



Institute of Transport Studies (Monash)
The Australian Research Council Key Centre in Transport Management

**Institute of Transport Studies, Monash
University
World Transit Research**

World Transit Research

9-1-2011

Investigating the Effects of Different Types of Travel Information on Travellers' Learning in a Public Transport Setting using An Experimental Approach

Joe Fai Poon

Peter R. Stopher

Follow this and additional works at: <http://www.worldtransitresearch.info/research>

Recommended Citation

Poon, J.F., & Stopher, P.R. (2011). Investigating the Effects of Different Types of Travel Information on Travellers' Learning in a Public Transport Setting using An Experimental Approach. Conference paper delivered at the 34th Australasian Transport Research Forum (ATRF) Proceedings held on 28 - 30 September 2011 in Adelaide, Australia.

This Conference Paper is brought to you for free and open access by World Transit Research. It has been accepted for inclusion in World Transit Research by an authorized administrator of World Transit Research. For more information, please contact pauline.forbes@eng.monash.edu.au.



MONASH University

Investigating the Effects of Different Types of Travel Information on Travellers' Learning in a Public Transport Setting using An Experimental Approach

Joe Fai Poon¹, Peter R. Stopher²

¹Institute of Transport and Logistics Studies, The University of Sydney, NSW 2006, Australia

²Institute of Transport and Logistics Studies, The University of Sydney, NSW 2006, Australia

Email for correspondence: joe_fai_poon@lta.gov.sg

Abstract

The effect of travel information on a traveller's decision making has been widely studied. However, its longer-term effect within the context of habitual travel, in which a traveller makes the same journey multiple times within a period of time and is exposed to the same travel information source repeatedly, is comparatively less investigated. A series of computer-based experiments were conducted to investigate the effect of information of various types and reliability on travellers' decision making over time. Participants were presented with repetitive departure time-choice tasks under several public transport scenarios in which the types of information and operating conditions were varied. Participants attempted a series of experimental sessions remotely from their work places using a simple program sent by email. This paper describes the design and implementation of the experiment, presents the preliminary findings, and discusses how such an experimental approach could contribute to existing knowledge of the inter-play between travel information and learning.

1. INTRODUCTION

The effect of travel information on a traveller's decision making has been the subject of extensive investigation. The broad consensus from the large body of literature is that travel information does have an effect on travel behaviour, ranging from quantified travel-time savings (Toledo and Beinhaker, 2006) to "positive psychological factors" and greater satisfaction with the transport service (Dziewan and Kottenhoff, 2007). However, less attention has been paid to a logical follow-on question: do these effects persist over time? Will the traveller continue to use the information when it is continuously supplied over time? These are pertinent questions 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 such a context, learning comes into play. Every trip involves a decision by the traveller on say, departure time. The traveller makes decisions based on his perceptions of the travel environment (e.g., likely range of travel time) and, if information is provided, of the information service (its reliability, etc.) 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 and/or the information. 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 repetitively exposed to the same travel environment and information service within the same travel context.

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 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. These include those by Jha *et al.* (1998) and Ettema *et al.* (2004, 2005), which model the iterative updates of traveller's perceptions of trip attributes and decisions, in both the presence and absence of information. Two particular studies that investigate the day-to-day evolution of decision-making under laboratory experimental settings are by Avineri and Prashker (2006) and Ben-Elia *et al.* (2008). In both studies, 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, when given either *a priori* information about the routes' travel times or no information at all. In the experiments of Avineri and Prashker (2006), the information provided is the mean travel time and is *static*, whereas in those of Ben-Elia *et al.* (2008), the information is *dynamic* and is provided as travel time ranges.

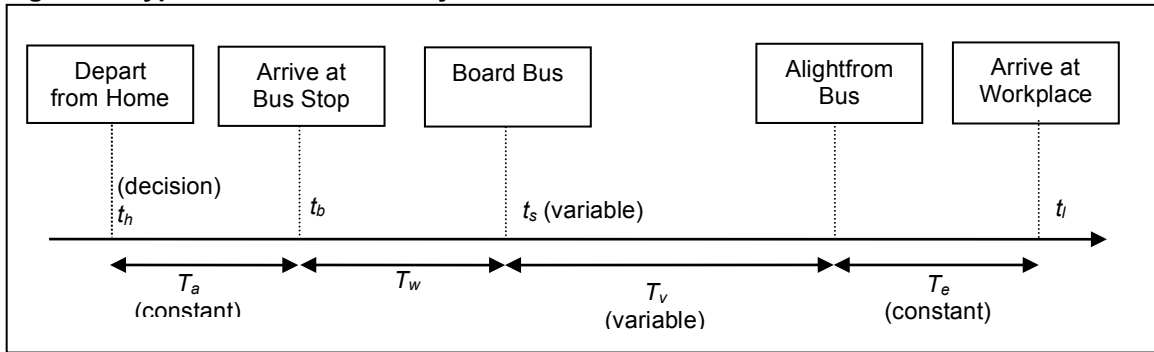
It should be fruitful if one builds on the experimental work of Avineri and Prashker (2006) and Ben-Elia *et al.* (2008) to compare empirically the differences between *static* and *dynamic* information in how they affect decision making over time and interact with the learning process under identical travel conditions. This research should shed light on whether Advanced Traveller Information Systems (ATIS) that respond dynamically to variable travel conditions exhibit significant advantages over the traditional (static) forms of information in terms of the likelihood of being acquired and enhancing the learning process. A similar question may be asked of the sustainability over time of such an advantage, if present. This research program therefore builds on 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 in an experimental setting. The key difference is that a *public transport* travel setting is used instead, considering that comparatively few studies investigate the effects on users of public transport of providing public transport schedule information. 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). Examination of the decisions of travellers making repeated trips on public transport offers an opportunity to examine aspects of decision-making different from the commonly investigated phenomena of route and/or departure time choice under highway scenarios.

