
16
% with change of tb from prev. day
std dev.

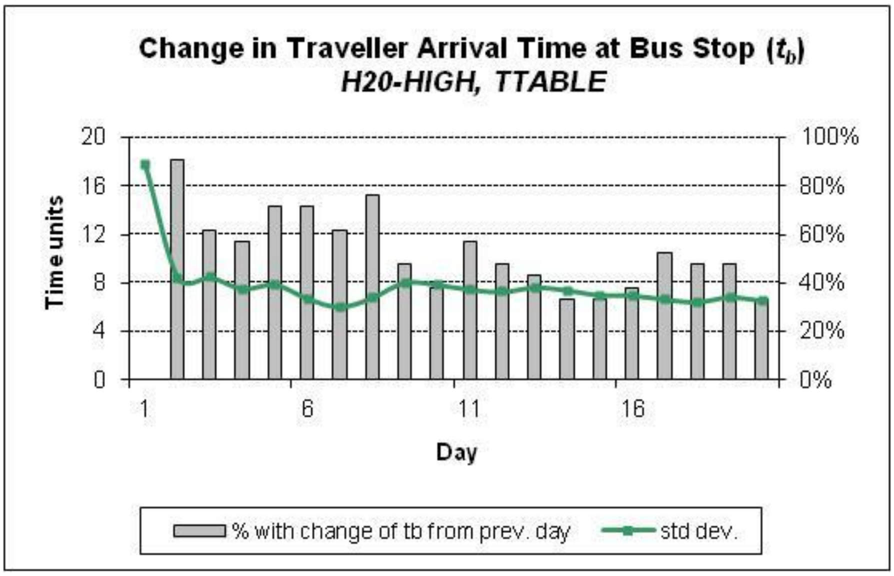

Mean Traveller Arrival Time at Bus Stop (t_b)
H20-HIGH, NO-INFO
Time
(PAT= 0)
Day
-40
-45
-50
-55
-60
-65
-70
0
5
10
15
20

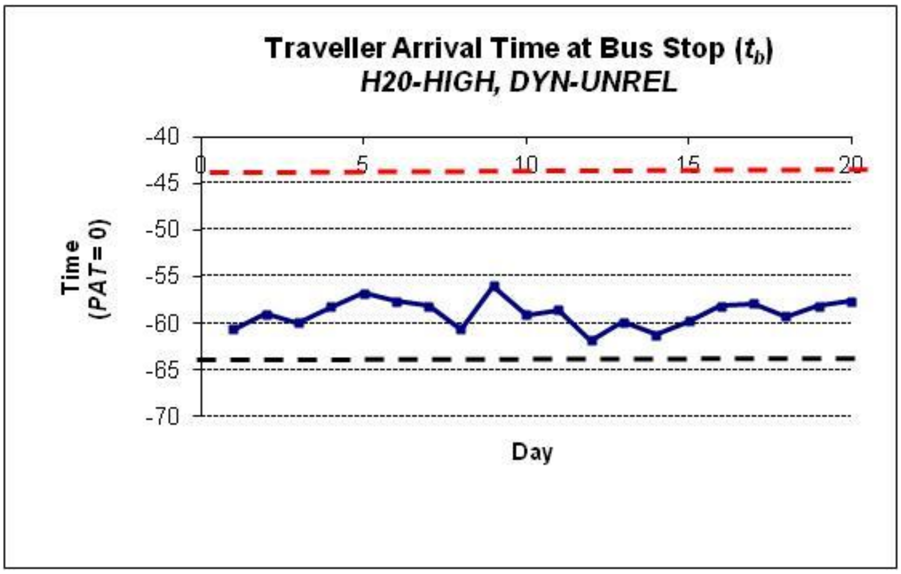

Change in Traveller Arrival Time at Bus Stop (t_b)
H20-HIGH, NO-INFO
Time units
Day
20
16
12
8
4
0
100%
80%
60%
40%
20%
0%
1
6
11
16
% with change of tb from prev. day
std dev.

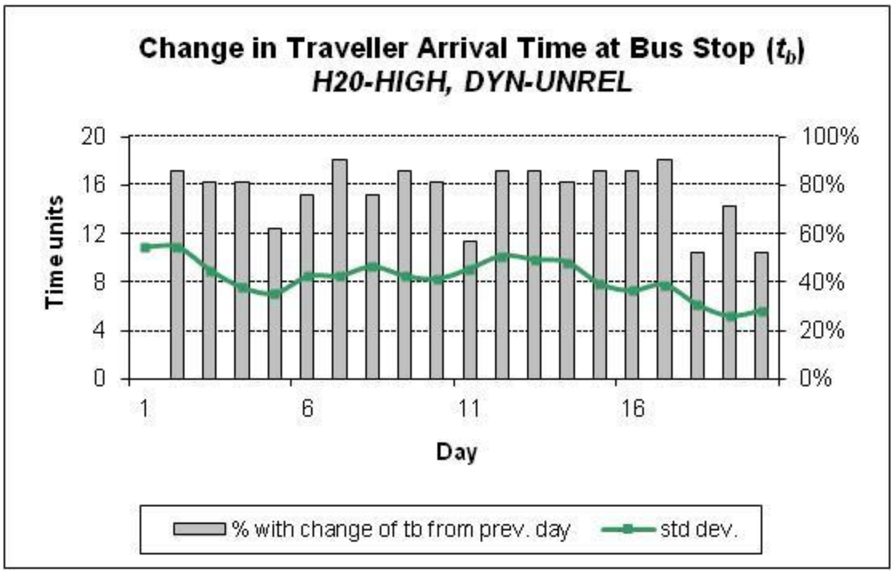

Mean Traveller Arrival Time at Bus Stop (t_b)
H20-HIGH, HDWAY
Time
(PAT = 0)
-40
-45
-50
-55
-60
-65
-70
0
5
10
15
20
Day

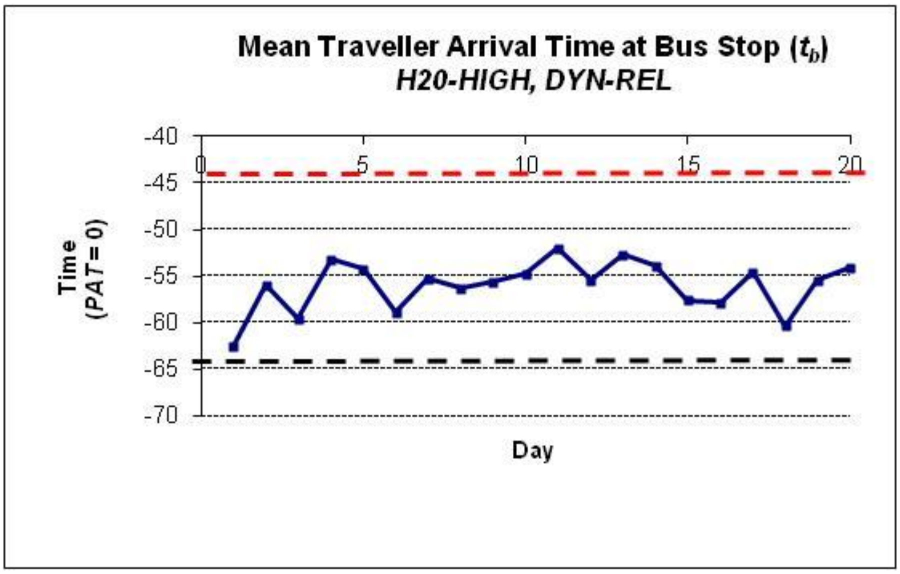

Change in Traveller Arrival Time at Bus Stop (t_b)
H20-HIGH, HDWAY
Time units
20
16
12
8
4
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Day
% with change of tb from prev. day
std dev.

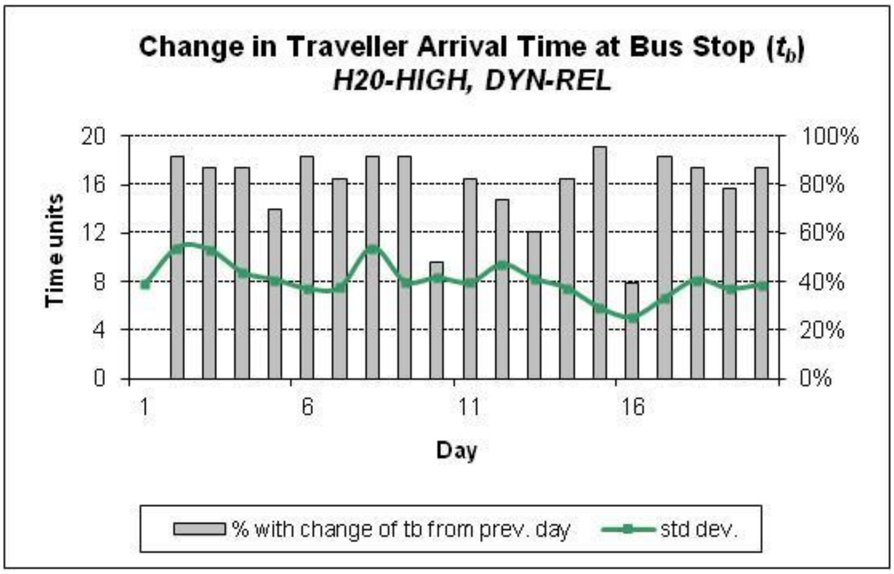

Mean Traveller Arrival Time at Bus Stop (t_b)
H20-HIGH, TTABLE
Time (PAT=0)
-40
-45
-50
-55
-60
-65
-70
0
5
10
15
20
Day

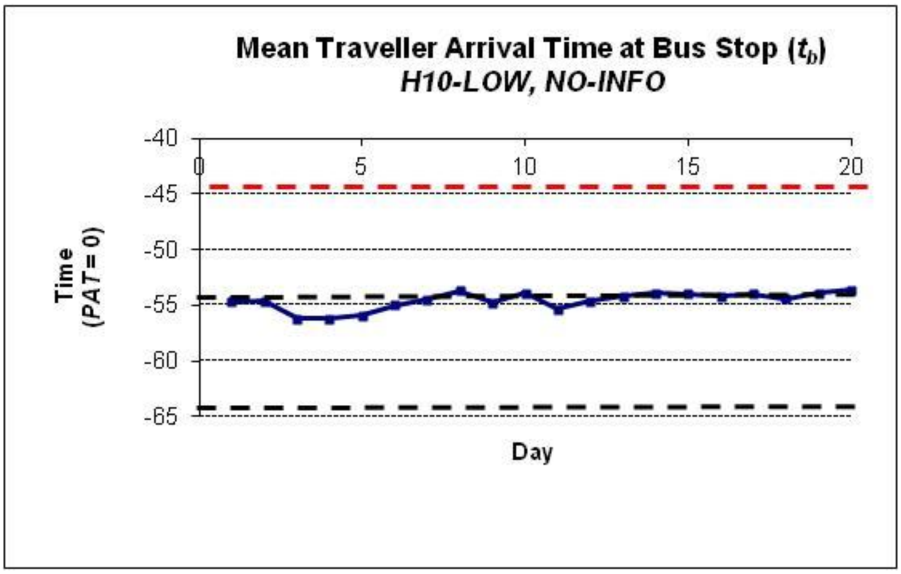

Change in Traveller Arrival Time at Bus Stop (t_b)
H20-HIGH, TTABLE
Time units
20
16
12
8
4
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Day
% with change of tb from prev. day
std dev.


Traveller Arrival Time at Bus Stop (t_b)
H20-HIGH, DYN-UNREL
Time
(PAT = 0)
-40
-45
-50
-55
-60
-65
-70
0
5
10
15
20
Day

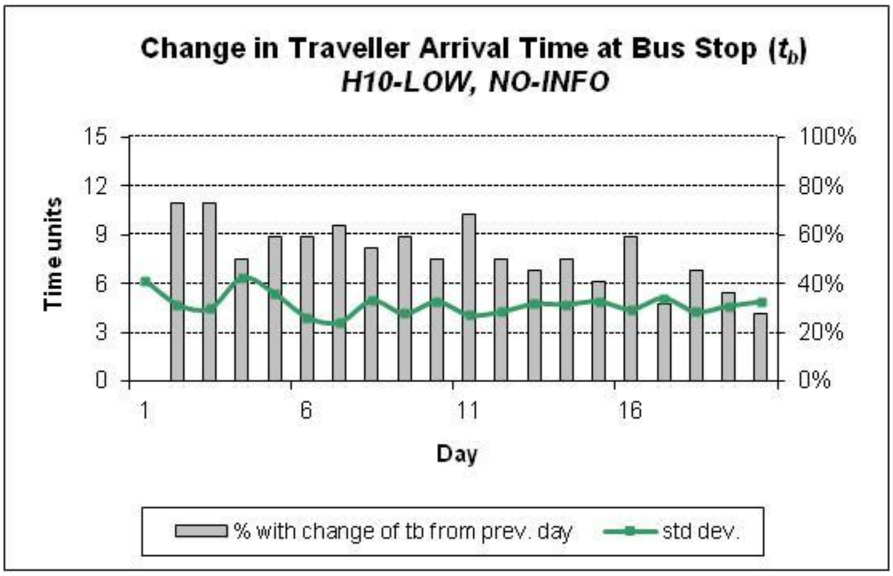

Change in Traveller Arrival Time at Bus Stop (t_b)
H20-HIGH, DYN-UNREL
Time units
20
16
12
8
4
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Day
% with change of tb from prev. day
std dev.


