DOES EXPERIENCE AFFECT ROUTE CHOICE? AN EMPIRICAL ANALYSIS USING INSTANCE-BASED LEARNING THEORY

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For a better understanding on daily dynamic decision-making process, a careful examination of the influences that past decisions exert on current behavior is needed. In the context of route choice, travelers may trade-off between their personal driving experience and conventional traffic information. To what extent the travelers value these two sources of information is of concern to better understand travelers' route choice behavior. This paper presents an empirical analysis using instance-based learning theory aiming at seeking how drivers rely on their experience and memory. We selected one OD-pair in Tokyo Metropolitan Expressway of Tokyo, Japan, with 3 routes and 5 segments in the expressway using vehicle trajectory data across 12 weeks in 2021. We formulated a weighting scheme to calculate the perceived travel time on each segment considering varying weights for actual travel time and experienced/learned travel time through their previous trips. The results show that, while actual travel time is the dominant factor determining their route choice decisions, experienced travel time would also have an unignorable impact on the decisions. We also found that such learning effects can be captured through the incorporation of individual-specific error components, but such a specification does not allow researchers to reveal the learning process.

Keywords: *Route choice, Instance Based Learning, Repeated Choice, Experience, Information*

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1. INTRODUCTION

Route choice is a fundamental aspect of travel behavior and represents one of the most frequently made decisions. Due to the complex nature of traffic congestion and the inherent difficulties in estimating travel time, the feasibility of making route choice decisions under perfect information has long been questioned[1]. Given the variation of travel time by recurrent or non-recurrent congestion, travelers are inevitably tackling uncertainty to a higher level than other travel decisions such as travel mode choice and destination choice.

The uncertainties introduce unpredictability. Accurate route-specific characteristics are inherently not observable a priori to travelers. In such a context, people may conventionally rely on their past experiences, which are likely subject to perception errors, to evaluate the attributes of each route alternative. However, with the advent of information communication technology (ICT) and, more specifically, advanced traveler information systems (ATIS), real-time travel information has emerged as another major source affecting route choice decisions.

The three types of information, categorized as Experiential Information (EI), Descriptive Information (DI), and Prescriptive Information (PI)[2], are expected to influence route choice behavior. EI refers to the personal experiences of travelers that influence their perception of the route. Meanwhile, DI refers to information about the prevailing conditions on the route such as the travel time, and can be obtained and updated pre-trip or en-route. On the other hand, PI, which has received relatively less attention in the literature involves providing travelers with a recommendation or a suggestion for an alternative.

DI can provide certainty and hence neutralize the potential bias from EI or travel time variability[3], leading route choice situation "from being a risky choice towards a riskless choice"[4]. However, a larger part of the existing literature has focused on the effect of DI while overlooking the effect of EI, which serves as the baseline for people's choices. The inter-relationship between these two types of information merits more research attention[2] and is the focus of the presented study.

A number of the existing literature has applied reinforced learning theory in the route choice context to study the information effects [1,5,6,7,8]. Among them, Tang et al.[7] and Yu and Gao[8] applied Instance-based Learning theory (IBLT) with a power decay function used as the memory activation function to mimic the decay of human memory. A power decay function is considered more behaviorally realistic from a psychological theory perspective[9]. However, neither of these studies explored the combined effects of EI and DI, nor did they apply their findings to real-world data.

To this end, this paper extends the existing literature, especially Tang et al.[7], using Instance-based Learning theory (IBLT) to study the trade-off between EI and DI in the context of route choice problem, aiming to better understand travelers' day-to-day dynamics. The presented study utilizes a real-world dataset for a selected origin-destination (OD) pair in the Tokyo Metropolitan Expressway, Japan.

(1) Literature Review

Random utility maximization-based discrete choice model has long been considered the main approach for studying route choice[10]. These models have been critiqued for not fully considering the human cognition paradigm[2], as they did not incorporate how travelers acquire and perceive information. Various alternative decision rules and modeling approaches have been proposed to describe people's cognitive capacity, including prospect theory, regret theory, and reinforced (or "reinforcement") learning

theory[2]. Among these, reinforced learning theory is arguably suitable and tractable for describing the effects of past choices in the repetitive choices context[1,2].

In the reinforced learning paradigm, travelers' adaptation to their previous choices is explicitly incorporated into the utility functions of discrete choice models, assuming their memories directly influence their current choice situation. There are a number of existing literature on applying reinforced learning paradigm in route choices. Computer experiments, where the participants are provided with a set of random scenarios based on which they have to make their decision is one of the most popular data collection methods in this context. Multiple studies utilized it to account for the memory effect, for example, Avineri and Prashker[11] tested two learning frameworks, firstly, a Bayesian learning framework similar to the framework proposed by Horowitz[12] (same authors utilized the same method in another study[5]), wherein the traveler formed their perception on travel time-based previous experiences. Secondly, a reinforcement learning model was developed to accommodate the feedback from previous experiences in estimating the probability of selecting a route at the current time period. Using a laboratory-based route choice experiment, they argued that there exists a trade-off between the elegance of utility-based choice models and the accuracy of learning models.