In this paper, the experimental scenario is set out in the next section. This is followed by a description of the experimental programme and design in the following two sections. The fifth section covers such implementation issues as conducting pilot experiments and recruiting participants. The preliminary findings are presented in the sixth section, while the last section discusses the main lessons learnt and identifies areas for further examination.

2. EXPERIMENTAL SCENARIO

The experimental scenario requires the participant to select a departure time from home (t_h) to catch a bus service for a hypothetical commute trip to work. She is required to reach the work place by the work start time, which is defined as her “preferred arrival time” (*PAT*) for expediency. Like most real-life commuters, when deciding on t_h , the participant has to consider the access time to the boarding bus stop (T_a), the egress time from the alighting bus stop (T_e), the waiting time for the service (T_w), the likely departure time of the service from the bus stop (t_s) and the in-vehicle time on the bus (T_v). The simulated bus service is timetabled, but the actual departure times, t_s and the in-vehicle trip times, T_v vary daily. For simplicity, T_a and T_e are kept constant. See Figure 1.

Figure 1: Hypothetical Bus Journey



Due to the variability of t_s and T_v , the participant will never be fully certain of their values on any given simulated day, although from experience, she will have some perceptions of what they are likely to be. She seeks not to be late for work, but is also reminded not to arrive too early. Hence, the choice of t_h should result in a reasonable chance to reach the bus stop at t_b to catch the one service that will bring her to the work place at time t_i that is as close to but not later than *PAT*, as well as minimising T_w ($=t_s - t_b$, $t_s \geq t_b$). Each day, she learns from the outcome of his trip decision, i.e., how late or early she is, and how long the wait for the service is. From this outcome, and from those from previous days, the traveller may adjust t_h for the following day. The above description assumes an *absence* of travel information. When information that provides estimates of the service departure and in-vehicle times is provided, she not only has to contend with her perceptions about t_s and T_v , but may also make reference to the estimates from the information service.

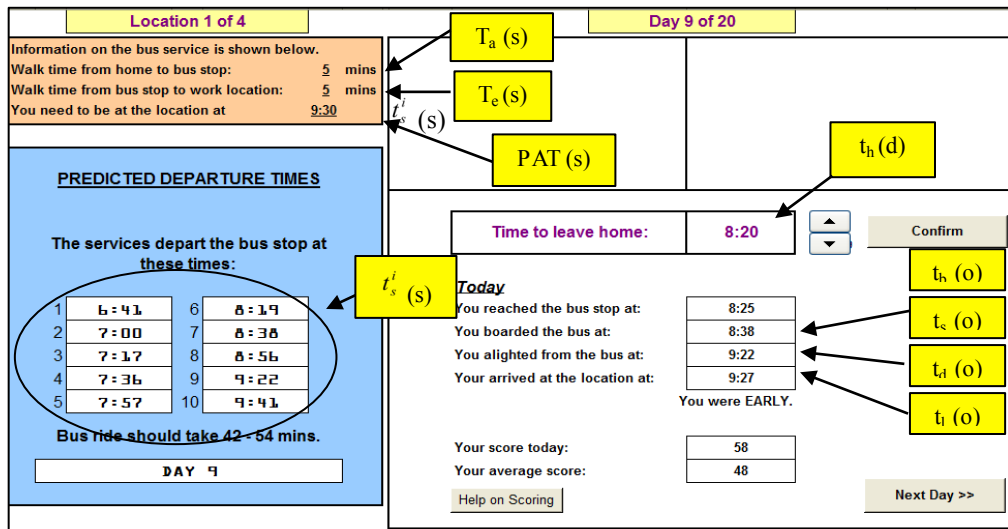
It is assumed the participant catches the first bus that arrives, and there is no possibility of failing to board it due to it being full, although this situation is likely in real life. Nor can she opt to wait for the second bus due to personal preference. Once the choice of t_h is made, the participant would be informed of the outcomes. She would know when the service actually departs (t_s), how long the wait (T_w) and the bus ride (T_v) have been, and when she arrives at the work location (t_i) (which will reveal if she is late for work). She can also note the discrepancy, if any, between t_s and its estimate by the information service, t_s^i . On the following day, the participant will again make a new decision on t_h , based on perceptions of the characteristics of the bus service and of the information, which are updated after learning about the outcomes of the previous day. This scenario is then repeated immediately upon the revelation of outcomes.

It is acknowledged that other factors affect the time of departure in real life, such as waking up late, and that the *PAT* may change occasionally (to attend a working breakfast). However, for simplicity, such real-life circumstances were assumed absent in the scenarios.

3. EXPERIMENTAL PROGRAMME

The experiments were programmed into a computer file developed in Microsoft Excel® software using Visual Basic for Applications (VBA). Figure 2 shows a typical screen display, with the various scenario (s), decision (d), and outcome (o) variables indicated. For each simulated day, the participant made a decision on t_h . Immediately the choice was made, the outcomes (t_s , T_w , T_v , t_d , t_i) were revealed. Also revealed is a score for the day. The score provides an indication to the participant of the quality of his decision making. The participants were told to attain two objectives: to minimise T_w and to minimise the schedule delays, which are the deviations of t_i from the *PAT*. The degree to which these objectives were met was measured by this score, the formula of which was also explained. 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 outcome attributes of T_w , early arrival at the destination (*SDE*), late arrival at the destination (*SDL*), and the fact of being late to work (*L*).

Figure 2: Typical Screen Display



4. EXPERIMENTAL DESIGN

The two primary phenomena of research interest, namely travel information and learning, are studied through the manipulation of experimental factors. A third factor of service operating characteristics was included in order to investigate the effects of information and learning across different operating environments.