Mean Traveller Arrival Time at Bus Stop (t_b)
H20-HIGH, DYN-REL
Time
(PAT = 0)
-40
-45
-50
-55
-60
-65
-70
0
5
10
15
20
Day

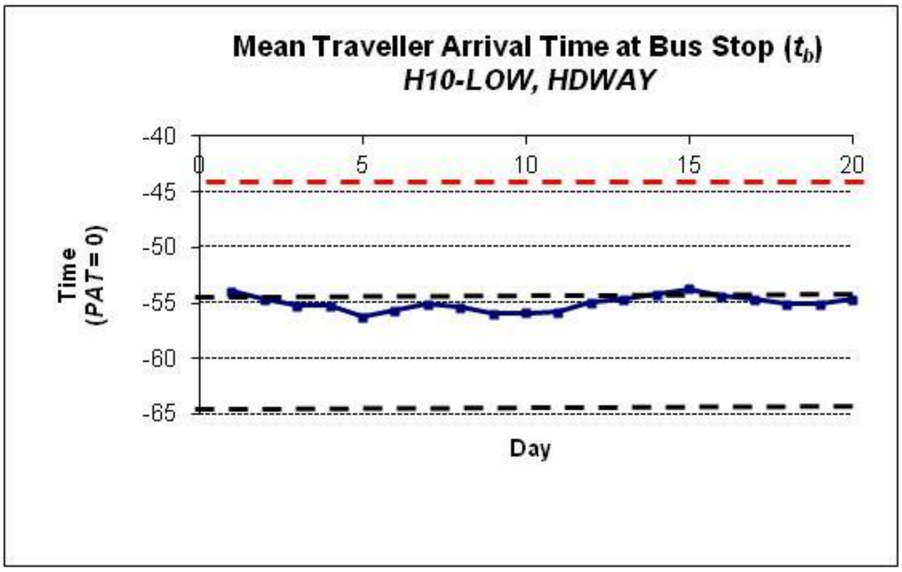

Change in Traveller Arrival Time at Bus Stop (t_b)
H20-HIGH, DYN-REL
Time units
20
16
12
8
4
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Day
% with change of tb from prev. day
std dev.

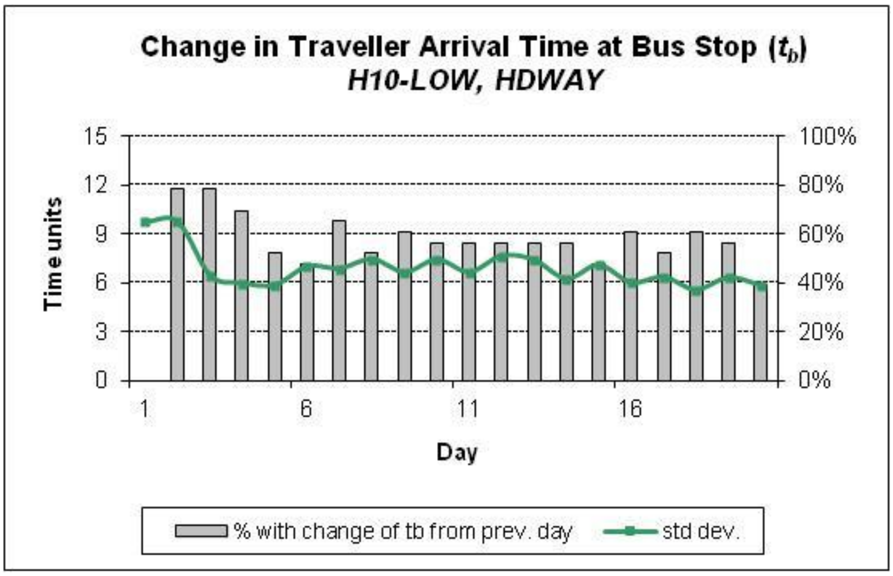


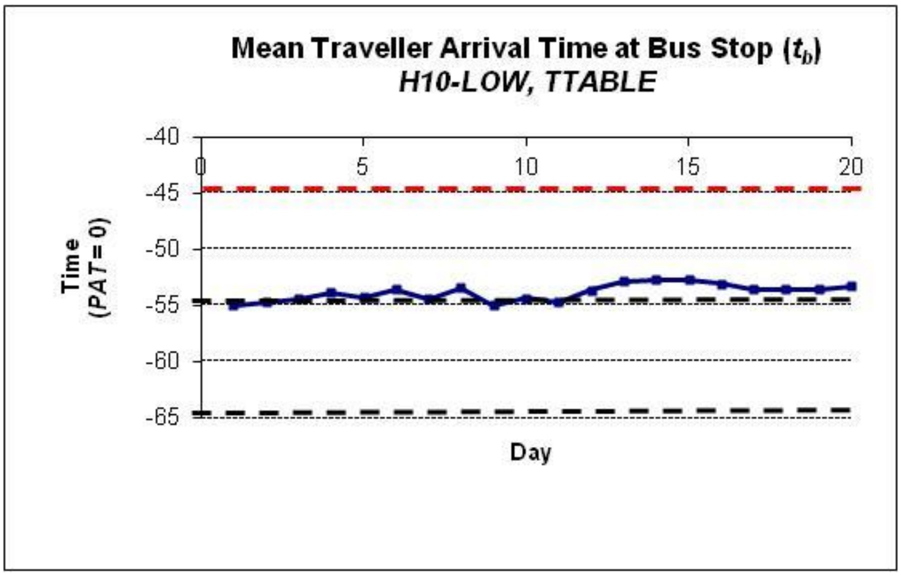
Mean Traveller Arrival Time at Bus Stop (t_b)
H10-LOW, NO-INFO
-40
-45
-50
-55
-60
-65
0
5
10
15
20
Time
(PAT = 0)
Day

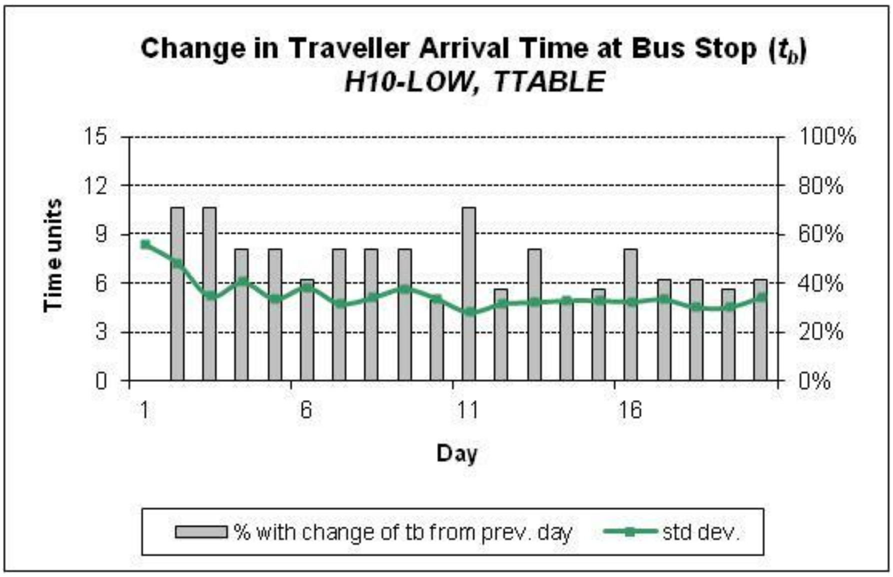


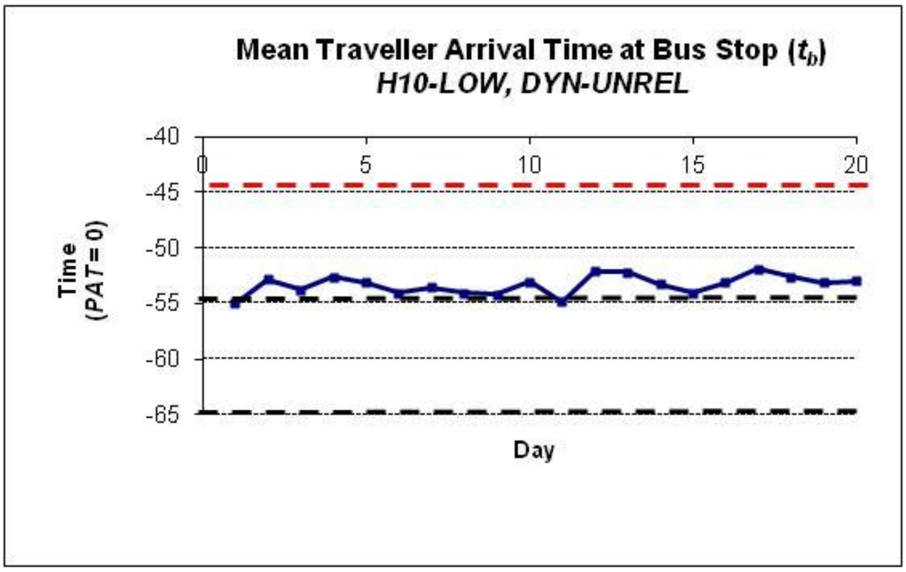
Change in Traveller Arrival Time at Bus Stop (t_b)
H10-LOW, NO-INFO
15
12
9
6
3
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Time units
Day
% with change of tb from prev. day
std dev.

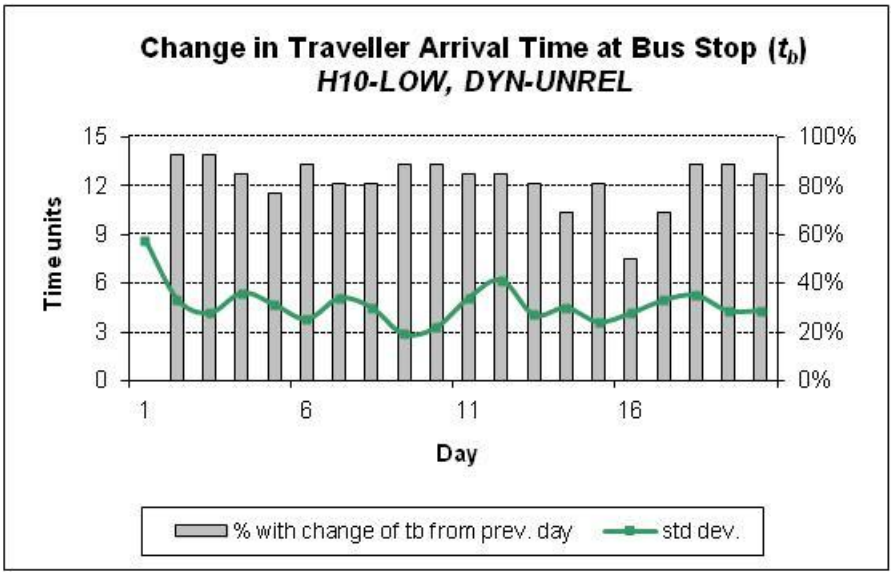

Mean Traveller Arrival Time at Bus Stop (t_b)
H10-LOW, HDWAY
Time (PAT = 0)
-40
-45
-50
-55
-60
-65
0
5
10
15
20
Day

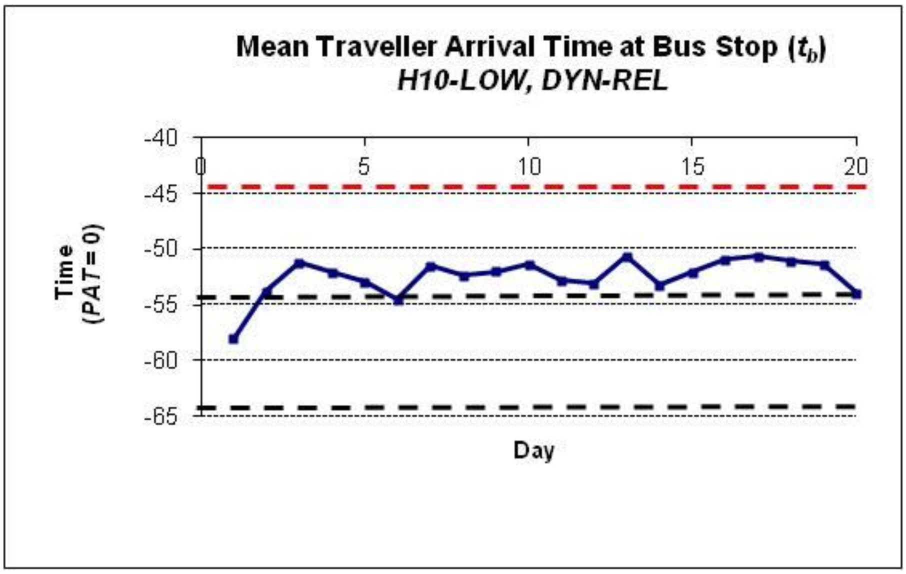

Change in Traveller Arrival Time at Bus Stop (t_b)
H10-LOW, HDWAY
Time units
15
12
9
6
3
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Day
% with change of tb from prev. day
std dev.

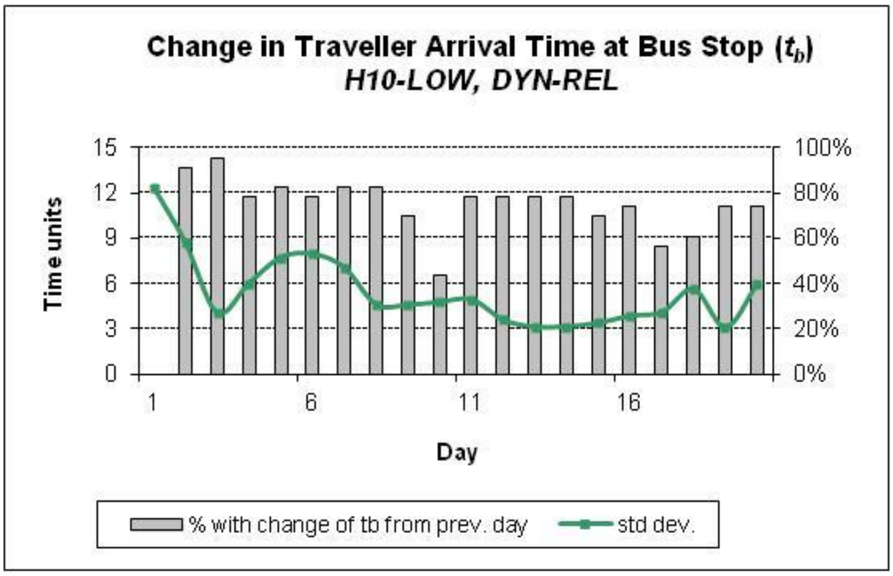

Mean Traveller Arrival Time at Bus Stop (t_b)
H10-LOW, TTABLE
Time
(PAT=0)
-40
-45
-50
-55
-60
-65
0
5
10
15
20
Day

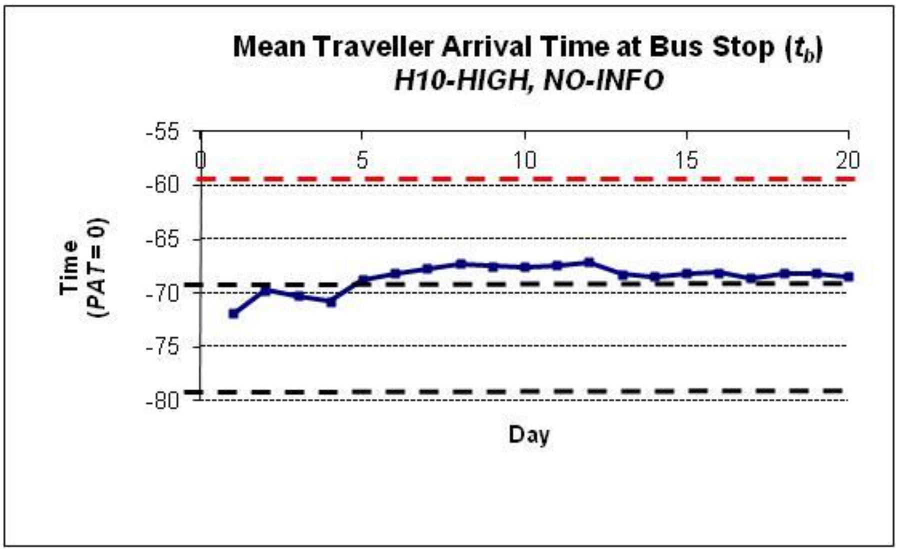

Change in Traveller Arrival Time at Bus Stop (t_b)
H10-LOW, TTABLE
Time units
15
12
9
6
3
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Day
% with change of tb from prev. day
std dev.