In Ben-Elia et al.[6], the researchers performed a laboratory experiment providing people with information on travel times and comparing it with a control group, which relied solely on experience. They observed that the information group showed risk-seeking behavior choosing routes that were more attractive but also had higher variability. Meanwhile, the control group with experience showed the payoff variability effect, which refers to decision-makers choosing options with more certainty even when their expected value is lower i.e., a tendency to be risk averse.

Ben-Elia and Shiftan[1] developed a mixed logit model for the experiment conducted in Ben-Elia et al.[6], adding variables capturing the repetition of previous behavior, which is similar to a lagged dependent variable (i.e., recency), and a cumulative weighted average of all previous experiences (i.e., memory) into the model and estimated its impact on route choice behavior. In addition, they also added levels of experience as dummy variables in the models. They observed that both factors signifying recency and memory had a significant impact on route choice decisions.

In Ben-Elia et al.[13], the impact of accurate travel information was evaluated by conducting a computer-based experiment where the participants had to choose options from a web-based simulation. The level of accuracy was varied through a set of 30 choice tasks, with the information provided to the participants before the task. They observed that higher levels of accuracy lead travelers to choose riskier routes. This means that accurate information made travelers maximize their payoffs, i.e., make more risky choices but have higher rewards.

In another study with a real-world experiment, van Essen et al.[14] evaluated the effect of information provision on route switching provision. The participants were asked to drive on selected routes for 20 days without information i.e., only relying on their experience and 11 days with information. They observed that information leads to more switch-prone behavior as opposed to travelers who only relied on their previous experience. Even though the study tested the behavior of travelers in the real world, it does not account for the fact that often the decision might be influenced by both DI and EI together. Many other studies also establish similar findings i.e., with accurate DI travelers tend to become more risk-prone and when relying on

experience, they tend to choose safer options with lower levels of rewards[2,15].

More recently, IBLT, which has its origins in cognitive psychology and decision sciences [16,17,18], has been applied to incorporate learning in route choice decisions[7,8]. The theory considers the recency of previous experiences known as instances using an activation function to weigh them. In Tang et al.[7] perceived travel time was calculated based on IBLT, where the more recent experiences were weighted higher than older experiences using a power decay activation function. A power decay function has been shown to mimic the phenomenon of memory decay more realistically than the exponential decay function used in Bayesian learning-based studies. Additionally, Tang et al.[7] utilized a synthetic dataset to demonstrate that IBLT can efficiently capture both the hot-stove effect[19),20] and the payoff variability effect [6]. They utilized the updated perceived travel time in a mixed logit model, using the data collected in Ben-Elia et al.[6] to test their IBLT-based framework. They observed that IBLT-based model performed better than baseline models in predicting the behavior. As of a following study of Tang et al.[7], Yu and Gao[8] modified the framework to adapt the subject of the route choice to specific strategies called routing policy.

However, their studies only considered that perceived travel time will be influenced by learning i.e., EI alone, whereas, both EI and DI would play a role in forming a traveler's perception of travel time in reality. This is much more relevant in today's times when ICT has become an important part of our lives and has a role to play in multiple activity and travel behavior decisions[21]. It is quite possible that travelers frequently access ATIS sources to update their knowledge about the alternatives, while previous experiences still have an impact on their final decision. Hence, there is a need for a unifying framework that accounts for both EI and DI together. Moreover, most studies analyzing route choice decisions have utilized data collected from a laboratory experiment where their previous experiences or instances are not that far apart. Therefore, even if a learning-based framework is implemented, it would not be able to achieve behavioral realism as the true impacts of experiences far apart from each other cannot be captured unless the models are applied to real-world data. With the availability of passive big data sources such as those from GPS-enabled devices or sensors, large-scale data with repetitive choices could be utilized to build learning-based route choice models. Previously, GPS data has been utilized to model route choice decisions[22,23] but learning from past experience and the impact of EI with real-world large-scale datasets have been rarely explored. This study aims to address these gaps in the literature.

(2) Research Contributions

Our study has two major differences from Tang et al.[7] and Yu and Gao[8]. Firstly, our study proposes a novel formulation to account for the impact of both EI and DI in the calculation of the perceived travel time. IBLT is utilized to learn from previous experiences, while a weighting scheme is adopted to incorporate the contribution of both EI and DI. Secondly, our study utilizes real-world driving dataset from devices equipped with TOYOTA connected vehicles in Tokyo, Japan to identify vehicle trajectories. The driving data records signal similar to a GPS device but have a higher level of resolution (close to 1s) and hence are more accurate. Most studies in the past, which have incorporated the impact of previous experiences in the form of learning have utilized an experimental dataset conducted within a laboratory or through a stated preference survey, with Vacca et al.[24] as a notable exception.