The contents provided by the simulated travel information service relate to service departure times (t_s). For this study, five experimental conditions were constructed but in this paper, only four are presented. The first depicts a (static) timetable (*TTABLE*) that lists the scheduled departure times of each service. The second (*DYN-REL*) represents a real-time passenger travel information system that provides service departure times

Investigating the Effects of Different Types of Travel Information on Travellers' Learning in a Public Transport Setting using An Experimental Approach

that are updated regularly with a high level of reliability. The third (*DYN-UNREL*) is identical to the second, except that it is less reliable. The last is the no-information control. Information relating to the in-vehicle time was also provided in all *Info* conditions in a single, non-varying format. Figure 2 shows the *Info* condition of either *DYN-REL* or *DYN-UNREL*, and Figure 3 shows displays representing *NO-INFO* and *TTABLE* in the same experimental instrument. The actual experiment involved additional scenarios that were developed by combining two out of the original five conditions, such that one condition was presented in the 10 first hypothetical days before changing to the second condition for the 11th through 20th days. This simulated a replacement of an existing information service with another, e.g., the commission of a dynamic travel advisory service to replace published timetables. For brevity, these scenarios are not described here.

For *Info* conditions *TTABLE*, *DYN-REL* and *DYN-UNREL*, the individual estimates of departure time of each of the bus services were represented by t_s^i . The values of t_s^i in *TTABLE* are invariant obviously. In the other two, the values of t_s^i were varied from day to day, and were drawn from a discrete distribution approximating a truncated normal distribution, with its mean at the actual t_s . The reliability of these estimates was expressed as the standard deviation of the distribution as shown in Figures 4 and 5.

Figure 3 Information Conditions of *NO-INFO* and *TTABLE*

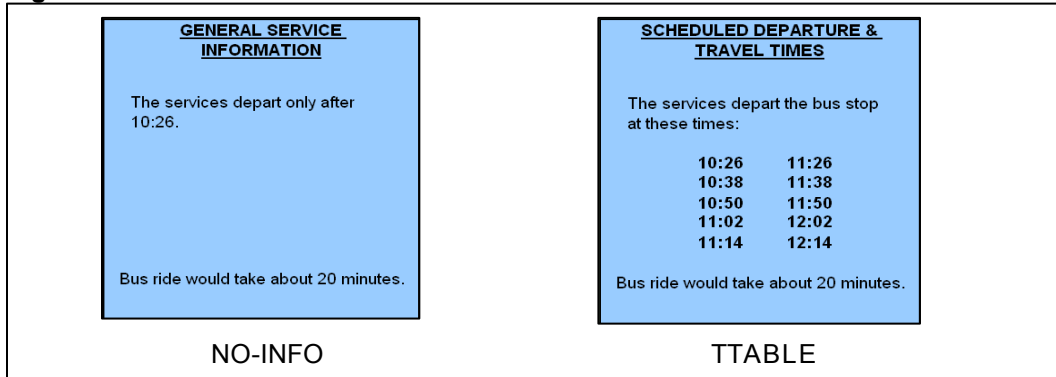


Figure 4: Distribution of Estimated Departure Times by “Reliable” Information Service (*DYN-REL*)

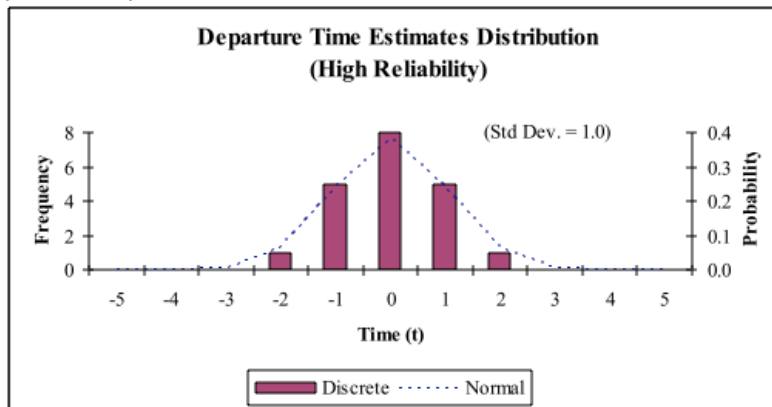
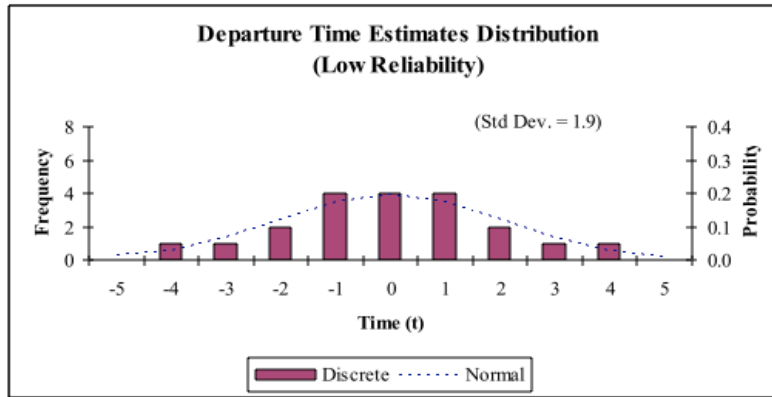


Figure 5: Distribution of Estimated Departure Times by “Unreliable” Information Service (DYN-UNREL)



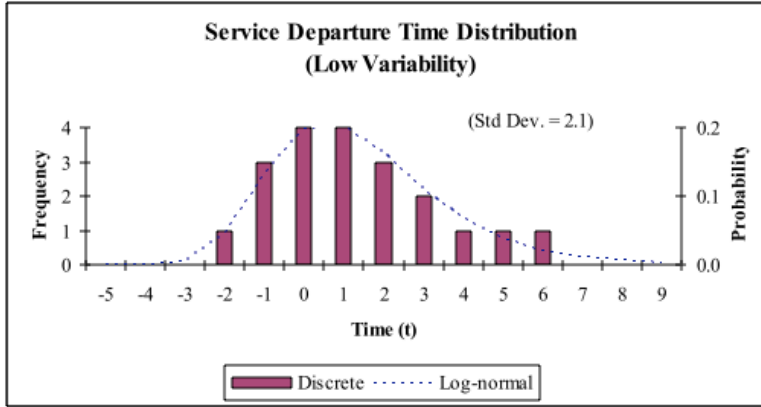
Learning was represented by a non-manipulative quantitative factor *Day*. Each of its levels, d , was a hypothetical travel day, and each successive day represents a gain in the level of experience or learning. The total number of days was set at $D = 20$.