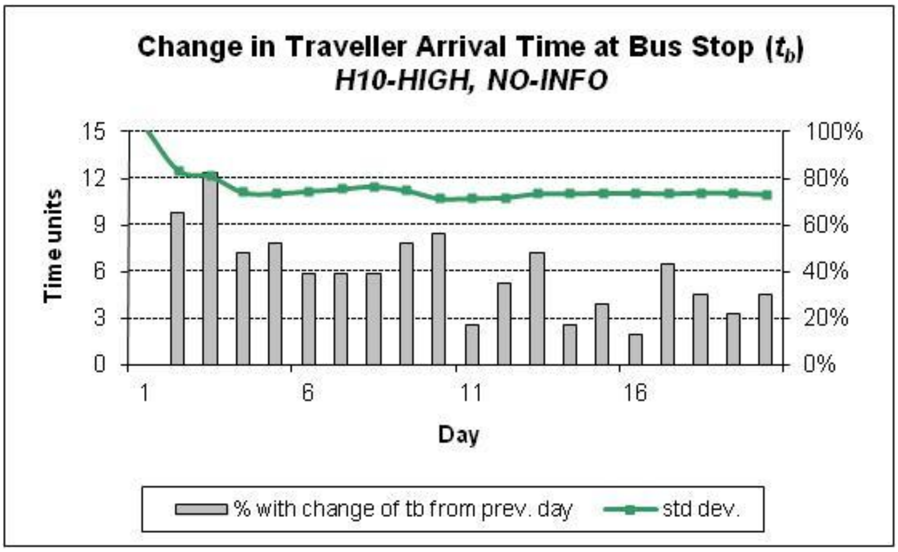

Mean Traveller Arrival Time at Bus Stop (t_b)
H10-LOW, DYN-UNREL
Time
(PAT = 0)
-40
-45
-50
-55
-60
-65
0
5
10
15
20
Day

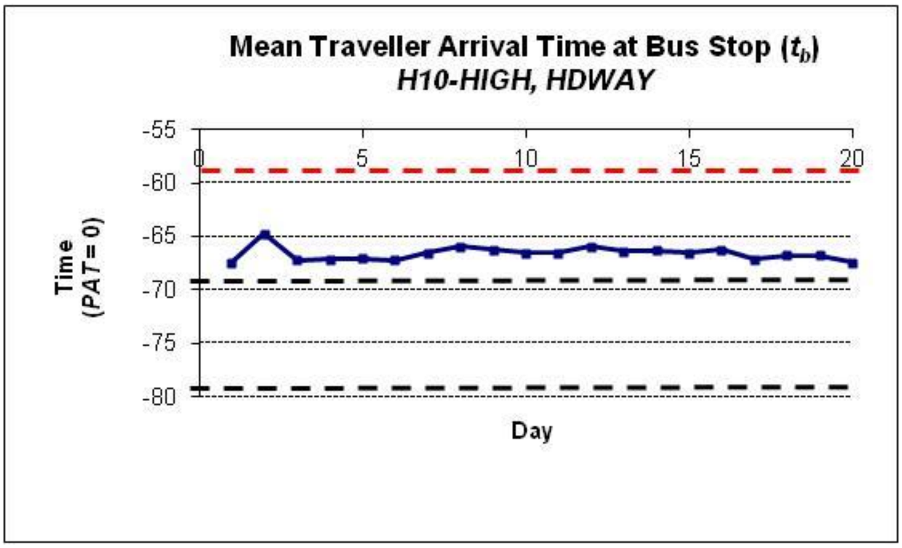

Change in Traveller Arrival Time at Bus Stop (t_b)
H10-LOW, DYN-UNREL
Time units
15
12
9
6
3
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Day
% with change of tb from prev. day
std dev.

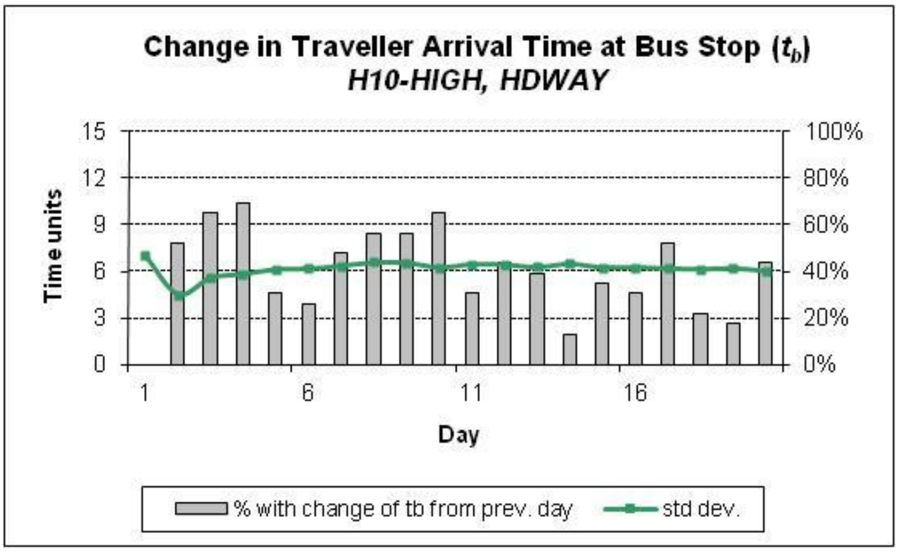

Mean Traveller Arrival Time at Bus Stop (t_b)
H10-LOW, DYN-REL
Time
(PAT = 0)
-40
-45
-50
-55
-60
-65
0
5
10
15
20
Day

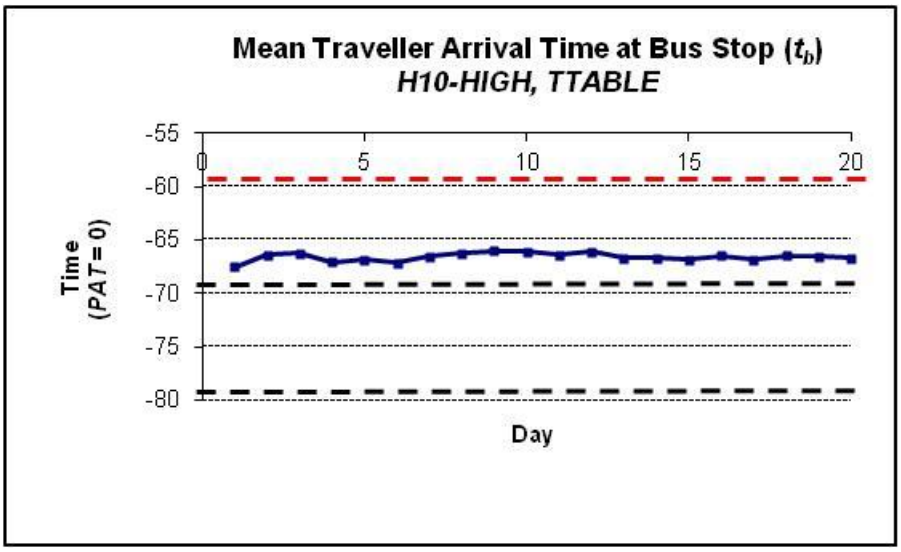

Change in Traveller Arrival Time at Bus Stop (t_b)
H10-LOW, DYN-REL
Time units
15
12
9
6
3
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Day
% with change of tb from prev. day
std dev.

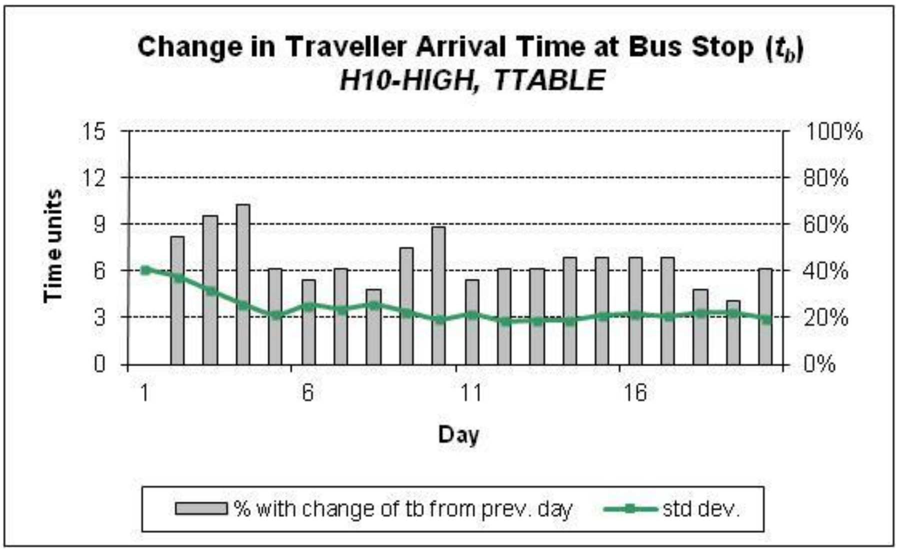

Mean Traveller Arrival Time at Bus Stop (t_b)
H10-HIGH, NO-INFO
Time
(PAT=0)
-55
-60
-65
-70
-75
-80
0
5
10
15
20
Day

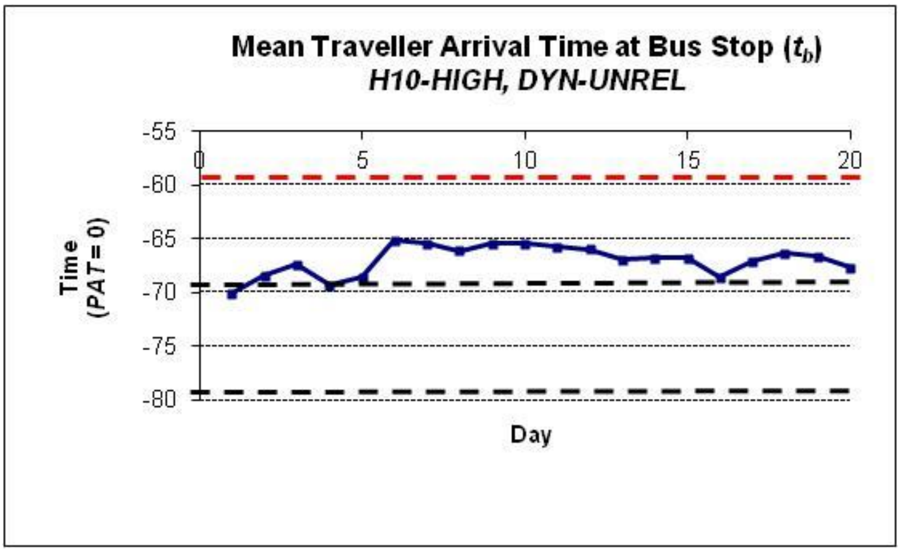

Change in Traveller Arrival Time at Bus Stop (t_b)
H10-HIGH, NO-INFO
Time units
15
12
9
6
3
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Day
% with change of tb from prev. day
std dev.

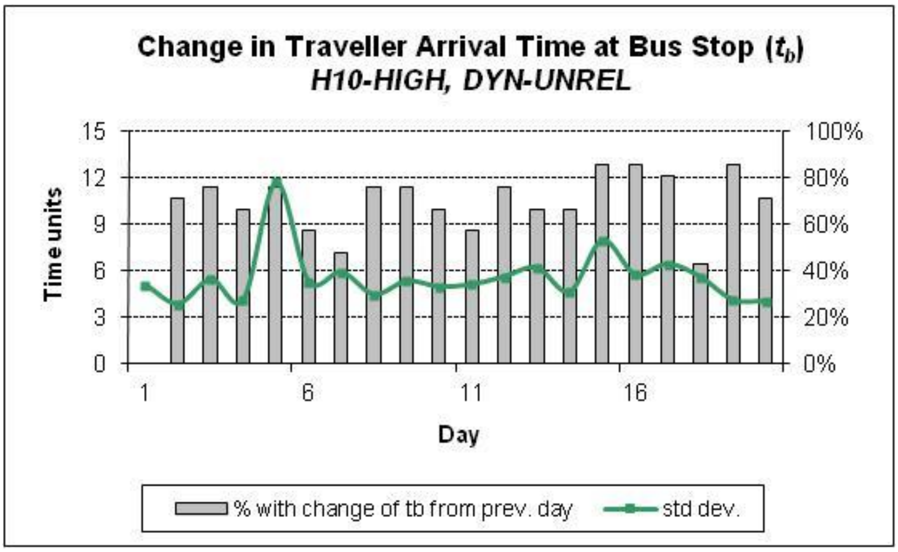

Mean Traveller Arrival Time at Bus Stop (t_b)
H10-HIGH, HDWAY
Time
(PAT = 0)
-55
-60
-65
-70
-75
-80
0
5
10
15
20
Day

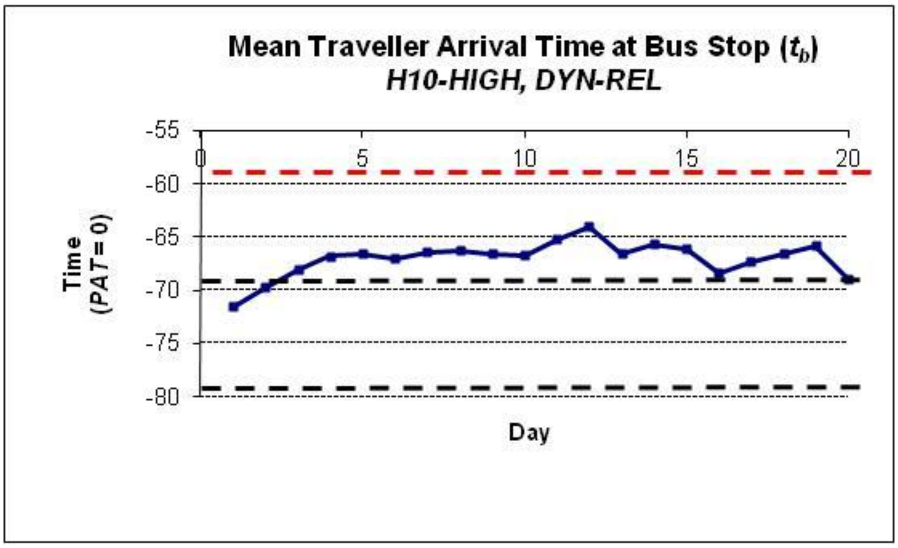

Change in Traveller Arrival Time at Bus Stop (t_b)
H10-HIGH, HDWAY
Time units
15
12
9
6
3
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Day
% with change of tb from prev. day
std dev.

