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Travel Decision Making Under Uncertainty and Road Traffic Behavior: The Multifold Role of Ambiguity Attitude

By
Jingjing Zeng[a], Zheng Li[ab*] , David A. Hensher[b]

[a] School of Economics and Finance, Xi'an Jiaotong University, Shaanxi 710049, PR China

[b] Institute of Transport and Logistics Studies (ITLS), The University of Sydney, Australia

*Correspondence: School of Economics and Finance, Xi'an Jiaotong University, Shaanxi 710049, PR China; Email: zheng_li@xjtu.edu.cn (Z. Li); ORCID: 0000-0002-2912-2103

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ABSTRACT: To aggregate commuters' mode choices to traffic behavior in the presence of travel time uncertainty, we develop a dynamic traffic simulation in terms of an agent-based model, which consists of two sub-models, the mode choice model and the traffic flow simulation model. The modeling framework accommodates the interplay between the two models and their co-evolution over time. We embed an extended list of empirical parameters including ambiguity/risk attitudes and heterogeneity , and time-money trade-offs within a rank-dependent and source-dependent utility framework to imitate commuters' daily mode choice behaviors. The improved behavioral realism at the micro-level results in an improved understanding of traffic flow in terms of modal split and average speed at equilibrium, compared to a conventional model which assumes risk neutrality and ambiguity neutrality. A novel finding is that ambiguity seeking, a typical behavior in the loss domain but largely ignored in the transport literature, acts as an important driver that shifts commuters from cars to public transport.

KEY WORDS: ***decision making under uncertainty; ambiguity attitude; traffic flow; context dependence; agent-based modeling***

AUTHORS: **Zeng, Li, Hensher**

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CONTACT: INSTITUTE OF TRANSPORT AND LOGISTICS STUDIES (H04)

The Australian Key Centre in Transport and Logistics Management
The University of Sydney NSW 2006 Australia
Telephone: +612 9114 1813
E-mail: business.itlsinfo@sydney.edu.au
Internet: http://sydney.edu.au/business/itls

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1. Introduction

Like other economic decisions such as investment and migration, daily travel choices are made under uncertainty given random variability in travel times existing at various spatial levels including link, route and the entire network (Zang et al., 2022). This is more so for the urban road network with challenges on the expected or planned arrival time such as varying congestion, the mix of traffic and traffic control (Li & Hensher, 2020). When making their daily choices, travelers need to assess possible travel time outcomes, and this assessment may be associated with vagueness. Evidence suggests that, given the same expected utility, individuals' preferences for choices with subjective probabilities (under uncertainty) and objective probabilities (under risk) are not consistent (Ellsberg, 1961), and experimental studies have demonstrated the prominent role of ambiguity attitudes in decision making under uncertainty (d'Albis et al., 2020; Driouchi et al., 2020). For example, ambiguity aversion may drive decision makers who are more cautious and discourage them from capturing the best opportunity (Driouchi et al., 2021), with a negative influence on the social system (Guillemin, 2020); while ambiguity seeking would encourage market entry (Gutierrez et al., 2020).

However, when investigating travel time variability, most experimental studies assume that the distribution of travel time occurrences is known in terms of objective probabilities, and therefore risk attitudes are the focus of current travel behavior research (see Li & Hensher, 2020 for a review). Given that, conventionally, travel time is a negative source of utility, a common finding is that travelers are more likely to act as risk takers so as to avoid a sure loss, a typical choice behavior in the loss domain. However, travelers' risk attitudes have been largely ignored by traffic simulation studies, more so for ambiguity attitudes (see, e.g., Vosough et al., 2022; Yildirimoglu et al., 2021; Han et al., 2021). As such there is a dearth of evidence on the interaction between travel decision making under uncertainty at the micro-level and traffic behavior at the macro-level.