To simulate the variety of travel environments, 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 headways (5, 10 and 20 minutes) and two levels of service arrival time variability (low and high). In this paper, only two are discussed. They are conditions with 20-minute and 5-minute headways, both with low service departure time variability (*H20-LOW* and *H5-LOW* respectively).

In each *Ops* condition, there were ten services scheduled to depart at regular headway, but whose actual departure times each day deviated from the schedule. The t_s values were drawn from two pre-defined discrete distributions approximating the lognormal (low and high departure time variability), and whose modes were set at the scheduled service departure time. Similarly, values of T_v were drawn from another discrete distribution approximating the lognormal. The lognormal distribution was used 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 rectify late running. Figure 6 presents the discrete distributions of t_s of low variability. The distribution of T_v is similar, except for a higher standard deviation. All units of t_s and T_v are measured relative to the *scheduled* departure time and *scheduled* in-vehicle time. Negative values indicate t_s which are earlier, or T_v which are shorter, than scheduled, while positive values denote late t_s or longer T_v than scheduled. In real life, commuters may identify certain services departing at certain times to be particularly fast or slow, or are more reliable in departure times, and can choose to catch or avoid them accordingly. However, in this scenario, because the t_s (and T_v) values of all services were all drawn from the same distribution, the services share the same characteristics, and there is no particularly fast or slow, or reliable or unreliable service.

Investigating the Effects of Different Types of Travel Information on Travellers' Learning in a Public Transport Setting using An Experimental Approach

Figure 6: Distribution of Actual Departure Times (t_s) (Low Variability)



5. CONDUCT OF EXPERIMENTS

In the full experiment, ten *Info* conditions are combined with 6 *Ops* conditions to provide $10 \times 6 = 60$ scenarios. Each participant underwent 4 different scenarios. No *Ops* and *Info* condition in any one scenario was repeated in the other three. Moreover, the parameters of PAT , T_v , T_a and T_e were assigned different values across the *Ops* conditions. To avoid further such undesirable effects as carryover effects which might threaten the validity of the experiments, the sequence of presentation of scenarios was varied, such that each scenario appeared as the first, second, third, and last sessions approximately an equal number of times.

Participants were recruited from the first author's sponsoring organisation, the Land Transport Authority (LTA) of Singapore. From a sampling frame consisting of 3,713 LTA staff members, 1,007 were randomly sampled and invited to participate. Of these, 338 attempted the experiment and returned the data file. The experimental program was sent by email to these participants, who completed the experiment in a single attempt. Data were stored, protected and hidden within the same file as the experiment progressed. Once the experiment was completed, the participants were instructed to send this file to the researcher by email. The alternative of conducting the experiments via an Internet website, as has been commonly done, was not adopted because a large proportion of potential participants did not have access to the Internet at their work places. On the other hand, all of them had access to email and to Microsoft Excel® at their workplaces.

6. PRELIMINARY FINDINGS

Analyses of the experimental data are still ongoing at the time of submission of this paper. The findings contained in this section are preliminary. They are presented to highlight some of the interesting aspects and serve to point to possible areas of further study.

6.1 Responses Under Long Headway Scenarios

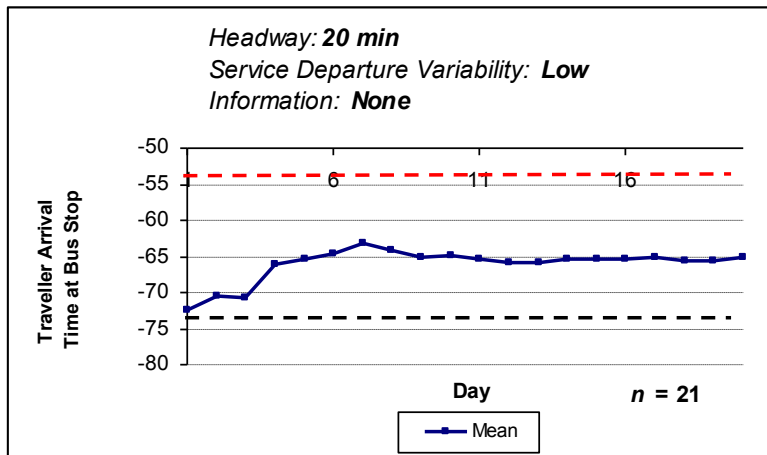
In this study, the only response variable that is directly obtainable from the participant in the experiments is t_h . Given that T_a is constant across the trial-days, one can examine t_b equivalently. The discussion starts with the scenario in which the services depart from the bus stop at long intervals of 20 minutes (*H20-LOW*). The plot of mean t_b under *NO-INFO* condition is presented in Figure 7. The *NO-INFO* plot describes how the participants made their choices over time in the *absence* of information. It serves as a

baseline against which the effects of information are compared. 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 each consecutive service. 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 20 days. This service is analogous to the route that has the lower average travel time in Avineri and Prashker (2006) and Ben-Elia *et al.* (2008). For ease of discussion, this service is termed the ‘maximising’ service.

Figure 7 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 flattens. A plausible explanation for this phenomenon is as follows: The participants had no information on when the services were scheduled to depart. However, based on the information on estimated range of T_v (See Figures 2 and 3), they would be able to infer that the service they should be catching (to maximise their score) must depart no later than a certain time to avoid arriving late at the destination. They would have initial perceptions of the range of times at which this service might depart, and this time range is likely to include t_s^{sch} of the maximising service. Nonetheless, at this initial stage, they are highly uncertain of their perceptions, and they build in a ‘safety margin’ in their choice of t_b , a likely strategy described by Bonsall (2004) in response to uncertainty. This margin is manifested by the initial mean t_b being substantially earlier than t_s^{sch} of the maximising service.