Such experiments may not fully capture the actual effects of forgetting or decay in memory and the spatial knowledge acquisition

of a realistic network by travelers[7]. Thereby by utilizing a real-world dataset, the presented paper explicitly studies repetitive route choice behavior, aiming to better understand travelers' day-to-day dynamics.

The remaining structure of this paper is as follows: a methodology section that details the model specification and scenario design is first presented. Subsequently, an empirical analysis is presented, demonstrating the application of the proposed methodology. Lastly, the paper concludes with a discussion and conclusion section, which also outlines potential future research directions for this study.

2. METHODOLOGY

Instance-based learning theory (IBLT) was proposed by Gonzalez et al.[16] to understand the learning process during repeated choices made by individuals. In dynamic decision making, individuals store the experiences related to their previous choices in their memory. These experiences are referred to as *instances*, which are then activated when they face a similar choice context. The *activation* occurs in the form of a function, where a more recent instance carries a higher weight than other instances. In the context of repeated route choices, individuals also store their travel time experiences from previous instances in their memory. It is well-established that travelers perceive travel time at the link or segment level[25,26]. For example, if there are two routes, route A (with segments S1-S2-S3) and route B (with segments S4-S2-S5), sharing a common S2 segment, and a traveler had a bad experience, such as facing severe congestion on segment S2 while traveling through route A, then it is likely that they will consider this past experience before choosing route B. In simple terms, the past experience of travelers would influence their perceived travel time in each segment and, consequently, influence their route choice decisions.

However, with the recent proliferation of mobile- and vehicle-based real-time information sources, travelers can now obtain close-to-full knowledge regarding the alternatives before making their choice i.e., accessing real-time information which might influence their perception of travel time. In such a case, it remains to be seen how learning from previous instances influences the perceived travel time. In mathematical terms, this means that the perceived travel time of a segment would be a function of both, their past experiences and the expected actual travel time, the knowledge of which they received from ATIS sources. In this section, we describe how we incorporated both the learning and actual travel time components into the perceived travel time formulations while modeling how travelers make their decisions.

(1) Model Specification

The primary idea behind the application of instance-based learning in route choice involves the activation of old experiences of segment s for an individual i based on an activation function. We adopt our formulation for the function based on the generalization of IBLT for discrete choice models proposed by Lejarraga et al.[18], as follows:

$$W_{is}(t,t') = \frac{(t-t')^{-d_i}}{\sum_{\tau \in H_{is}(t)} (t-\tau)^{-d_i}} \quad (1)$$

where,

$W_{is}(t,t')$: weight of the experienced travel time of instance t' for the learned travel time of the current instance t for traveler i on segment s,

d_i: decay parameter for traveler i, the higher the decay parameter, the faster the rate of forgetting, and

$H_{is}(t)$: set of all previous instances of traveler i on segment s before the current instance t.

In the above equation $(t-t')^{-d_i}$ works as the activation function which accounts for both how far back in the past a particular traveler has experienced a segment and also their rate of forgetfulness. The sum of weights W_{is} for all instances in $H_{is}(t)$ is equal to 1 with the most recent instance having the highest weight. All these weights can then be multiplied by the experienced travel time of each of the segments to obtain the learned travel time as follows:

$$TT_{is}^{l}(t) = \sum_{t' \in H_{is}(t)} W_{is}(t,t') X_{is}(t') \quad (2)$$

where, $TT_{is}^{l}(t)$: perceived travel time from learning for traveler i traveling on segment s at time instance t, and

$X_{is}(t')$: experienced travel time of traveler i for segment s on previous instance t'.

In previous studies[7,8], $TT_{is}^{l}(t)$ was considered to be the perceived travel time for segment s on instance t. However, this ignores the possibility that information on expected actual travel time might modify their perception of travel time. To account for this, we modified the formulation for perceived travel time as follows:

$$TT_{is}^{w}(t) = \begin{cases} w^{l} TT_{is}^{l}(t) + w^{a} TT_{s}^{a} & \text{if at least one experience} \\ TT_{s}^{a} & \text{otherwise} \end{cases} \quad (3)$$

where,

$TT_{is}^{w}(t)$: weighted perceived travel time for traveler i traveling on segment s at time instance t,

TT_{s}^{a}: actual travel time on segment s,

w^{l}: weight associated with perceived travel time by learning $TT_{is}^{l}(t)$, and

w^{a}: weight associated with actual travel time TT_{s}^{a}.

The TT_{s}^{a} was generated from the dataset itself which provided the hourly travel time for every segment s. The assumption here is that the actual travel time observed from the data would be close to the travel time obtained from ATIS sources i.e., from DI.