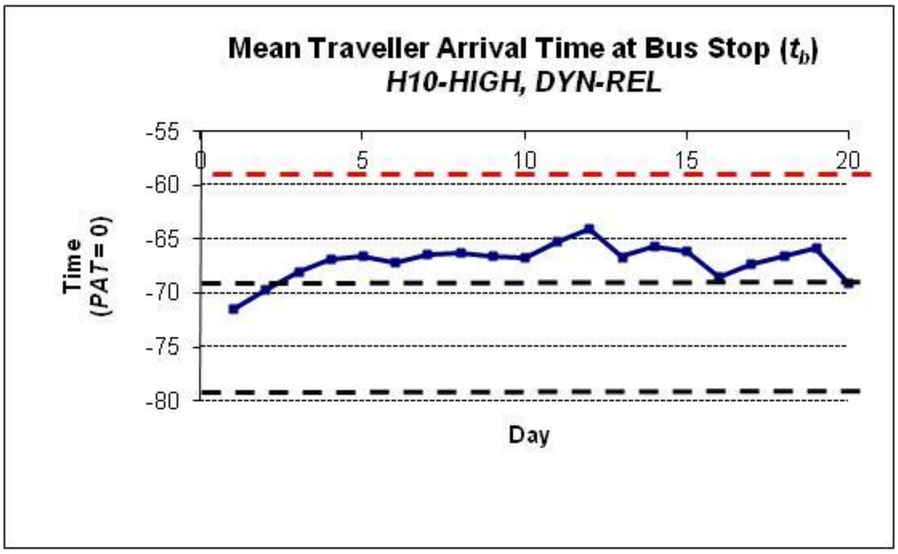

Mean Traveller Arrival Time at Bus Stop (t_b)
H10-HIGH, TTABLE
Time
(PAT = 0)
-55
-60
-65
-70
-75
-80
0
5
10
15
20
Day

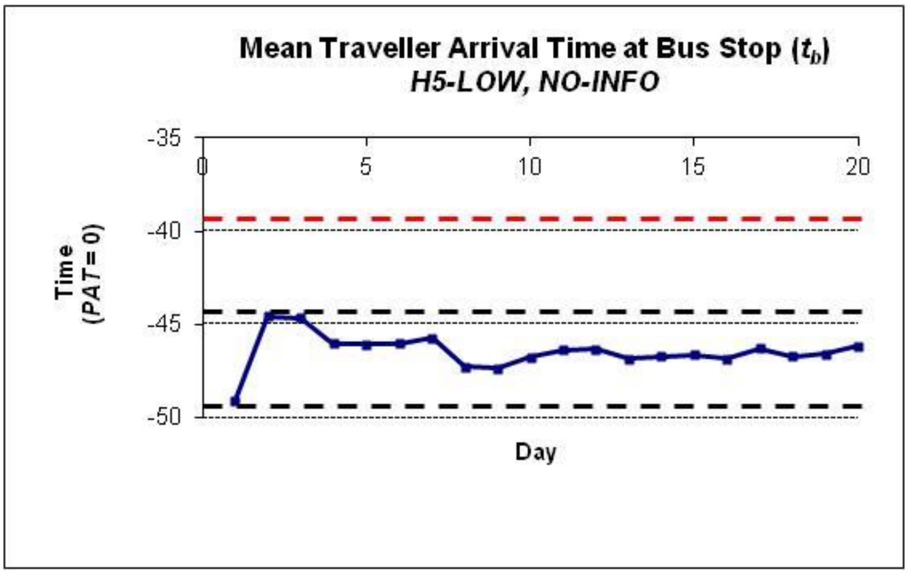

Change in Traveller Arrival Time at Bus Stop (t_b)
H10-HIGH, TTABLE
Time units
15
12
9
6
3
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Day
% with change of tb from prev. day
std dev.


Mean Traveller Arrival Time at Bus Stop (t_b)
H10-HIGH, DYN-UNREL
-55
-60
-65
-70
-75
-80
0
5
10
15
20
Time
(PAT = 0)
Day

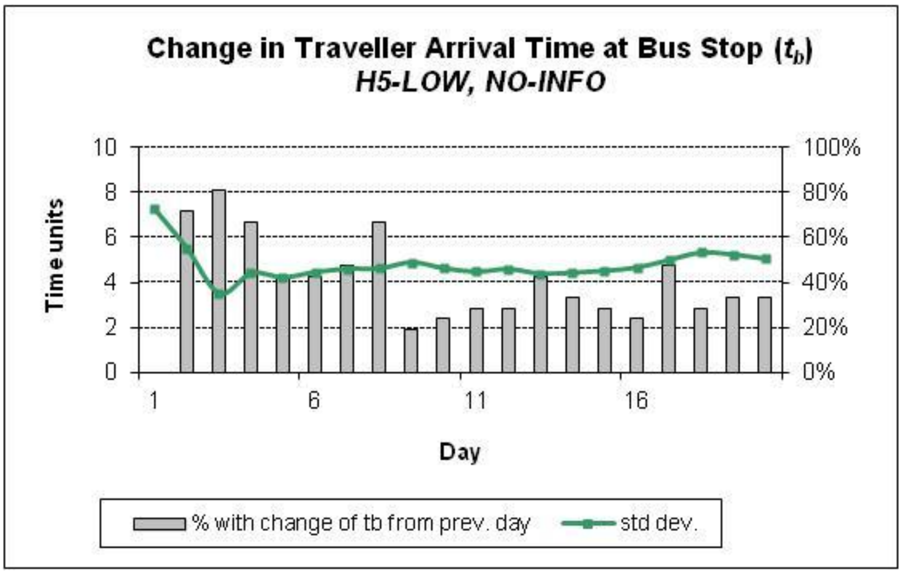

Change in Traveller Arrival Time at Bus Stop (t_b)
H10-HIGH, DYN-UNREL
15
12
9
6
3
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Time units
Day
% with change of tb from prev. day
std dev.


Mean Traveller Arrival Time at Bus Stop (t_b)
H10-HIGH, DYN-REL
Time
(PAT=0)
-55
-60
-65
-70
-75
-80
0
5
10
15
20
Day

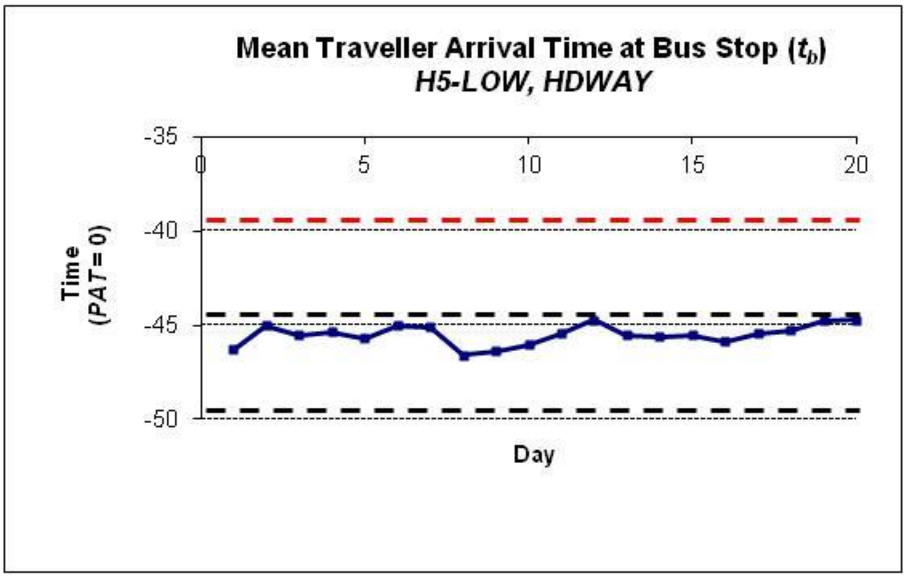

Mean Traveller Arrival Time at Bus Stop (t_b)
H10-HIGH, DYN-REL
Time
(PAT=0)
-55
-60
-65
-70
-75
-80
0
5
10
15
20
Day

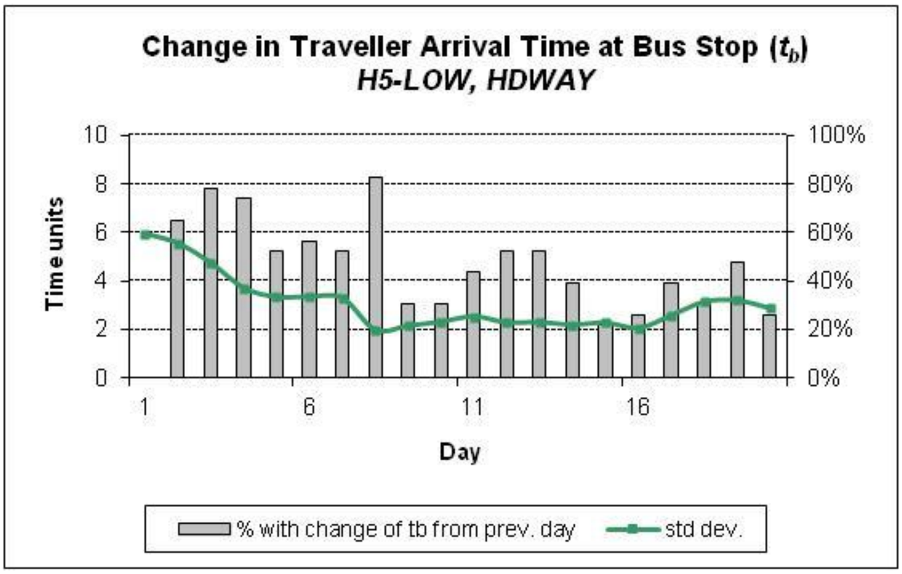


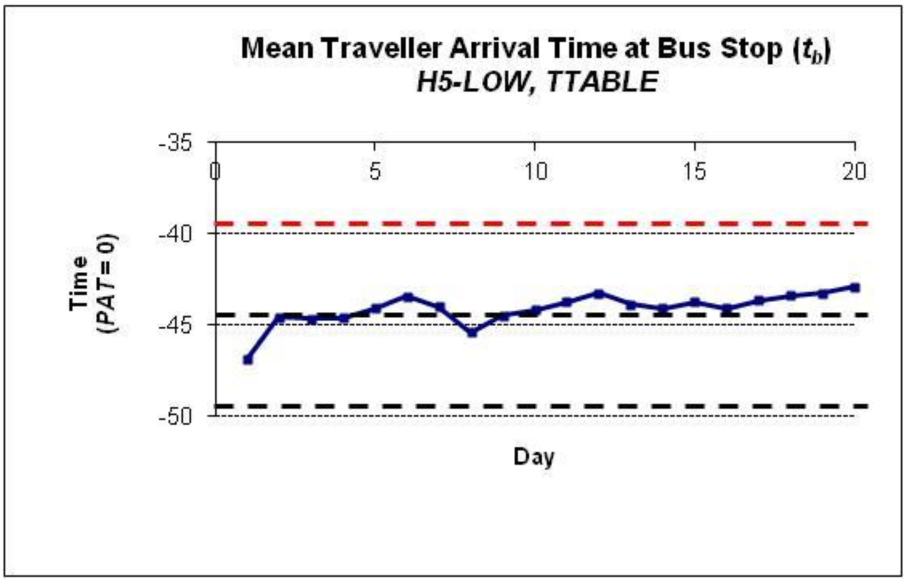
Mean Traveller Arrival Time at Bus Stop (t_b)
H5-LOW, NO-INFO
Time
(PAT = 0)
-35
-40
-45
-50
0
5
10
15
20
Day

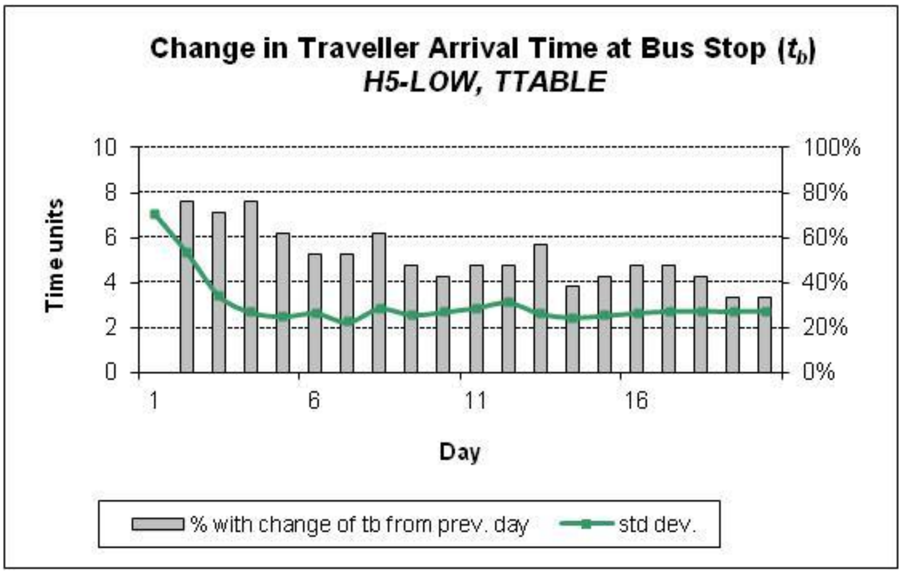


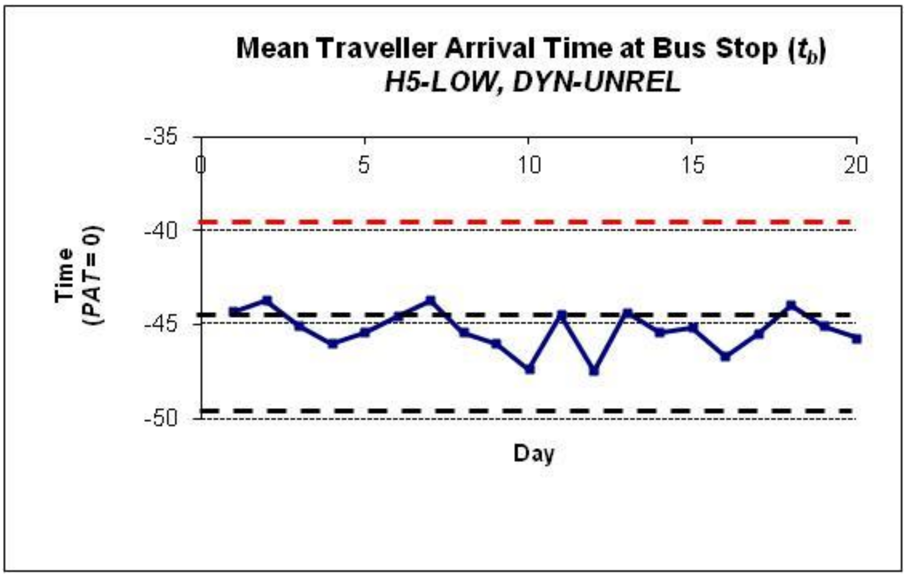
Change in Traveller Arrival Time at Bus Stop (t_b)
H5-LOW, NO-INFO
Time units
10
8
6
4
2
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Day
% with change of tb from prev. day
std dev.