Over the next several days, the participants learnt about the departure characteristics of the service from the actual t_s encountered. With learning, they were able to reduce the level of uncertainty with respect to t_s and hence the safety margin reduced correspondingly. This is shown in the upward trend of t_b up to day 7. This trend did not persist subsequently. It is argued that the participants continued to maintain a minimum safety margin because the perceived uncertainty with respect to t_s cannot be eliminated fully despite the experience gained about the service.

Figure 7: Traveller Arrival Time at Bus Stop t_b for H20-LOW, NO-INFO Scenario

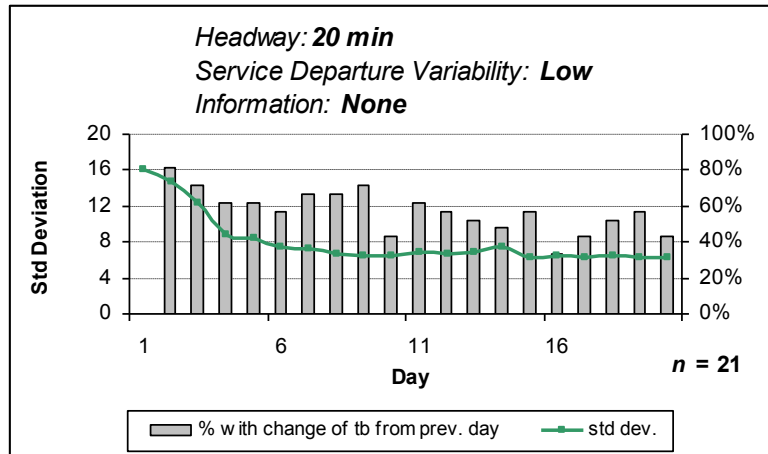


The effect of learning can also be seen using two other measures, namely the standard deviation (s.d.) of t_b (the line plot) and the proportion of participants who changed t_b from the preceding day (the bar plot) as shown in Figure 8. There is an observable reduction in the s.d. within the same period in which the mean t_b is also trending upwards (Days 1 to 7). As with the t_b trend, the s.d. also stabilises after that. The proportion of participants

Investigating the Effects of Different Types of Travel Information on Travellers' Learning in a Public Transport Setting using An Experimental Approach

making changes to t_b from the preceding day is also generally higher in this period compared to the later days. These observations for this period indicate a large but rapidly diminishing dispersion of t_b values and frequent decision changes over successive days in the initial period. They suggest that the participants have engaged in an exploratory process about t_s in this period. The spread of t_b becomes smaller, as shown by the reduced s.d., and the frequency of changes to t_b also reduces, indicating the cessation of this process.

Figure 8 Standard Deviation of t_b and Proportion of Participants with t_b Change for H20-LOW, NO-INFO Scenario



How then does the provision of information affect the learning and response of the participants? Figures 9 and 10 show the variation of the same three measures described in the preceding paragraphs of this Section under the same operating condition (H20-LOW) but with static information (TTABLE) provided. The trend of the mean t_b appears similar to that in NO-INFO, except that there is some volatility in the middle period. The s.d. is similarly higher in the initial period before settling to a lower level. There is however no discernible pattern with regard to the proportion of participants engaging in t_b changes.

It appears that the provision of scheduled departure times $t_i = t_s^{sch}$ has not eliminated the need for the participants to engage in the exploratory process, as evidenced by the trends in both the mean and s.d. of t_b in the initial period, as shown in Figures 9 and 10. This is not surprising though. Without information (NO-INFO), participants need to learn about the likely location of t_s of the service they intended to catch and how variable it is. With static information, they knew when their service was scheduled to depart in the first instance, but they were still highly uncertain about its departure time variability. Hence, a large initial safety margin in t_b was still introduced before it was reduced.

Figure 9 Traveller Arrival Time at Bus Stop t_b for H20-LOW, TTABLE Scenario

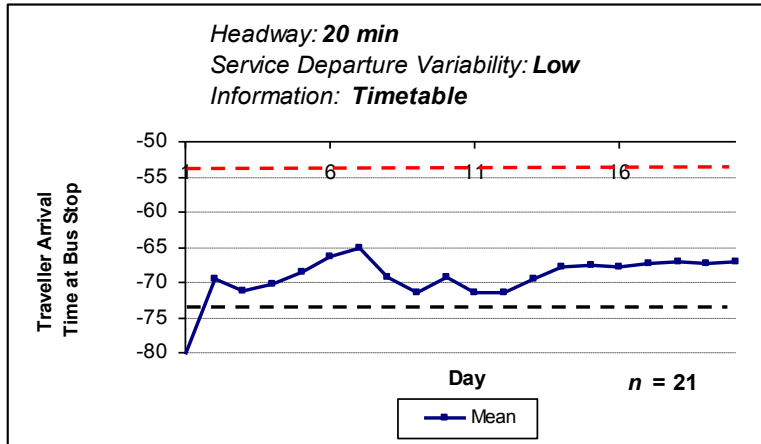
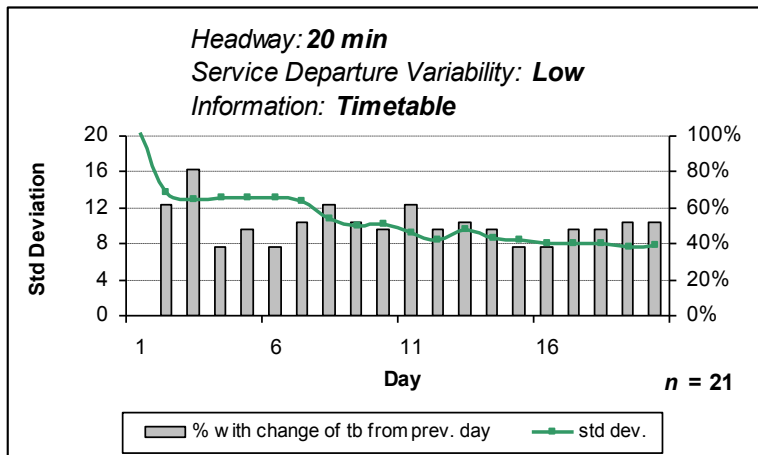