Once the perceived travel time is generated at the segment level, then that information can be used to generate the perceived travel time at the route level ($TT_{ir}(t)$), which can be denoted as follows:

$$TT_{ir}(t) = \sum_{s} TT_{is}^{w}(t) \quad (4)$$

The calculated perceived travel time at the route level was then incorporated into a mixed path size logit model[27] to test its influence on route choice. The utility function of the mixed path size logit model could be written as follows:

$$U_{ir}(t) = \beta_{tt} TT_{ir}(t) + lnS_r + \eta_{ir} + \epsilon_{ir}(t) \quad (5)$$

where,

$U_{ir}(t)$: utility of choosing route r for traveler i on time instance t,

β_{tt}: parameter coefficient for travel time,

η_{ir} : individual-specific error components accounting the effect of unobserved variables for traveler i choosing route r,

$\epsilon_{ir}(t)$: error term which is independent and identically distributed over travelers, alternatives, and time instances, and

S_r: path size for route r, which is denoted as follows:

$$S_r = \sum_{s \in \Gamma_r} \frac{l_s}{L_r} \frac{1}{\sum_{j \in C} \delta_{sj}} \quad (6)$$

where,

Γ_r: set of segments in route r,

l_s: length of segment s,

L_r: length of the route r,

C: set of all routes, and

δ_{sj}: segment-route incidence variable. It is 1 if segment s is on route j, 0 otherwise.

Based on the utility equations, the probability of a traveler i choosing route r is expressed as follows:

$$P_{ir} = \int_{\eta} \left(\Pi_t \frac{e^{\beta_{tt} TT_{ir}(t) + lnS_r + \eta_{ir}}}{\sum_c e^{\beta_{tt} TT_{ic}(t) + lnS_c + \eta_{ic}}} \right) f(\eta) d\eta \quad (7)$$

The η_{ir} term is assumed to be randomly distributed across individuals with mean 0 and variance σ_r^2. Two error components were added into the utility equations (with three alternatives) and 1000 Halton draws[28] were generated for each term. The models for all scenarios were estimated using the apollo R package[29].

(2) Scenario Design

To evaluate the role of past experience in route choice, we estimated the impact of perceived travel time on travelers' decisions. As explained earlier, we modified the formulations, resulting in three hyperparameters that influence the model's performance. These include, firstly, \the decay parameter (**d**), which determines the rate of forgetting. In Adaptive Control of Thought-Rational (ACT-R) models, it is common to adopt a value of d=0.5[7,17]. However, there is limited evidence regarding the appropriate value of d for route choice decisions. **Table 1** presents the different scenario settings describing the levels of memory decay tested in the analysis. Four levels of decay parameter were tested, which included a) strong memory retention with d=0.01, this value of d would lead individuals to learn even from extremely old instances, b) moderate memory retention, with d=0.5, c) limited memory retention with d=1, Tang et al.[7] in their study on the application of IBLT on route choice utilized experimental data from Ben-Elia and Shiftan[1], where they estimated the value of d to be close to 1 (1.11 and 1.64), indicating that the respondents in the survey have limited memory retention. However, these results were based on a computer experiment where a series of choices were presented to the respondents. It is not yet established how real-life experiences, which are often far apart from each other in days would affect the choice. Hence, the identification of a realistic value for *d* which aptly captures the learning process is necessary. Finally, d) high forgetfulness with a d=5, which assumes a very low-level retention of memory.

Table 1 Description of Design of Scenarios

Scenario Setting	Decay Parameter	Weights
1	Strong Memory Retention (d = 0.01)	w^l = {0,0.1,0.3,0.5,0.7,0.9,1} w^a = {0,0.1,0.3,0.5,0.7,0.9,1} s.t.: $w^l + w^a = 1$
2	Moderate Memory Retention (d = 0.5)	
3	Limited Memory Retention (d = 1)	
4	High Forgetfulness (d = 5)	

Apart from the decay parameter, the weights associated with perceived travel time by learning (w^l) and the weights associated with actual travel time (w^a) were also varied across different scenarios as hyperparameters to identify the weights that result in the best model performance. For each of these parameters, seven unique values were used (**Table 1**), ensuring that the sum of w^l and w^a always equaled 1. These combinations of hyperparameter values resulted in testing 25 unique scenarios (there is only one scenario in which w^a is 1, as the decay parameter has no impact in this case) for each error component and simple path size logit model, totaling 50 models. The performance of the model was evaluated by comparing the final log-likelihood value, which describes how well the variables in the model predict behavior. Log-likelihood is commonly used in travel behavior research to compare different models[30,31]. Additionally, for all scenarios, out-of-sample validation tests were conducted. In these tests, the parameter estimates obtained from models developed using the first 8 weeks of data were

utilized to predict the performance of data from the remaining 4 weeks.

3. EMPIRICAL ANALYSIS

To fulfill the research objective of investigating how drivers rely on their experience and memory in the context of route choice, we conducted an empirical analysis using data from the Tokyo Metropolitan Expressway in Tokyo, Japan.