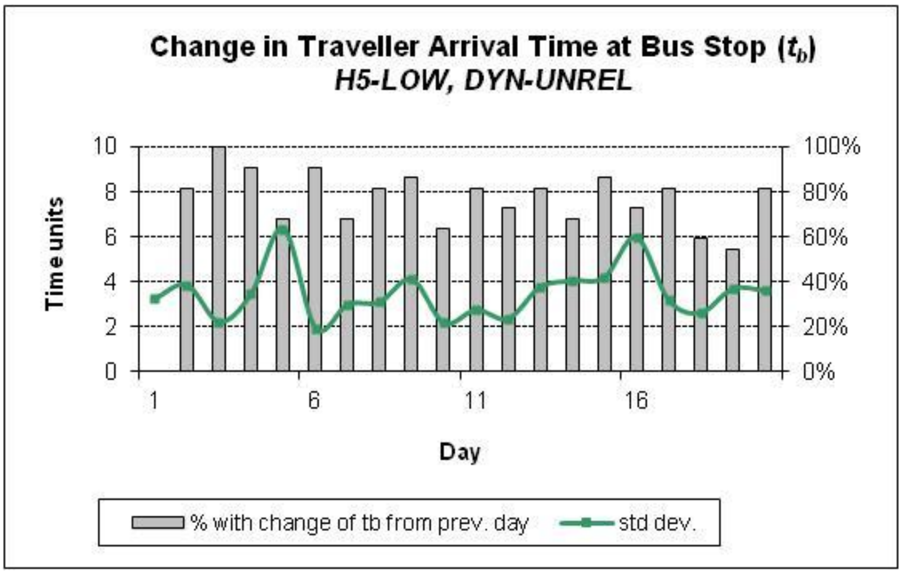

Mean Traveller Arrival Time at Bus Stop (t_b)
H5-LOW, HDWAY
Time
(PAT = 0)
-35
-40
-45
-50
0
5
10
15
20
Day

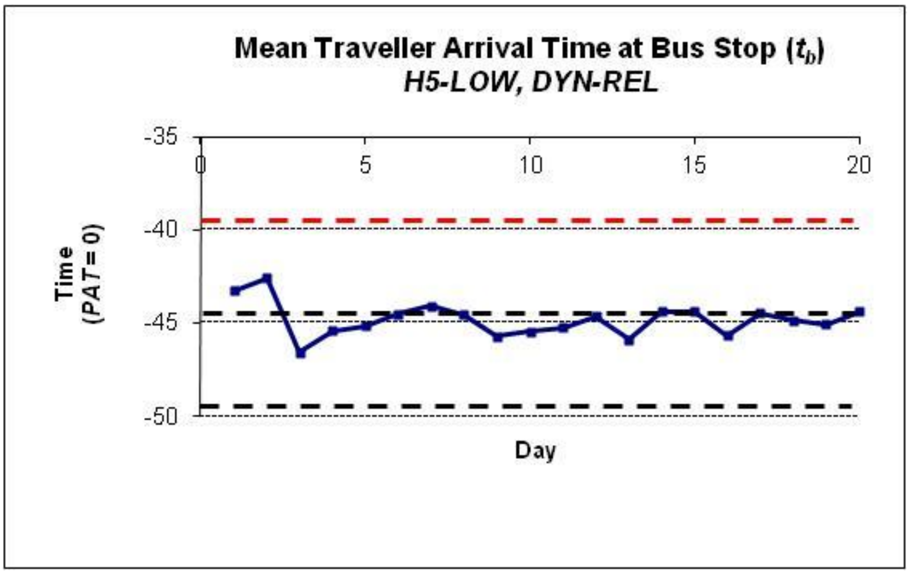

Change in Traveller Arrival Time at Bus Stop (t_b)
H5-LOW, HDWAY
Time units
10
8
6
4
2
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Day
% with change of tb from prev. day
std dev.

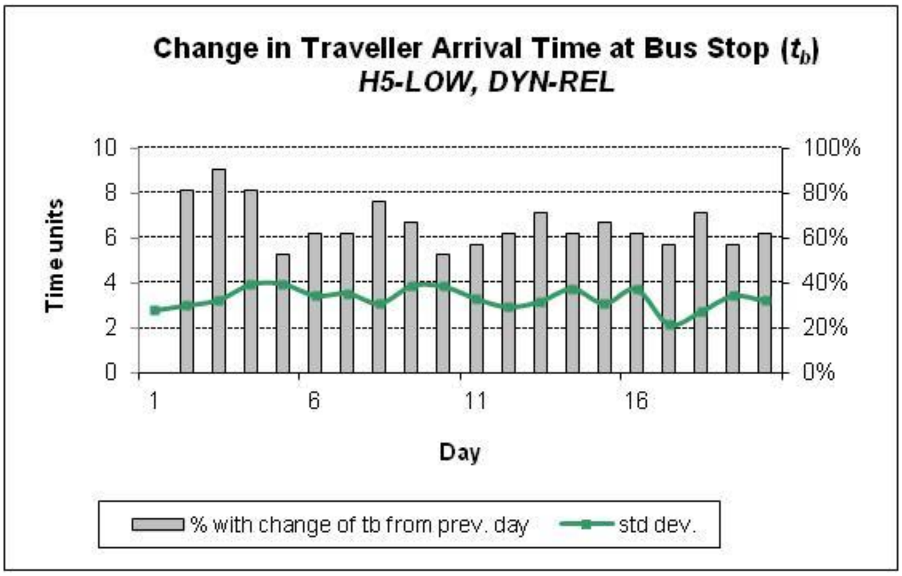

Mean Traveller Arrival Time at Bus Stop (t_b)
H5-LOW, TTABLE
-35
-40
-45
-50
0
5
10
15
20
Time
(PAT=0)
Day

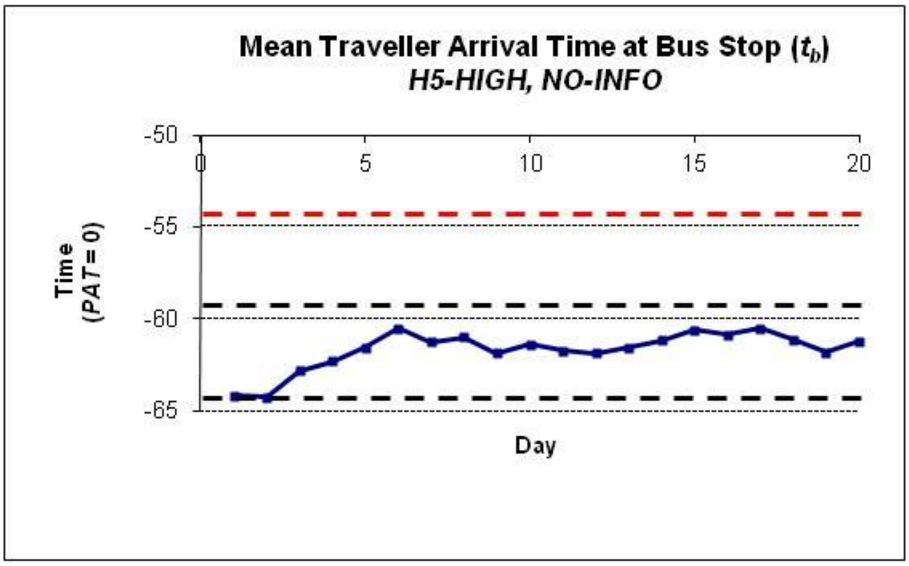

Change in Traveller Arrival Time at Bus Stop (t_b)
H5-LOW, TTABLE
10
8
6
4
2
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Time units
Day
% with change of tb from prev. day
std dev.


Mean Traveller Arrival Time at Bus Stop (t_b)
H5-LOW, DYN-UNREL
Time (PAT = 0)
-35
-40
-45
-50
0
5
10
15
20
Day

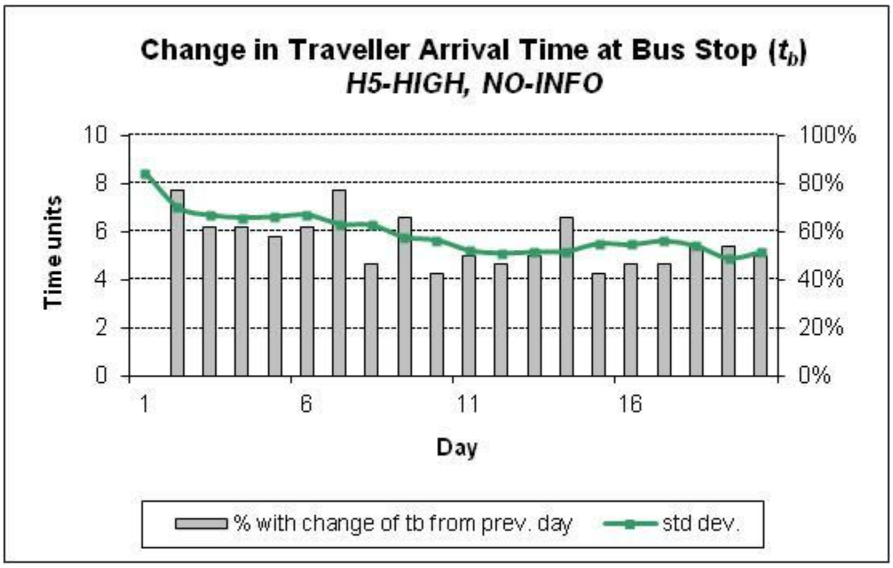

Change in Traveller Arrival Time at Bus Stop (t_b)
H5-LOW, DYN-UNREL
Time units
10
8
6
4
2
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Day
% with change of tb from prev. day
std dev.


Mean Traveller Arrival Time at Bus Stop (t_b)
H5-LOW, DYN-REL
-35
-40
-45
-50
0
5
10
15
20
Time
(PAT = 0)
Day

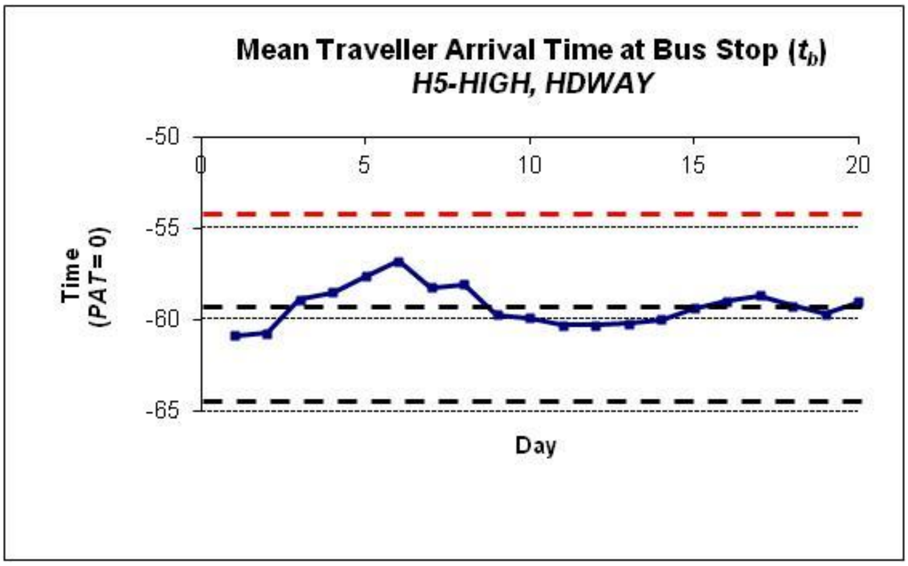

Change in Traveller Arrival Time at Bus Stop (t_b)
H5-LOW, DYN-REL
10
8
6
4
2
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Time units
Day
% with change of tb from prev. day
std dev.