Figure 10 Standard Deviation of t_b and Proportion of Participants with t_b Change for H20-LOW, TTABLE Scenario



When (reliable) dynamic information (*DYN-REL*) was provided, the manifestation of the learning effect can be detected similarly (through the initial trends of the mean and s.d. of t_b). See Figures 11 and 12. However, after the initial period, the t_b responses were different from those when given no or static information in other aspects in two ways. One, there was greater day-to-day fluctuations in the mean t_b . It appears that the participants were responding to the varying service departure time estimates t_s^i , and persistently so. Second, with few exceptions, more than 60% of the participants made changes to their t_b choices on any given day, and this high proportion was sustained at such a high level after the initial period. In comparison, the number of days in which the proportion exceeds 60% in *NO-INFO* and *TTABLE* is substantially fewer, and they occur mainly in the first 10 days when the learning process took place.

Investigating the Effects of Different Types of Travel Information on Travellers' Learning in a Public Transport Setting using An Experimental Approach

Figure 11 Traveller Arrival Time at Bus Stop t_b for H20-LOW, DYN-REL Scenario

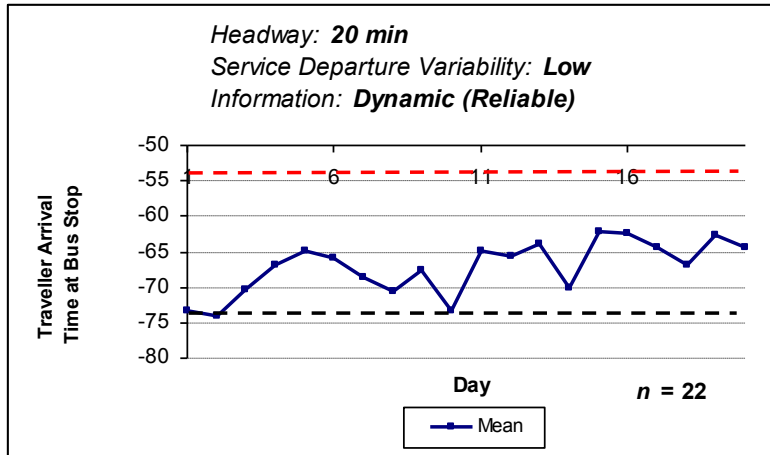
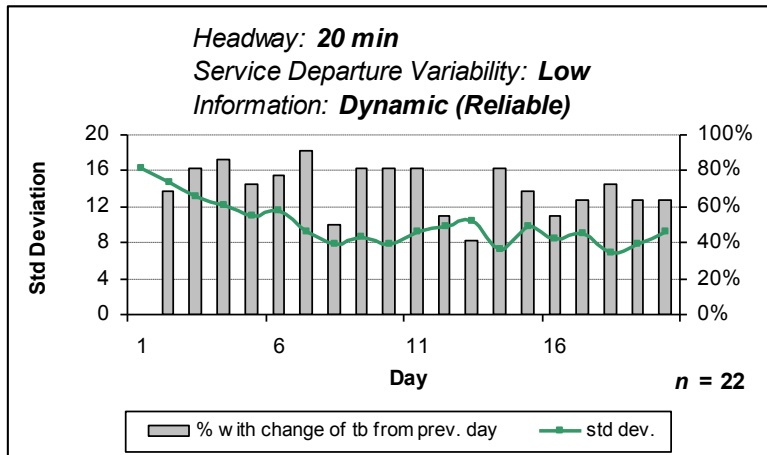


Figure 12 Standard Deviation of t_b and Proportion of Participants with t_b Change for H20-LOW, DYN-REL Scenario



That the participants' t_b choices changed frequently in response to the varying t_s^i is unsurprising. After all, the t_s^i estimates were fairly reliable (± 2 minutes of actual t_s , see Figure 4), and using them will help them time t_b to be as close to actual t_s of their targeted service. They were understandably uncertain about the information reliability in the initial days. Hence a large safety margin was established, but it was reduced as they learnt about the characteristics of both t_s and t_s^i . Over time, once the participants learnt how closely t_s^i values were to the t_b values, they anchored their t_b choices to t_s^i , albeit still with some safety margin, resulting in the fluctuations of and frequent changes in t_b .

What happened if the information was unreliable? Intuitively, one can reason that if the participants were to rely on unreliable t_s^i , they 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). As a result, they would not base their t_b decisions on t_s^i as much as if the latter are more reliable. One considers the responses under *DYN-UNREL* (t_s^i were ± 4 minutes of actual t_s , Figure 5). Figures 13 and 14 do not appear to support such an assumption. The overall trend, day-to-day fluctuations and the proportion of participants changing t_b do not appear substantially different from those under *DYN-REL*.