(1) Case Study Description

We utilized driving data from TOYOTA connected vehicles as our primary data source for vehicle trajectory information. The driving data is collected from dedicated vehicle-equipped devices designed by TOYOTA to enhance vehicle driving experience and performance. This data contains actual driving-related statistics at a one-second level, similar to GPS point data, with very fine resolution and quality.

Considering both daily vehicle volume and appropriate network complexity, trips traveling from West Shinjuku to Shin-Kiba (**Fig. 1**) via Tokyo Metropolitan Expressway were selected as the subject of this study. For the sake of convention, we hereafter refer to the two points as one Origin-Destination(OD) pair. However, it should be emphasized that the trips counted in this study are not necessarily restricted to those starting or ending precisely at these points. For instance, a selected trip's actual destination could be far along Tokyo Bay or even in Chiba, a neighboring prefecture.

We collected driving data for 12 weeks from October 1st to December 23rd, 2021[note1)]. After data processing, the total sample comprises 7,548 travelers and 10,961 trips for the selected OD pair. For studying how people react to their experiences, we then specifically selected travelers who exhibited repetitive behavior, i.e., with multiple trips within the chosen OD pair, as the effective sample for this study. This procedure resulted in an effective sample composed of 1,608 travelers and 5,021 trips, with an average of 3.12 trips per traveler. The initial trips of each traveler were further excluded from the subsequent modeling as they were considered the baseline for each traveler. As a result, the applied logit models were constructed using a sample size of 3,413 trips.

Three major routes have been identified for the selected OD pair (**Fig. 1**). They are subsequently referred to as the "Nihonbashi Route", "Odaiba Route", and "Shibuya Route" named after prominent landmarks along the paths. The three routes were further divided into five segments to identify the overlapping section among them (**Fig. 1**).

The distributions of travelers and trips by each route for both the total sample and the sample for repetitive travelers are shown in **Fig. 2**. We can tell from **Fig. 2** that the traffic volumes across the three routes are moderately distributed, indicating a relatively balanced distribution without notable extreme values.



Fig. 1 Selected OD Pair in Tokyo Metropolitan Expressway. Source: OpenStreetMap

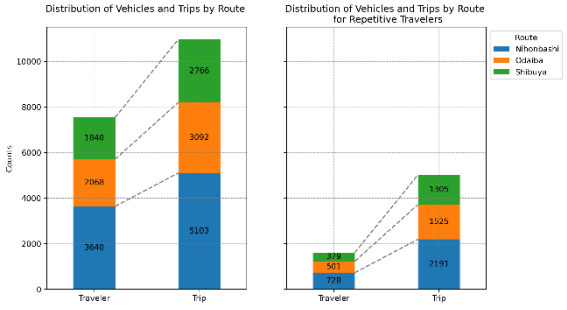


Fig. 2 Distribution of Vehicles and Trips across Routes

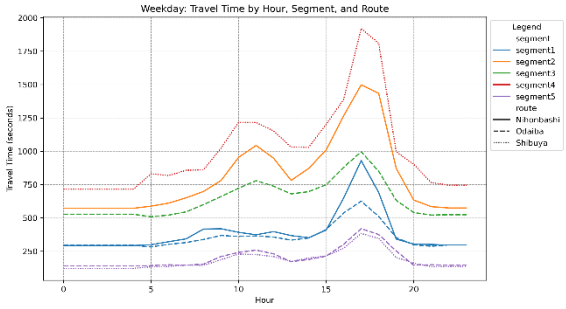


Fig. 3 Distribution of Travel Times by Hour and Route for Weekdays

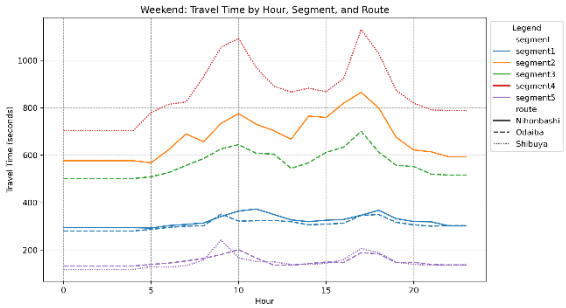


Fig. 4 Distribution of Travel Times by Hour and Route for Weekends

Fig. 3 and **Fig. 4** demonstrate the daily travel time variations of the three routes by displaying the average travel time distribution for each hour, segment, and day of the week, differentiating between weekdays and weekends. To account for the limited observations during late-night hours, values for periods from 22:00 to 23:59 and from 24:00 to 04:59 are averaged based on the observations of the entire respective periods. **Fig. 3** and **Fig. 4** also include travelers with no repetitive choices.

It is important to highlight that the selected OD pair, which transits through Tokyo's central business area, differs from those typical OD pairs commonly used for commuting trips. This distinction explains the weak weekday morning peaks in the travel time distribution pattern (**Fig. 3**). On weekends, travel times show lower congestion levels compared to weekdays, as expected, but the daily variation pattern remains similar (**Fig. 4**), with traffic volumes slightly concentrating around midday and evening peaks during the weekends.