In this paper, we use both psychological and economic factors including ambiguity/risk attitudes and heterogeneity in these constructs, and time-money trade-offs, empirically estimated from an earlier study using commuting mode decisions associated with subjective probabilities (Li et al., 2022), as inputs of the travel choice problem. For the utility function that represents travel choice behavior under uncertainty, the relative source preference parameter conditioning on experiential information is embedded in a hybrid choice model under RUM and Rank-Dependent Utility Theory (RDUT), while accommodating important time-money trade-offs. A behavioral advantage of this rank-dependent and source-dependent utility approach is that it is capable of accounting for the paradoxes of Allais (1953) under risk and Ellsberg (1961) under uncertainty, respectively (Wakker, 2010). The contribution of this paper is two-fold: (1) establishing the dynamic interplay between commuters' mode choices under uncertainty and road-system behavior and (2) demonstrating the aggregated role of individuals' behavioral mechanisms in terms of the impact on road traffic.

Importantly, by introducing the attitude toward ambiguity in the model system, we find that ambiguity seeking acts as an important behavioral driver that shifts commuters from cars to public transport (PT), where car drivers have no or limited information on the latter. Their relatively positive attitudes toward this source of uncertainty encourage modal-switching behavior. Another novel finding is that our empirical accommodation of ambiguity attitudes in traffic simulation within an agent-based modeling framework leads to a more-realistic estimation of market share and traffic speed, which demonstrates that a more realistic representation of individuals' choice behavior is associated with a gain in aggregating them to the level of system behavior. The remainder of the paper is organized as follows. The following section presents a brief literature review. Our proposed models are presented in Section 3, which are then applied to a Sydney corridor in Section 4. Important conclusions are drawn in the last section.

2. Literature review

Two main-stream approaches have been extensively used in the traffic simulation literature, namely the substantive and procedural bounded rationality models. The substantive form focuses on the results of traffic flow, in particular under user equilibrium (UE) conditions. Various UE modeling forms are developed by adding in bounded rationality factors, such as stochastic-user-equilibration (SUE, Daganzo & Sheffi, 1977), boundedly rational user equilibrium (BRUE, Mahmassani & Chang, 1987), and inertia user equilibrium (IUE, Zhang & Yang, 2015). However, the traffic flow in conventional UE studies has been assumed to be in a static-equilibrium state, within which it is difficult to capture the dynamic adjustment and to understand the variation rules shaped by combined changes of multiple attributes in a complex decision-making environment. Over the past decades, with the aid of information systems, modeling the day-to-day evolution of traffic flow with the consideration of cognitive adaptation has provoked scholars' interests, using, for example, dynamic user equilibrium (Wang et al, 2019; Ye & Yang, 2017), Markov chains (Zong et al., 2019; Wu et al., 2018), evolutionary game theory (Pu et al., 2020; Yang et al., 2018), and dynamic traffic assignment (Yu et al., 2018; Batista et al., 2018).

Unlike the substantive bounded rationality model with a focus on traffic outcomes, the procedural bounded rationality model emphasizes individuals' dynamic cognitive and learning processes. It involves numerous choice rules, and allowing for more complex simulation procedures with flexible behavioral inputs. One state-of-practice modeling framework is the agent-based model, which is capable of accounting for preference heterogeneity and dynamic interactions between individuals and the traffic environment (Zhang & Vorobeychik, 2019). Zou et al. (2016) established an agent-based model (ABM) for evaluating congestion charging policies based on the Bayesian learning process. Within the ABM framework, Chen et al. (2017) introduced a belief-desire-intention (BDI) method to forecast public transport (PT) demand. Table 1 summarizes recent agent-based traffic simulation studies, in which all reviewed studies assume that travelers are risk neutral and ambiguity neutral. However, recent experimental studies have empirically estimated risk-taking attitudes for travelers (Li & Zeng, 2022; Li, 2018; Dixit et al., 2015) and ambiguity seeking (Li et al., 2022) in the presence of travel time variability. As such, travelers' 'true' attitudes need to be embedded in traffic simulation studies so that policy implications can be evidence-based.