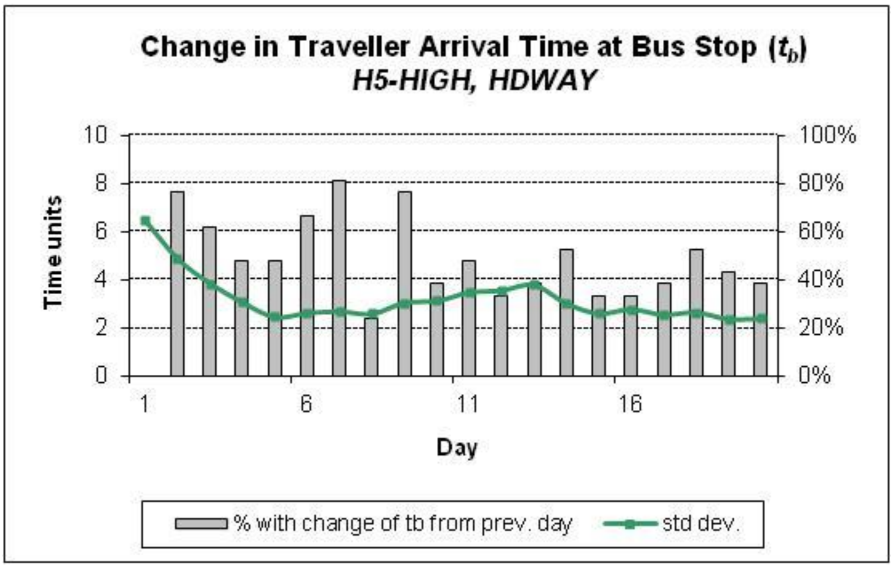


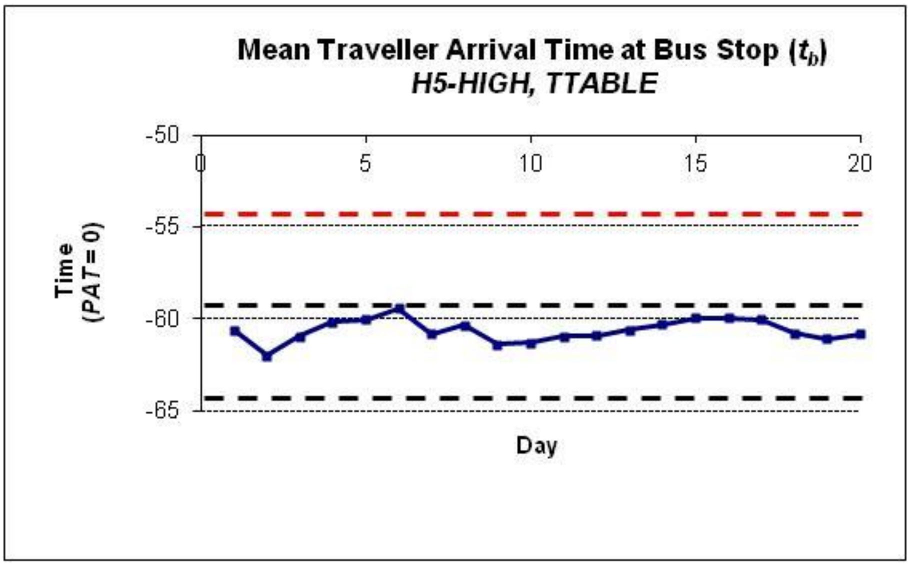
Mean Traveller Arrival Time at Bus Stop (t_b)
H5-HIGH, NO-INFO
-50
-55
-60
-65
0
5
10
15
20
Time
(PAT = 0)
Day

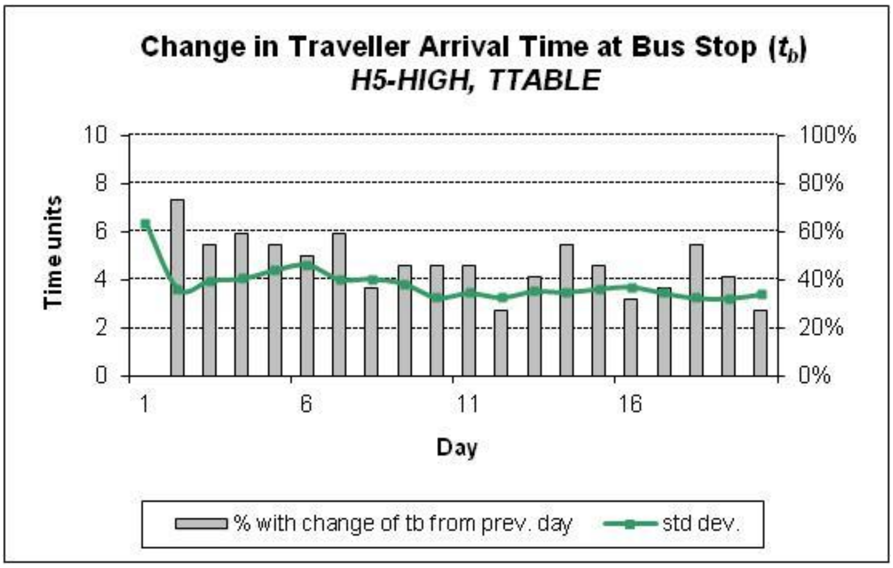


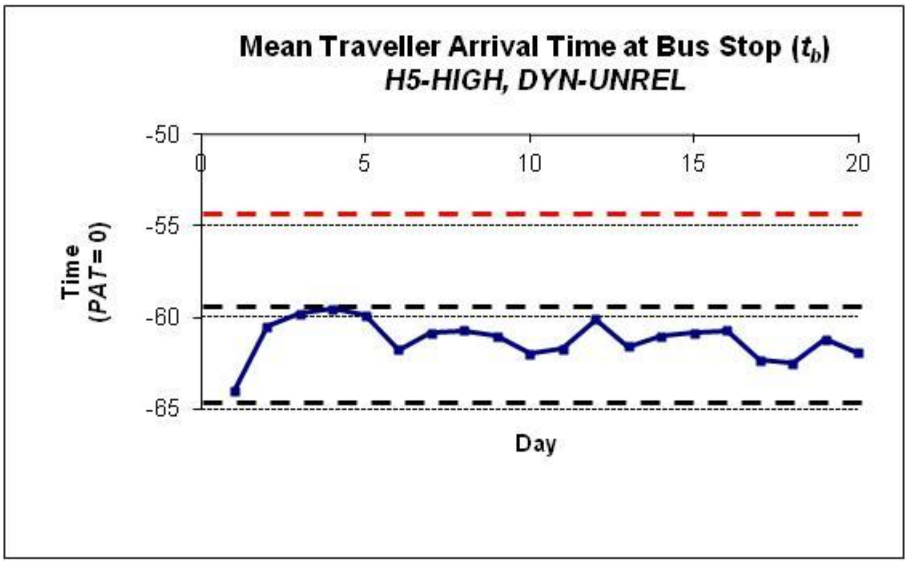
Change in Traveller Arrival Time at Bus Stop (t_b)
H5-HIGH, NO-INFO
10
8
6
4
2
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Time units
Day
% with change of tb from prev. day
std dev.


Mean Traveller Arrival Time at Bus Stop (t_b)
H5-HIGH, HDWAY
Time (PAT=0)
-50
-55
-60
-65
0
5
10
15
20
Day

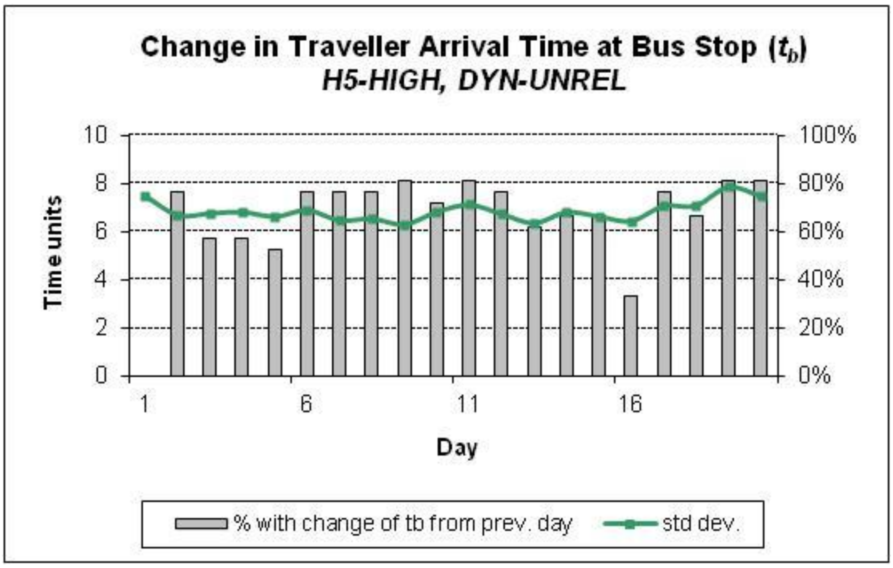

Change in Traveller Arrival Time at Bus Stop (t_b)
H5-HIGH, HDWAY
Time units
10
8
6
4
2
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Day
% with change of tb from prev. day
std dev.


Mean Traveller Arrival Time at Bus Stop (t_b)
H5-HIGH, TTABLE
-50
-55
-60
-65
0
5
10
15
20
Time (PAT = 0)
Day

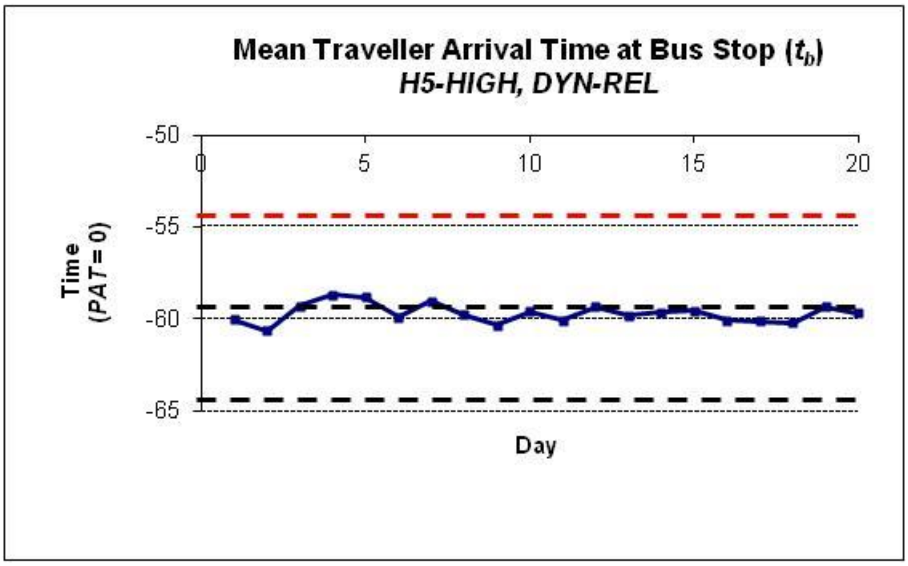

Change in Traveller Arrival Time at Bus Stop (t_b)
H5-HIGH, TTABLE
10
8
6
4
2
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Time units
Day
% with change of tb from prev. day
std dev.

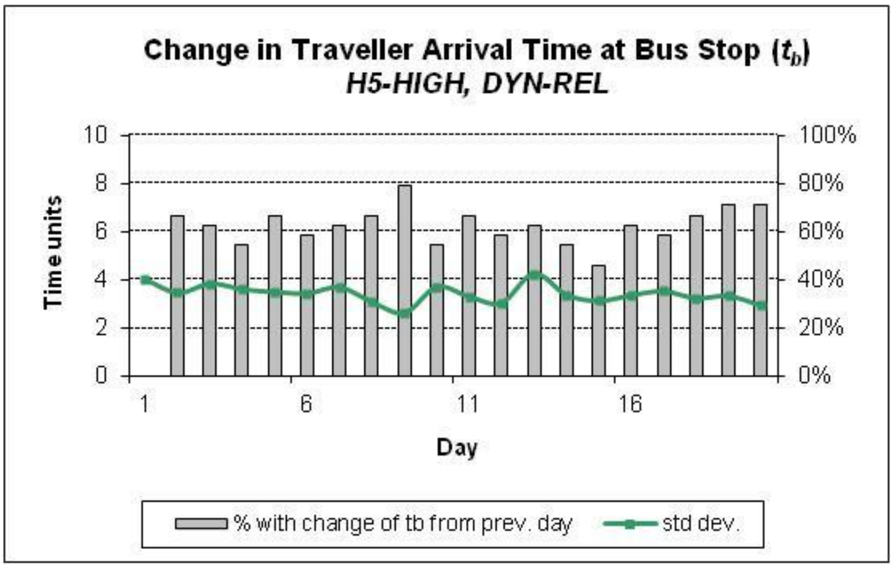


Mean Traveller Arrival Time at Bus Stop (t_b)
H5-HIGH, DYN-UNREL
-50
-55
-60
-65
0
5
10
15
20
Time
(PAT=0)
Day