(2) Model Estimation Results

Two different types of models were estimated across the 25 unique scenario settings: a simple path size logit model (PSL) and a path size logit model with error components (PSL-ec), which accounts for the effects of unobserved variables across individuals. These models estimated the impact of only one variable, namely the perceived travel time. The perceived travel time was formulated based on the learned travel time of travelers and the actual travel time between the origin and destination chosen in this study. The models were estimated utilizing two different datasets, a) first 8 weeks data, which consisted of 1,815 trips made by 923 travelers. and, b) all 12 weeks data, which included 3,413 trips made by 1,608 travelers. Additionally, an out-of-sample validation was conducted using the parameters estimated from the first 8 weeks data. The validation was performed on the remaining 4 weeks of the data, considering only the observations that contained travelers common to both the first 8 weeks and the last 4 weeks of data. This resulted in 751 trips made by 362 travelers for the validation process.

The results show that for each unique value of *d*, the best-performing model is the one when the weights w^l and w^a are 0.1 and 0.9, respectively. This indicates that the models which best describe the behavior of travelers are primarily influenced by actual travel time, which they might have obtained from real-time ATIS sources to update their perceived travel time. However, a small part of the contribution does come from learning, highlighting the contribution of learning in the formation of their perception of travel time. These findings were consistent across the models developed with 8 weeks of data and 12 weeks of data.

Table 2 shows the results of the log-likelihood values across different values of *d*, w^l and w^a for both PSL and PSL-ec models. When we consider that the perceived travel time is purely derived from travelers' previous experience (i.e., a case when w^l = 1 and w^a = 0), then the performance of the models is the worst. However, in the case with *d* = 0.01 (i.e., strong memory retention), the models perform relatively better than other higher values of *d*. This is again indicative of the contribution of learning in model performance. In the case of PSL, the model performance improves as the weight of learned travel time (w^l) decreases and the weight of actual travel time (w^a) increases.

Meanwhile, for PSL-ec, the log-likelihood value even for the case when w^l =0 and w^a =1 is much higher than that of PSL. This indicates that the error components i.e., the individual-specific unobserved variables explain the behavior of travelers better as compared to when they are not considered. Furthermore, in the case of PSL-ec, the best-performing scenario also involves the weights w^l and w^a being set to 0.1 and 0.9, respectively. Interestingly, for the case when w^l =0 and w^a =1, that is when the perceived travel time is just based on the actual travel time information, PSL-ec models might be able to capture the individual-specific learning through the error components. It is an obvious advantage that PSL-ec models have over PSL models but the major drawback here is that the specific contribution of learning cannot be disentangled from the unobserved variables. A PSL model with taste heterogeneity in the perceived travel time could also be developed that accounts for individual-specific variation in the effect of perceived travel time, while controlling for weights of w^l and w^a. However, for our empirical case, the sample size of repeat observations was low (1608 travelers making 3413 repetitive trips for the 12-week data) and hence obtaining stable estimates is difficult. This also limits the generalizability of our findings. One possible reason behind this could be the selection of the origin and destination in our study. The three routes selected in this study are likely to have fewer regular commute travelers and a potentially high frequency of trips for discretionary activities. This could also be the reason behind the low contribution of learning in explaining travel behavior in PSL models.

A comparison of decay parameters for the same model type reveals that scenarios with *d*=0.01 or *d*=0.5 generally yield the best model performance (in terms of log-likelihood values) for both the 8-week and 12-week data tested. However, one major limitation of applying Instance-Based Learning Theory (IBLT) to real-world datasets is its adoption of a weighting scheme to assign weights to previous instances. In cases where a traveler has only one previous instance on a particular segment, IBLT assigns it a weight of 1, without considering how far back in time the traveler

Table 2 Log-likelihood Results[note2)]