Figure 13 Traveller Arrival Time at Bus Stop t_b for *H20-LOW, DYN-UNREL* Scenario

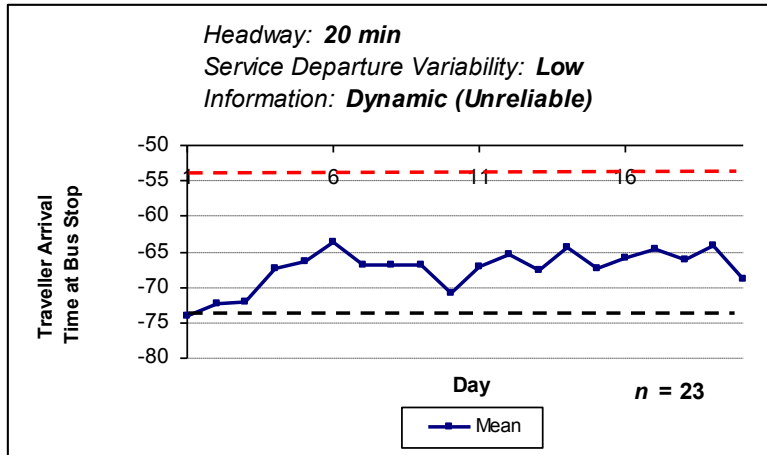
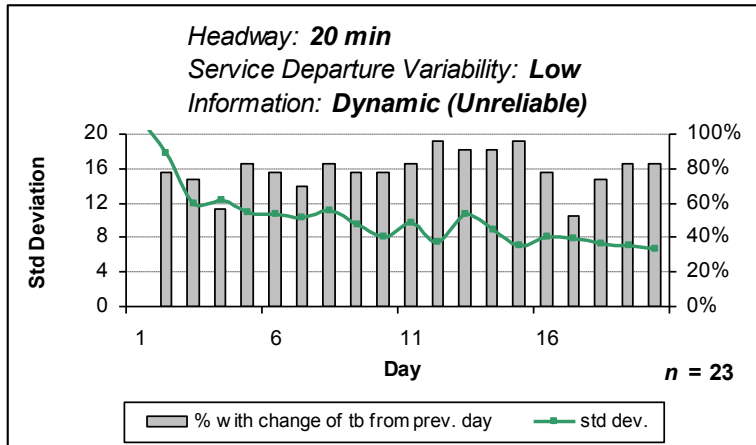


Figure 14 Standard Deviation of t_b and Proportion of Participants with t_b Change for *H20-LOW, DYN-UNREL* Scenario



6.2 Responses Under Short Headway Scenarios

The discussion thus far focuses on participants' responses in long-headway (20 minutes) scenarios. If services were to arrive more frequently, say every 5 minutes, what would the outcomes be? One can now turn attention to *H5-LOW* scenarios. Similar observations are made. First, the learning effect in the initial days is still discernible, though less pronounced. This is to be expected because, with short headways, any safety margin in t_b and any reduction of it through the learning process would be smaller correspondingly. Second, the variation of mean t_b again takes place at a margin from t_s^{sch} of the maximising service, and within the vicinity of t_s^{sch} of the service immediately preceding it and gives the appearance that the participants were seeking to catch the latter service. An alternative explanation is that they were indeed targeting the maximising service, but by setting a safety margin, their t_b choices were within the range of t_s^{sch} of its preceding service.

The third, and most noteworthy, observation is that, when dynamic information was provided, the participants appeared to respond to the variable t_s^i , in a repeat of the observations made in the *H20-LOW* scenario. In both *Ops* conditions, those receiving dynamic information (*DYN-REL* and *DYN-UNREL*) have proportions (65% - 79%) that

Investigating the Effects of Different Types of Travel Information on Travellers' Learning in a Public Transport Setting using An Experimental Approach

are substantially higher than their static and no-information counterparts (41% - 57%). The differences between the two groups are significant statistically ($p = 0.000$ for both at $\alpha = 0.05$). That the participants appeared to respond to t_s^i regardless of their reliability and service characteristics is a strong indication of the effect of dynamic information.

6.3 Effect of Information on Decision Quality

The preceding discussion has focused on the participants' explicit choice of t_b . However, this variable does not inform one of the quality of decision-making; an earlier or later t_b cannot inform if the participant has identified the appropriate service to catch nor if he has caught the service he intends to board. Another measure that represents the decision quality is required. One such measure is T_w . Its magnitude can be considered a measure of the degree of success with which the participant is able to catch his intended service. If she is able to catch her intended service with a short wait, she would be deemed to have made a good decision. Hence, the smaller T_w is, the better the outcome.

In the literature, dynamic information, as typically provided through ATIS, is viewed to be generally superior to static forms of information, and of course, to the absence of information. Hence one should expect dynamic information to assist the participants to attain the lowest mean T_w , followed by static information and lastly, no information. Table 1 shows that this may not be the case. In both *H20-LOW* and *H5-LOW* scenarios, the mean values appear in the expected order, with the highest T_w when no information is provided, and the lowest when the dynamic information is reliable. However, in *H20-LOW* scenarios, analysis using difference contrasts reveals that there are no significant differences between *NO-INFO* and *TTABLE* ($p = 0.559$ at $\alpha = 0.05$), and between *TTABLE* and *DYN-UNREL* ($p = 0.088$). The only difference of statistical significance is between *DYN-REL* and *DYN-UNREL* ($p = 0.000$). In the *H5-LOW* scenario, contrast tests find, once again, no significant difference between *NO-INFO* and *TTABLE* ($p = 0.071$). However, there is a significant difference between *TTABLE* and *DYN-UNREL* ($p = 0.015$), but no significant difference between *DYN-REL* and *DYN-UNREL* ($p = 0.810$). This set of findings once again supports the view that dynamic information can indeed be superior, over static and no information, in helping travellers to reduce wait time, although it appears that the level of its reliability is more critical when the headway is longer than when it is shorter. In comparison, timetables have limited utility to regular users.

Table 1 also shows that the absolute difference in T_w among *Info* conditions is less than 1 minute when the headway is 5 minutes, in contrast to between 2 and 3 minutes for a longer headway of 20 minutes. While this is not surprising (given that the maximum possible difference is the headway itself), it does raise the question whether the provision of information is worthwhile when services depart very frequently. On the other hand, it may be easier to justify investment in information services, especially ATIS, at stops with high volumes of passengers and services. Perhaps, by obtaining any estimation of the wait-time savings through such experiments and valuing these savings, one could come to more informed investment decisions.