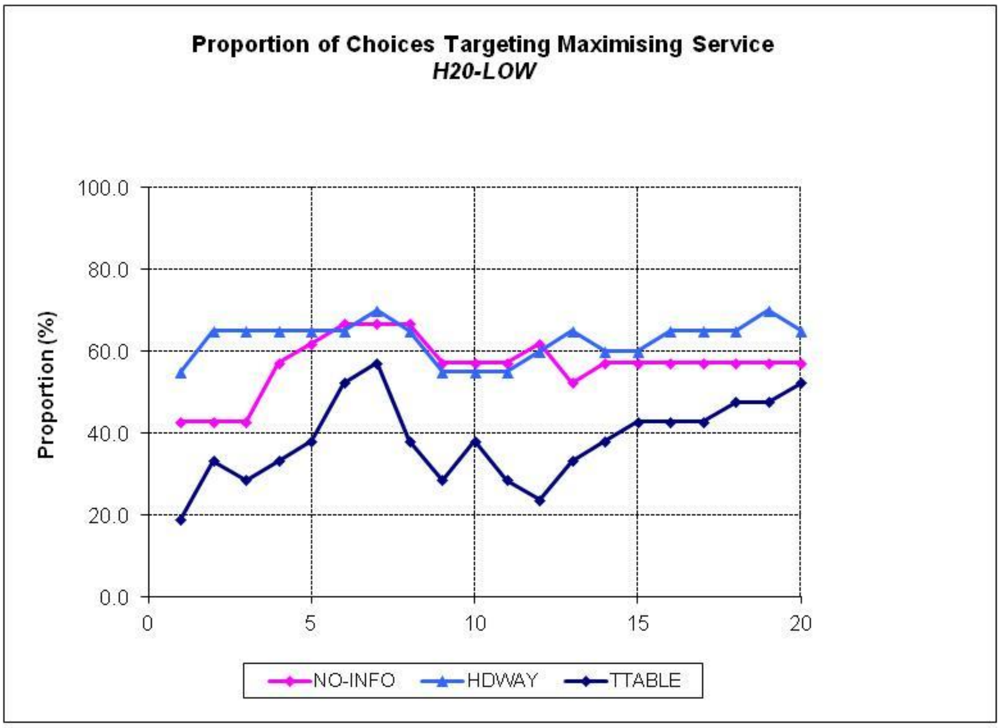


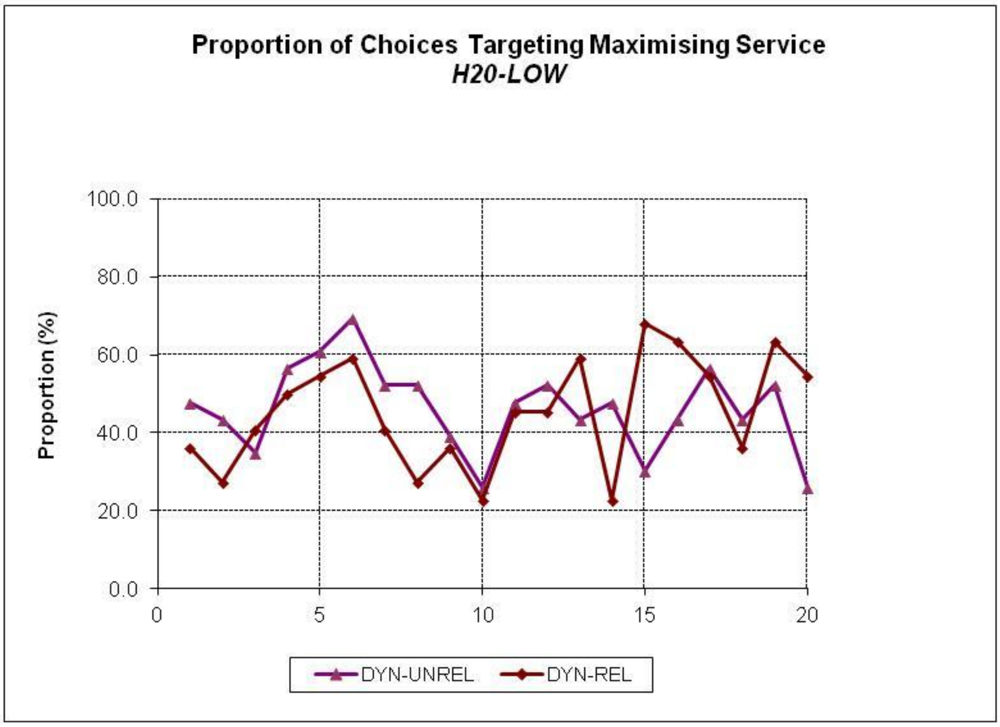
Change in Traveller Arrival Time at Bus Stop (t_b)
H5-HIGH, DYN-UNREL
10
8
6
4
2
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Time units
Day
% with change of tb from prev. day
std dev.

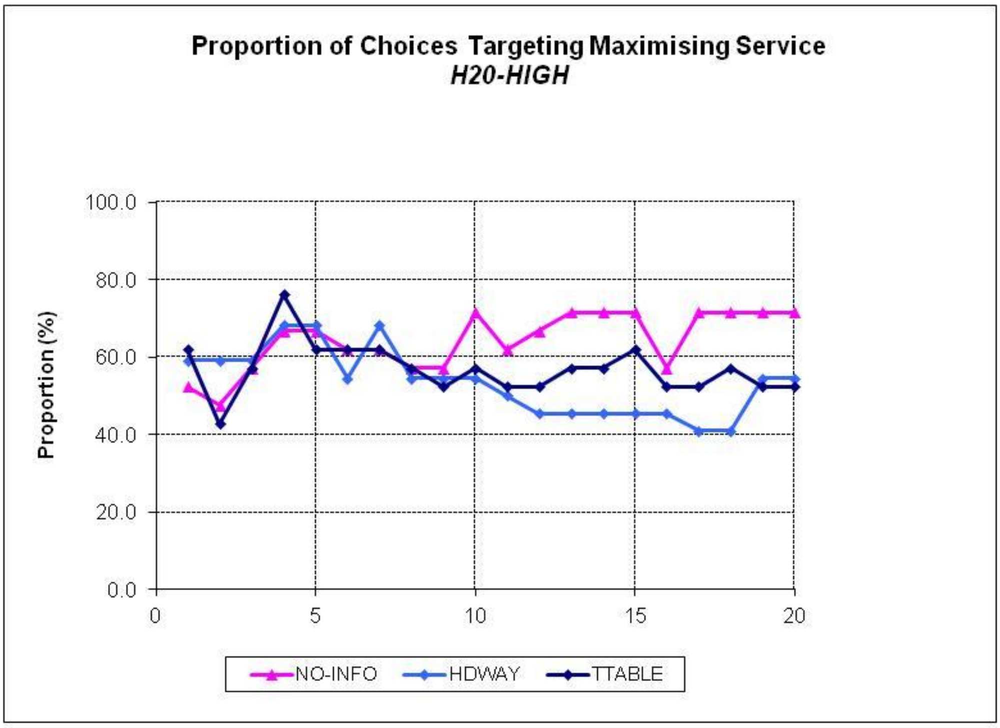

Mean Traveller Arrival Time at Bus Stop (t_b)
H5-HIGH, DYN-REL
-50
-55
-60
-65
0
5
10
15
20
Time
(PAT = 0)
Day

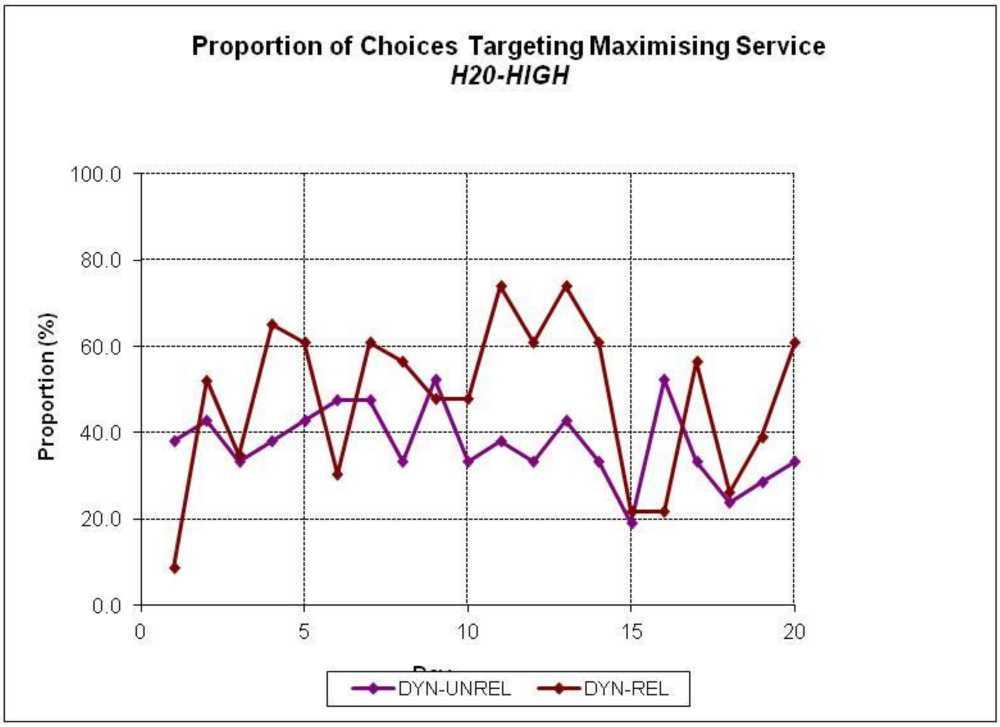

Change in Traveller Arrival Time at Bus Stop (t_b)
H5-HIGH, DYN-REL
10
8
6
4
2
0
100%
80%
60%
40%
20%
0%
1
6
11
16
Time units
Day
% with change of tb from prev. day
std dev.

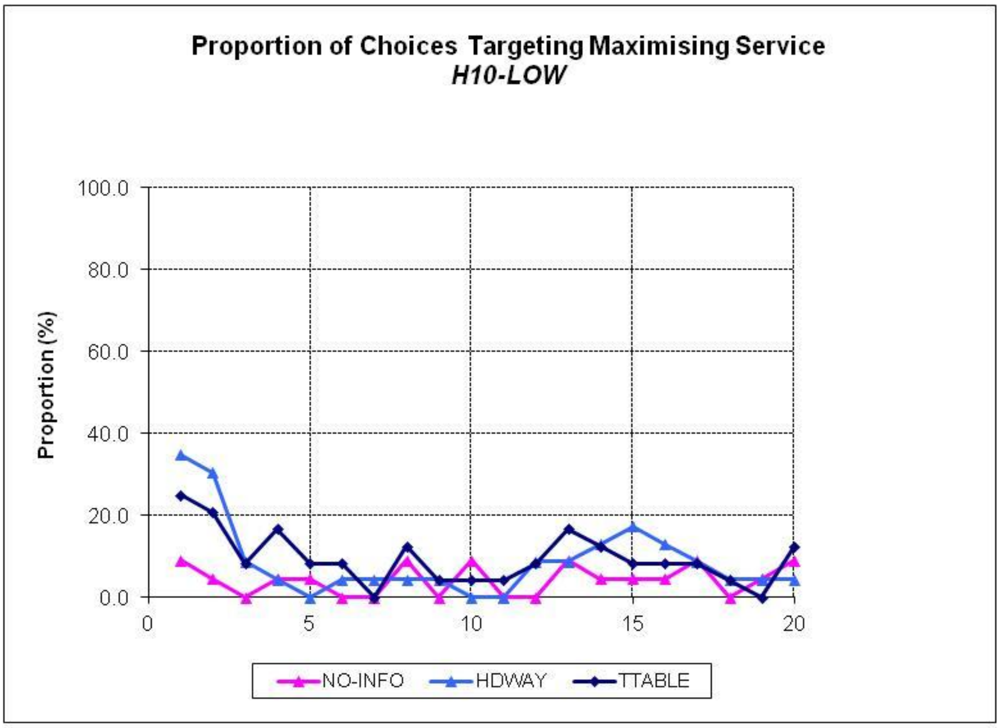
APPENDIX 5: PLOTS OF PROPORTION OF CHOICES TARGETTING MAXIMISING SERVICE BY SCENARIO