w^l	w^a	d = 0.01	d = 0.5	d=1	d=5
Sample Path Size Logit Model (8 weeks)					
1	0	-1939.0	-1940.3	-1941.8	-1950.2
0.9	0.1	-1935.1	-1963.4	-1938.0	-1946.7
0.7	0.3	-1924.4	-1925.9	-1927.5	-1937.1
0.5	0.5	-1908.2	-1909.7	-1911.5	-1921.7
0.3	0.7	-1886.9	-1888.3	-1889.9	-1899.3
0.1	0.9	**-1886.6**	**-1887.2**	**-1887.8**	**-1890.9**
0	1	-1911.2	-1911.2	-1911.2	-1911.2
Error Components Model (8 weeks)					
1	0	-1547.8	-1548.0	-1548.2	-1549.4
0.9	0.1	-1547.1	-1547.3	-1547.5	-1548.9
0.7	0.3	-1544.8	-1545.1	-1545.5	-1547.2
0.5	0.5	-1540.6	-1541.1	-1541.6	-1544.0
0.3	0.7	-1532.6	-1533.1	-1533.8	-1536.8
0.1	0.9	**-1523.8**	**-1524.0**	**-1524.2**	**-1525.4**
0	1	-1525.3	-1525.3	-1525.3	-1525.3
Sample Path Size Logit Model (12 weeks)					
1	0	-3701.6	-3705.8	-3711.0	-3723.8
0.9	0.1	-3695.7	-3700.1	-3705.5	-3719.2
0.7	0.3	-3679.0	-3683.8	-3689.9	-3705.6
0.5	0.5	-3651.1	-3656.4	-3663.1	-3681.4
0.3	0.7	-3606.1	-3611.4	-3618.0	-3636.6
0.1	0.9	**-3575.3**	**-3577.6**	**-3580.3**	**-3587.3**
0	1	-3602.7	-3602.7	-3602.7	-3602.7
Error Components Model (12 weeks)					
1	0	-2902.5	-2902.2	-2902.2	-2902.8
0.9	0.1	-2901.2	-2901.1	-2901.0	-2901.8
0.7	0.3	-2897.4	-2897.2	-2897.3	-2898.6
0.5	0.5	-2889.2	-2889.4	-2889.8	-2892.3
0.3	0.7	-2872.1	-2872.6	-2873.2	-2877.3
0.1	0.9	**-2847.8**	**-2847.6**	**-2847.6**	-2848.9
0	1	-2848.4	-2848.4	-2848.4	**-2848.4**

experienced that instance. This dilutes the impact of the time difference and the decay parameter ($(t-t')^{-d_i}$). In our empirical context, the mean number of trips per traveler was notably lower compared to previous IBLT applications that collected the data from controlled experiments, allowing analysts to have multiple repetitions to develop the models. The limited number of repetitive choices in our dataset makes it challenging to determine the impact of varying decay parameters on model performance. For many travelers, there might be very few instances of past experiences, which hinders our ability to draw conclusive results.

The parameter estimates for perceived travel time show expected signs across different model types, data sizes, and scenario settings (**Table 3**). As expected, the trends observed mirror the log-likelihood results, with the value of the parameter estimate (i.e., the marginal utility of perceived travel time) increasing with an increase in the weight of actual travel time (w^a). A comparison across model types, i.e., between PSL and PSL-ec, shows that in most scenarios, the value of β_{tt} is generally higher for PSL, except for cases when $w^l = 0.1$ and when $w^l = 0$ (i.e., when the contribution of the learned travel time is very low). This also indicates that the error components added in the PSL-ec models might be accounting for learning from previous instances. These trends were observed to be similar across models tested with both 8 weeks and 12 weeks of data.

Table 3 Estimated Parameter Values for Perceived Travel Time[note3)]

w^l	w^a	d = 0.01	d = 0.5	d=1	d=5
Sample Path Size Logit Model (8 weeks)					
1	0	-0.088	-0.087	-0.085	-0.075
0.9	0.1	-0.100	-0.099	-0.097	-0.086
0.7	0.3	-0.136	-0.135	-0.132	-0.118
0.5	0.5	-0.198	-0.196	-0.193	-0.174
0.3	0.7	-0.302	-0.299	-0.296	-0.275
0.1	0.9	-0.384	-0.383	-0.381	-0.373
0	1	-0.346	-0.346	-0.346	-0.346
Error Components Model (8 weeks)					
1	0	-0.050	-0.047	-0.045	-0.034
0.9	0.1	-0.059	-0.057	-0.053	-0.041
0.7	0.3	-0.089	-0.085	-0.081	-0.063
0.5	0.5	-0.146	-0.141	-0.134	-0.108
0.3	0.7	-0.261	-0.254	-0.245	-0.210
0.1	0.9	-0.406	-0.404	-0.400	-0.386
0	1	-0.398	-0.398	-0.398	-0.398
Sample Path Size Logit Model (12 weeks)					
1	0	-0.067	-0.065	-0.061	-0.050
0.9	0.1	-0.078	-0.075	-0.071	-0.058
0.7	0.3	-0.109	-0.105	-0.100	-0.084
0.5	0.5	-0.166	-0.161	-0.154	-0.132
0.3	0.7	-0.271	-0.266	-0.258	-0.232
0.1	0.9	-0.387	-0.384	-0.381	-0.370
0	1	-0.369	-0.369	-0.369	-0.369
Error Components Model (12 weeks)					
1	0	-0.042	-0.041	-0.039	-0.033
0.9	0.1	-0.050	-0.049	-0.047	-0.039
0.7	0.3	-0.078	-0.075	-0.072	-0.059
0.5	0.5	-0.133	-0.128	-0.123	-0.101
0.3	0.7	-0.256	-0.249	-0.240	-0.205
0.1	0.9	-0.441	-0.439	-0.438	-0.422
0	1	-0.444	-0.444	-0.444	-0.444

Finally, an out-of-sample validation was conducted to further substantiate the model's performance under different scenarios[32)]. The parameter estimates generated from models developed with 8 weeks of data (**Table 3**) were utilized to estimate probabilities of the chosen alternative in the remaining 4 weeks of data. The results (**Table 4**) show that for PSL models, the best performance is in the scenario with w^l=0.1 and w^a=0.9, across all values of the decay parameter, where the highest performance was observed for the case when d=0.01.