Table 1 Mean Wait Time (T_w) over 20 Days by Ops and Info Conditions

		Mean T_w (minutes)	
		Ops condition	
Info condition	<i>NO-INFO</i>	<i>H20-LOW</i>	<i>H5-LOW</i>
	<i>TTABLE</i>	8.6	2.8
	<i>DYN-UNREL</i>	8.3	2.7
	<i>DYN-REL</i>	7.5	2.3*
		5.5*	2.3

* significantly different from preceding condition at $\alpha = 0.05$

7. SUMMARY AND FURTHER AREAS OF ANALYSES

This study tracks the day-to-day evolution of a traveller's behaviour over time, when given different types of information. The experimental scenarios replicate the real-life experience of public transport commuting in which the traveller has to catch a bus service, offering a departure from most research work that adopt driver-traveller scenarios. The successful completion of the experiments demonstrated the feasibility of conducting computer-based experiments using programs sent to participants by email as an alternative to the more common approaches of using Internet websites or laboratories, when the latter procedures are not available or feasible.

The preliminary findings indicate that travellers do not behave differently when given static (timetable) information from when they do not receive any information at all. In both cases, they engage in an initial exploratory process to locate what they perceive to be the best time to arrive at the bus stop. During this short initial period, as they learn about the variability of the service departure time, they choose to arrive progressively later by the day. However, the magnitude and frequency of changes in their arrival time soon stabilise. In contrast, travellers given dynamic information appear responsive to the varying service departure time estimates even after the initial period. In addition, dynamic information appears to help the traveller attain higher utility in their decision-making. The mean wait time for those given dynamic information is significantly lower than those given no or static information. Consistent with intuition, as the information is made more reliable, the wait time can be further reduced. However, the reduction is more significant when the service headway is longer.

Although the arrival time at the bus stop appears to be the only choice phenomenon, the decision-making is two-fold: which service to choose, and once identified, when to arrive at the bus stop to catch this service. In addition, the traveller has to contend with variability in two attributes: the in-vehicle time (T_v) and the departure time of the services (t_s). Clearly, this public transport scenario is a complex one. (Contrast this with the simpler experimental scenarios of Avineri and Prashker (2006) and Ben-Elia *et al.* (2008), and other similar studies with a typical highway route choice scenario, in which the travel time is often the only attribute pertinent to the decision-making.)

So, the measure of T_w described earlier covers only one aspect of decision-making. The other aspect of decision-making, i.e., which of the services to catch, has not been examined. Thus far, it has been assumed that the participants had attempted to catch only the maximising service. This assumption is clearly subject to challenge. Indeed, Ben Elia *et al.* (2008) reveal that although an increasing proportion of their participants learnt over time to choose the faster of two routes (that is analogous to the maximising service), there is still a significant minority that did not. So there is a strong case to study

Investigating the Effects of Different Types of Travel Information on Travellers' Learning in a Public Transport Setting using An Experimental Approach

the participant's choice of service to have a more complete insight into whether the provision of information does lead to maximising utility. To this end, it would be necessary to examine each t_b choice to infer which of the services he is most likely catching. This would require analysis of the data at a more disaggregate level. Future work will use a more disaggregate approach to investigate the behavioural mechanism that captures the interplay between the learning process and the types of information.

Acknowledgement: The authors would like to thank Land Transport Authority, Singapore for its support in the recruitment of participants and The University of Sydney for funding the participation incentives. Gratitude is expressed especially to Catherine Teo for her help in liaising with the participants.

REFERENCES

- Abdalla, M., Abdel-Aty, M., 2006, "Modeling travel time under ATIS using mixed linear models", *Transportation*, vol. 33, pp. 63 – 82.
- Avineri, E., Prashker, J., 2006. "The impact of travel time information on travelers' learning under uncertainty", *Transportation*, vol. 33, pp. 393–408.
- Ben-Elia, E., Erev, I., Shiftan, Y., 2008. "The combined effect of information and experience on drivers' route-choice behavior", *Transportation*, vol. 35, pp. 165-177.
- Bonsall, P., 2004. "Traveller behaviour: decision-making in an unpredictable world". *Intelligent Transportation Systems*, vol. 8, no. 1, pp. 45 – 60.
- Dziekian, K., Kottenhoff, K., 2007. "Dynamic at-stop real-time information displays for public transport: effects on customers", *Transportation Research Part A*, vol. 41, pp. 489–501.
- Ettema, D., Timmermans, H., Arentze, T., 2004. "Modelling perception updating of travel times in the context of departure time choice under ITS", *Intelligent Transportation Systems*, vol. 8, pp. 33–43.
- Ettema, D., Tamminga, G., Timmermans, H., Arentze, T., 2005. "A micro-simulation model system of departure time using a perception updating model under travel time uncertainty", *Transportation Research Part A*, vol. 39, pp. 325–344.
- Jha, M., Madanat, S., Peeta, S., 1998. "Perception updating and day-to-day travel choices dynamics in traffic networks with information provision", *Transportation Research Part C*, vol. 6, pp. 189–212.
- Jou, R., Lam, S., Liu, Y., Chen, K., 2005. "Route switching behaviour on freeways with the provision of different types of real-time traffic information", *Transportation Research Part A*, vol. 39, pp. 445–461.
- Lappin, J., Bottom, J., 2001. *Understanding and Predicting Traveler Response to Information: A Literature Review*. Federal Highway Administration, U.S. Department of Transportation, Washington D.C.

Toledo, T., Beinhaker, R. 2006. "Evaluation of the potential benefits of advanced traveller information system", *Journal of Intelligent Transportation Systems*, vol. 10, no. 4, pp. 173–183.

Zhang, F., Clifton, K., Shen, Q., 2009. "Examination of traveler responses to real-time bus arrival information using panel data" *Transportation Research Record*, vol. 2082, pp. 107–115.