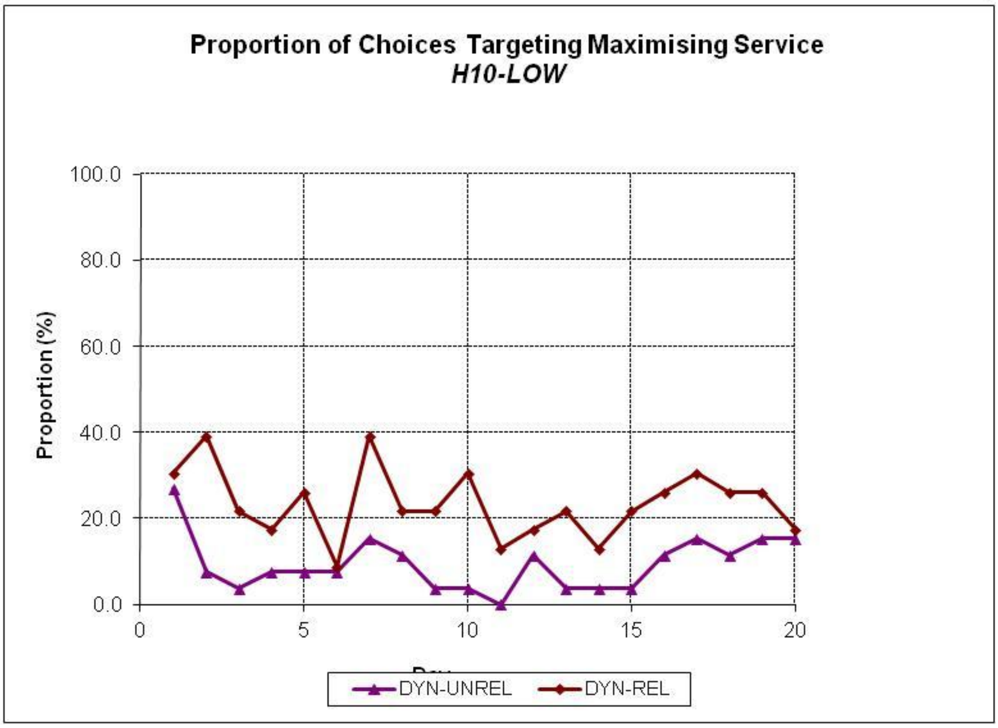


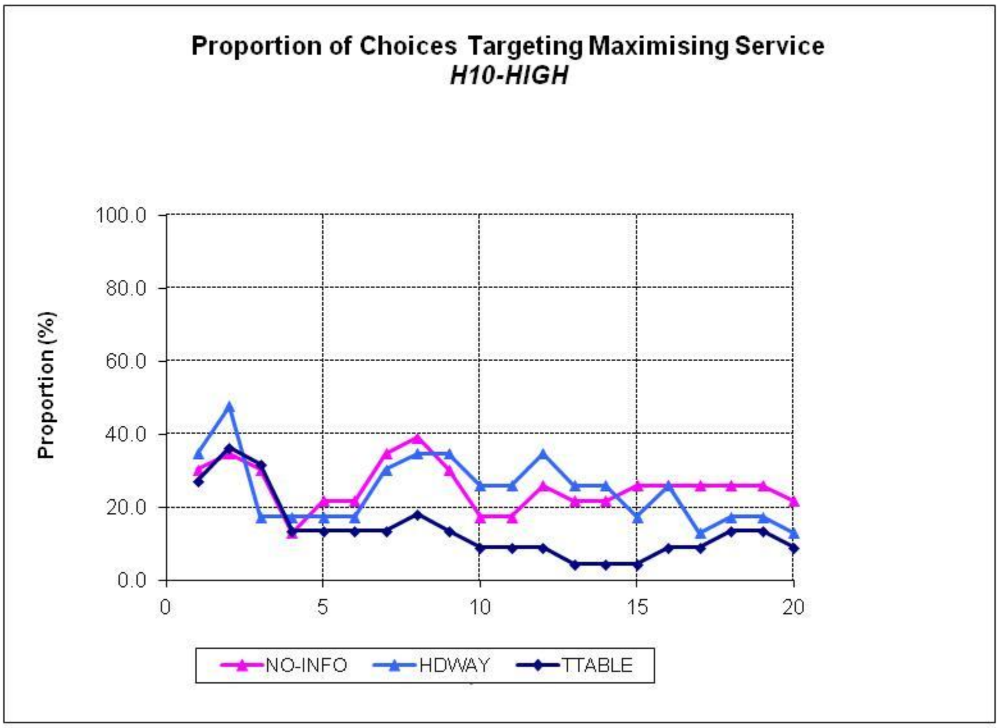


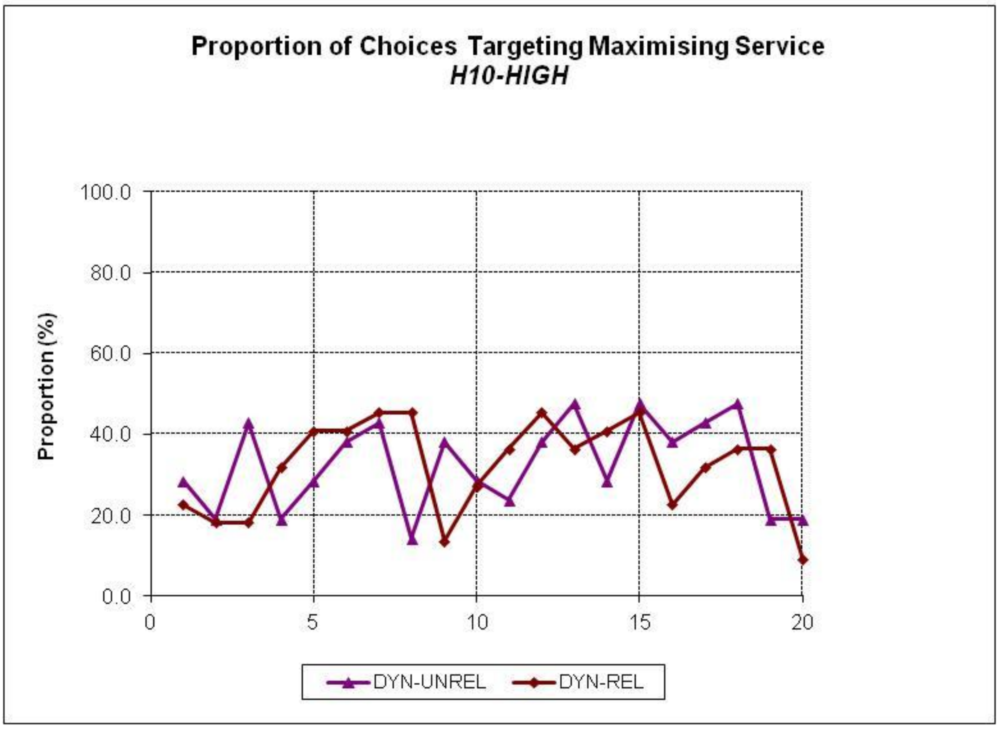

Proportion of Choices Targeting Maximising Service
H20-HIGH
Proportion (%)
100.0
80.0
60.0
40.0
20.0
0.0
0
5
10
15
20
NO-INFO
HDWAY
TTABLE

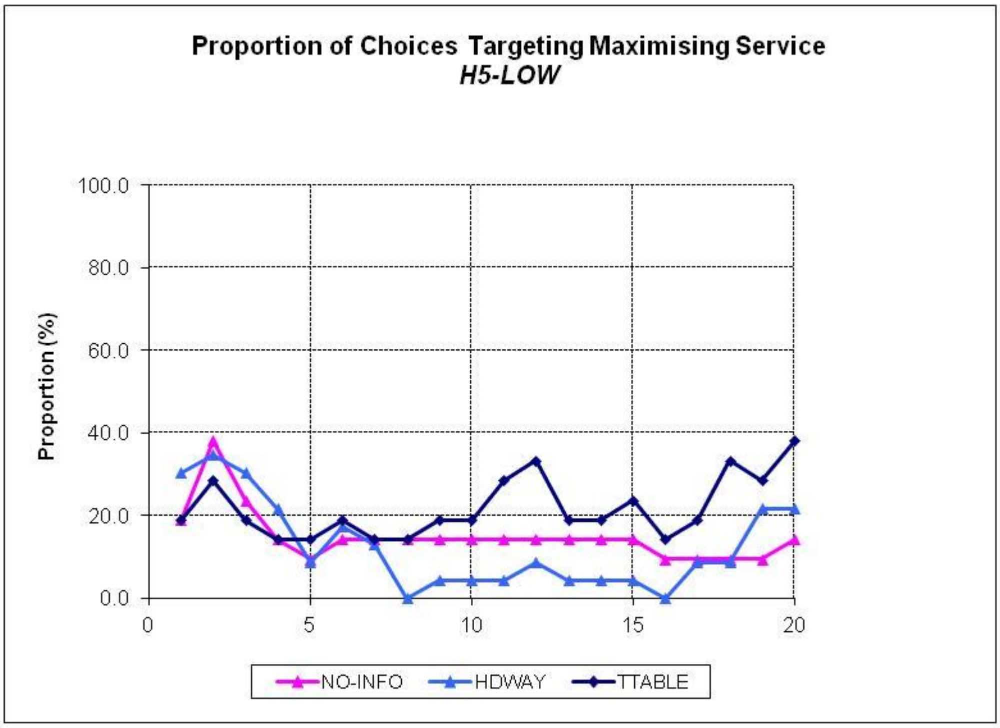

Proportion of Choices Targeting Maximising Service
H20-HIGH
Proportion (%)
100.0
80.0
60.0
40.0
20.0
0.0
0
5
10
15
20
DYN-UNREL
DYN-REL

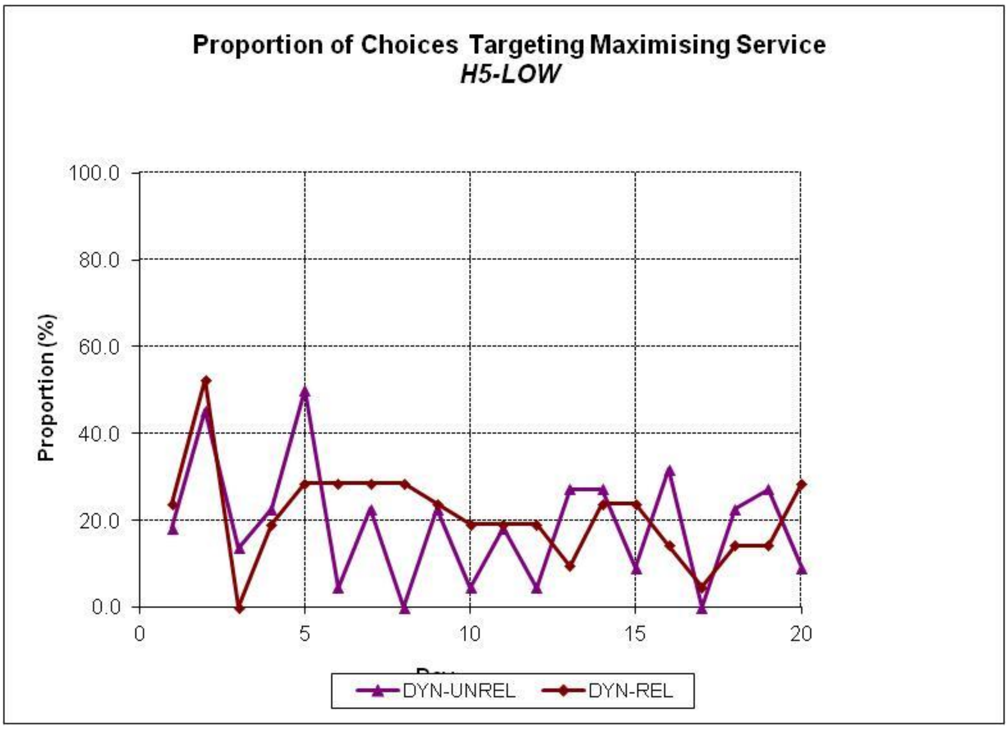

Proportion of Choices Targeting Maximising Service
H10-LOW
Proportion (%)
100.0
80.0
60.0
40.0
20.0
0.0
0
5
10
15
20
NO-INFO
HDWAY
TTABLE

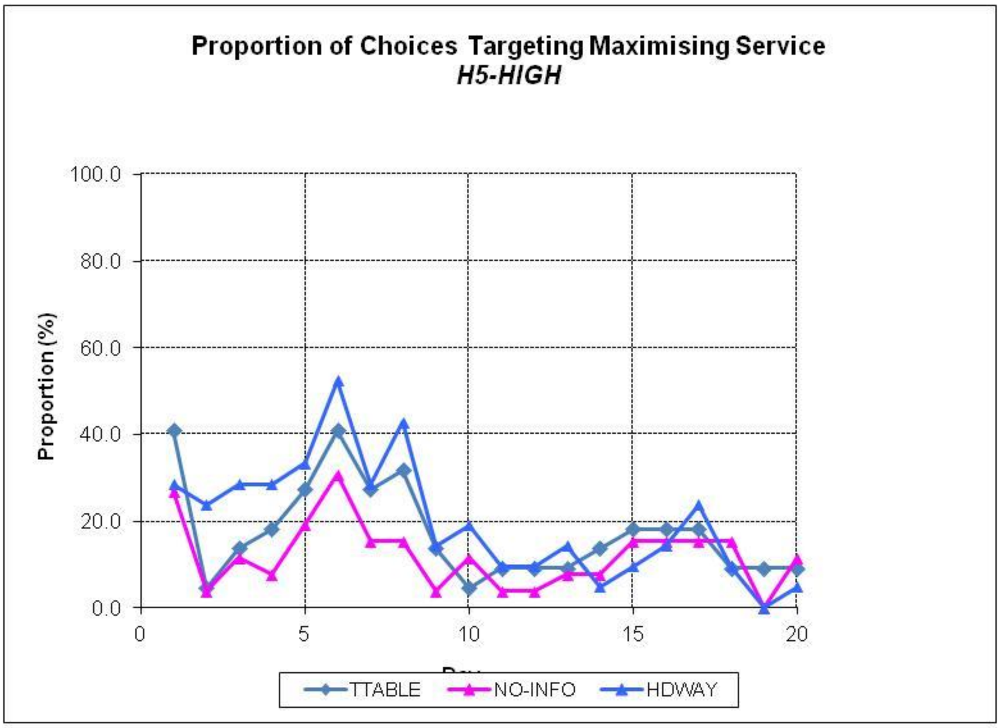

Proportion of Choices Targeting Maximising Service
H10-LOW
Proportion (%)
100.0
80.0
60.0
40.0
20.0
0.0
0
5
10
15
20
DYN-UNREL
DYN-REL


Proportion of Choices Targeting Maximising Service
H10-HIGH
Proportion (%)
100.0
80.0
60.0
40.0
20.0
0.0
0
5
10
15
20
NO-INFO
HDWAY
TTABLE

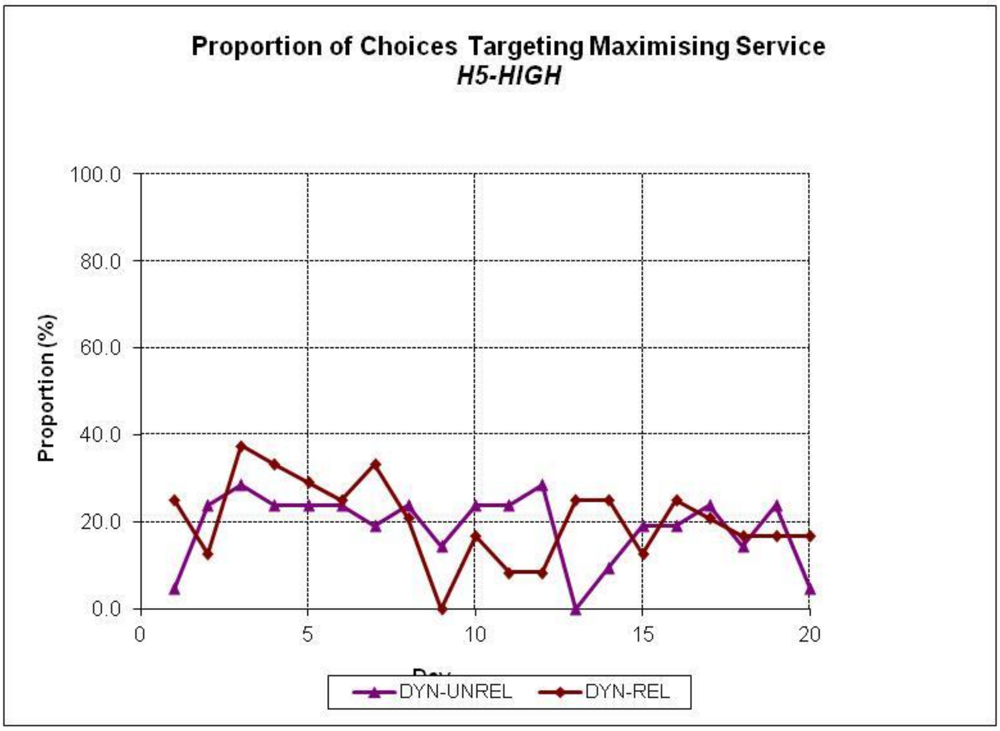

Proportion of Choices Targeting Maximising Service
H10-HIGH
Proportion (%)
100.0
80.0
60.0
40.0
20.0
0.0
0
5
10
15
20
DYN-UNREL
DYN-REL


Proportion of Choices Targeting Maximising Service
H5-LOW
Proportion (%)
100.0
80.0
60.0
40.0
20.0
0.0
0
5
10
15
20
NO-INFO
HDWAY
TTABLE


Proportion of Choices Targeting Maximising Service
H5-LOW
Proportion (%)
100.0
80.0
60.0
40.0
20.0
0.0
0
5
10
15
20
DYN-UNREL
DYN-REL



Proportion of Choices Targeting Maximising Service
H5-HIGH
Proportion (%)
100.0
80.0
60.0
40.0
20.0
0.0
0
5
10
15
20
TTABLE
NO-INFO
HDWAY



Proportion of Choices Targeting Maximising Service
H5-HIGH
Proportion (%)
100.0
80.0
60.0
40.0
20.0
0.0
0
5
10
15
20
DYN-UNREL
DYN-REL