This finding is consistent with the log-likelihood results across different scenarios. Additionally, there is a difference of nearly 2% in the prediction as the weight for the learned travel time (w^l) changes across scenarios. For the PSL-ec model, we observed substantial improvement in validation performance. In this case, the best-performing scenario corresponds to w^a=1.0, where the mean value of the estimated probability of the chosen alternative increases to 68.46%. However, this difference is less than 0.5% in the PSL-ec model among different scenarios, which again substantiates the previous discussion on how the error components could capture the effects of learning.

4. CONCLUSION

This paper conducts an empirical analysis by applying instance-based learning theory (IBLT) in the context of route choice to investigate the impacts of both experiential information i.e., past experiences, and descriptive information i.e., information on expected actual travel time. The study involves estimating and comparing two model specifications: a path size multinomial logit and a path size mixed logit using real-world vehicle trajectory data collected from the Tokyo Metropolitan Expressway in Tokyo, Japan. A weighting scheme to calculate the perceived travel time at the segment level is formulated for both model specifications, considering varying weights for learned travel time through travelers' previous experiences using IBLT and actual travel time. Three hyperparameters, weight for learned travel time, weight for actual travel time, and decay parameter are adjusted to account for memory effects, resulting in 25 distinct scenarios used to test their respective influence. The results show that actual travel time is the dominant factors determining the model performance, while the learned travel time also has a significant impact. This indicates that travelers usually rely on actual travel time more than their past experience, although some contribution of learning was observed. Additionally, it is observed that the error component model specification can capture these learning effects to a large extent.

Table 4 Results of Out of Sample Validation[note4)]

w^l	w^a	d = 0.01	d = 0.5	d=1	d=5
Sample Path Size Logit Model (8 weeks on 4 weeks)					
1	0	34.44	34.36	34.27	34.06
0.9	0.1	34.56	34.47	34.38	34.16
0.7	0.3	34.89	34.80	34.70	34.45
0.5	0.5	35.42	35.32	35.21	34.93
0.3	0.7	36.18	36.08	35.97	35.69
0.1	0.9	**36.47**	**36.42**	**36.37**	**36.25**
0	1	35.95	35.95	35.95	35.95
Error Components Model (8 weeks on 4 weeks)					
1	0	34.78	34.75	34.71	34.64
0.9	0.1	34.82	34.78	34.75	34.67
0.7	0.3	34.94	34.89	34.85	34.75
0.5	0.5	35.15	35.10	35.04	34.90
0.3	0.7	35.53	35.47	35.40	35.24
0.1	0.9	**35.85**	**35.82**	**35.81**	**35.72**
0	1	35.70	35.70	35.70	35.70

This study makes two major contributions to the existing literature. First, it postulates a unified formulation to account for both past experiences and actual expected travel time in the calculation of perceived travel time. From a theoretical standpoint, this formulation exhibits a higher level of behavioral realism than previous studies, which formulated perceived travel time as a function of experience alone and tested the difference across groups who either received information or did not. However, in reality, a traveler's perception of travel time would be a combination of both their past experiences and their knowledge about expected actual travel time through information. Using this novel formulation, this study could analyze how these two sources contribute to explaining travel behavior. Second, it utilized real-world vehicle trajectory data to analyze route choice behavior while accounting for the contribution of both learning and information acquisition.

The findings and contributions of this research should be discussed alongside its major limitations. Firstly, the study did not have actual data on whether travelers accessed information or not; it solely incorporates the actual travel time value from the real-world data and evaluates its contribution. Secondly, the sample size of repeat observations was low. This diluted the true effects of memory decay as IBLT adopts a proportion-based weighting scheme. In the future, the study should be extended to a dataset with a larger sample size for repeat observations. Additionally, different specifications to handle the weights of previous instances can also be explored. Finally, the study could be expanded to other origin-destination pairs within Tokyo as well, preferably other ODs with a higher level of commute trips, so that the results of

different ODs can be compared. Addressing these limitations in this case-specific study will ensure the generalizability of these results.

NOTES

Note1) It is worth noting that Tokyo Metropolitan Government's state of emergency measures (on mitigating the spread of the Coronavirus Pandemic) ended on September 30th, 2021. Although travel behaviors such as trip frequency cannot be ignored during the pandemic after all, we determined the data duration to be fitting for addressing its effects, particularly in the route choice context.

Note2) Values in bold represent the best-performing model in each model type and scenario setting.

Note3) All parameters were significant at 95% level.

Note4) The validation results show the mean of estimated probability of the chosen alternative * 100 for each scenario for only common travelers. Values in \textbf{bold} represent the best-performing model in each model type and scenario setting.

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