Table 1 A summary of reviewed simulation studies

	Simulation platform	Application	Empirical risk attitudes	Empirical ambiguity attitudes
Li et al. (2011)	Model based on descent search solution framework and BRP function	To explore individuals' adjustment process of travel route with different information accessibility	×	×
Cats et al. (2016)	BusMezzo	To establish a dynamic congestion model	×	×
Ma et al. (2016)	DTALite	To build a traffic route optimization model with real-time information	×	×
Axhausen et al. (2016)	MATSim	To set up an activity-based simulation framework for large-scale transportation scenarios	×	×
Zou et al. (2016)	Matlab	To evaluate congestion charge policies	×	×
Chen et al. (2017)	AnyLogic 6 professional	To forecast public traffic demand	×	×
Zhang & Huang (2017)	Bottleneck model	To understand the impact of network information on people's choice of departure time	×	×
Djavadian & Chow (2017)	Matlab	To verify the welfare effects of policies	×	×
Li et al. (2018)	VISSIM	To study the optimal toll rates with the aim of maximizing the toll revenue while ensuring a minimum desired level of service	×	×
Xiong et al. (2018)	DTAlite	To predict the dynamic change of travelers' behavior, including mode choice, route choice, departure time choice	×	×
Aziz et al. (2018)	Repast-HPC	To investigate the impact of walk-bicycle infrastructure on mode choice	×	×
Yildirimoglu et al. (2021)	Macroscopic fundamental diagrams	To work out the optimal work schedule problem with the aim of minimizing the travel time and preventing schedule delay	×	×
Han et al. (2021)	Stochastic bottleneck model	To investigate the welfare effects of pre-trip information on morning commuters	×	×
Vosough et al. (2022)	METROPOLIS	To explore the impacts of tolls on urban emissions and congestion externalities.	×	×

3. The interplay between mode choices and traffic flow

To aggregate individuals' mode choices under uncertainty to the road system, we develop a dynamic traffic simulation in terms of an agent-based model, which consists of two sub-models, the traveler's dynamic mode choice model, and the traffic flow simulation model. The mutual effect of these two models simulates the day-to-day interaction between travelers' decisions and traffic flow. For commuters traveling in the mode chosen in the mode choice model, their behaviors are summarized in real time by the traffic simulation model, which then aggregates individuals' choice behaviors to a dynamic traffic flow. Once their trips end, the traffic simulation model again transfers all trip information to the decision module and then commuters make their mode choices for the next day. It is this module that allows their future decisions to be affected by observed traffic flow, which adds an important feedback loop. Specifically, the mode-specific utility functions are influenced by their own experiences and knowledge, the values of which are updated on a daily base according to new trip information. Once the expected travel times are close enough to the real travel times, the day-to-day interaction between travelers' choices and traffic flow reaches stability, and, consequently, the traffic flow equilibrium can be obtained. Details of the mode choice model and traffic flow simulation model are presented as follows.

3.1 Dynamic mode choice model embedded with risk and ambiguity attitudes

To accommodate the relative source preference between two distinctive sources of uncertainty: bus vs. car, we use Li et al. (2022)'s empirical findings, and the procedure applied in our simulation is illustrated as follows. Before undertaking a commuting trip, all commuters are assumed to choose a mode on the basis of generalized travel costs. Considering the important role of information on travel behavior (Ye et al., 2021; Liu et al., 2017; Delle Site, 2018), a person's perceived travel time is a weighted result of their experience and real-time information provided by the ATIS system, which can be described as follows:

$$t^e = \beta_{IS} t^{IS} + (1 - \beta_{IS}) t^{individual,e}, \tag{1}$$

where β_{IS} indicates an individual's degree of trust towards provided information; t^{IS} denotes the travel time given by the information system; $t^{individual,e}$ is the individual's raw perceived travel time according to his/her experience. In a person's mind, for a travel mode with travel time uncertainty, there are m possible outcomes of travel time for a trip ranking, from the worst to the best ($t_1^{individual,e}, t_2^{individual,e}, \dots, t_m^{individual,e}$) with their corresponding probabilities $(p_1, p_2, \dots, p_m)$, which satisfy the conditions: $p_k \geq 0, k = 1, \dots, m, \sum_{k=1}^{m} p_k = 1$. The total utility of an individuals raw expectation for travel time without an information system is a weighted sum of utilities over all possible time outcomes. Embedding risk attitudes, the perceived utility of each possible travel time is modeled as a power specification under the assumption of constant relative risk aversion (CRRA): $u(t_k^{individual,e}) = \frac{(t_k^{individual,e})^{1-\alpha}}{1-\alpha}$, where $1-\alpha$ is the risk attitude parameter. The weight of the kth travel time outcome is its subjective probability of occurrence, which is quantified with the source function: $\omega(p_k) = F[\mathrm{w}(p_k)], k = 1, \dots, m$, where $F(\cdot)$ is a transformation function depending on the source of uncertainty. Thus, an individual's raw perceived travel time can be calculated by:

$$t^{individual,e} = \sum_{k=1}^{n} \omega(p_k) \frac{{t_k^{individual,e}}^{1-\alpha}}{1-\alpha}. \tag{2}$$

In particular, following Li et al. (2022)[1], we embed this source function within a Rank-Dependent Utility model (Quiggin, 1982) allowing for risk attitudes and beliefs, as shown in equation (3). This model form accounts for attitudes toward ambiguity and risk, both concepts of uncertainty, while only the former can generate first-order

[1] Li et al. (2022) compared different nonlinear probability weighting functions, and this one-parameter function delivers the best result. For elicitation of subjective probabilities and decision weights, their sampled respondents were asked to three commuting time outcomes and the subjective probability for each outcome to rank their provided three outcomes.

welfare effects (Ilut & Schneider, 2022).

$$\begin{cases} \omega(p_k) = [w(p_k + p_{k+1} + \ldots + p_m) - w(p_{k+1} + \ldots + p_m)]^{\theta}, k = 1,2, \ldots m-1 \\ \omega(p_m) = w(p_m)^{\theta} \end{cases}, \quad (3)$$

p_k is the probability of the kth outcome, which is estimated by the frequency of empirical data falling in $[\frac{t_{k-1}^{individual,e} + t_k^{individual,e}}{2}, \frac{t_k^{individual,e} + t_{k+1}^{individual,e}}{2})$ for k=2,..,m-1, or $(-\infty, t_1^{individual,e})$ for k=1, or $[t_n^{individual,e}, +\infty)$ for k=m; $w(\cdot)$ is the probability weighting function (e.g., $w(p_k) = \frac{p_k^{\psi}}{[p_k^{\psi} + (1-p_k)^{\psi}]^{\frac{1}{\psi}}}$ proposed by Tversky and Kahneman (1992), and is used in our paper). The curvature of probability weighting is determined by the parameter estimate of ψ, which transforms the cumulative distribution based on the rank of outcome into decision weights (m is the best outcome) with beliefs towards probabilities. θ is the relative source preference, and the functional form proposed by Fox and Tversky (1998) is $\omega(p)$ =$(\mathrm{w}(p))^{\theta}$, where $\theta > 1$ is inversely related to the attractiveness of the source of uncertainty in a gain domain and *vice versa*, which is also a quantitative indicator of ambiguity attitude (Abdellaoui et al., 2011). In Li et al. (2022), the value of θ is normalized to be '1' for the car mode's utility function as the base for relative source preference, while θ for the bus mode is shown in equation (4):

$$\theta = \theta^0 + \theta_{trip} * num_{bus}, \quad (4)$$

where num_{bus} denotes the number of bus trips during the last two months which varies across the sampled commuters, θ^0 and θ_{trip} are parameters to be estimated, and θ_{trip} reflects the corresponding role of experiential information on ambiguity attitudes.

The mode-specific utility function is expressed as equation (5), in terms of a mix of RDUT for the uncertain attribute (travel time) and RUM for the deterministic cost attribute (e.g., fare). This utility functional form allows time-money trade-offs in travel decision making with embedded ambiguity attitudes and risk attitudes and can be directly linked to welfare measures.

$$U = const + \beta_t t^e + \beta_{cost} tc + \varepsilon, \quad (5)$$

where tc is the monetary cost of a single trip, β_{cost} and β_t are the coefficients of monetary cost and travel time, $const$ is the alternative-specific constant, and ε is the unobserved disturbance term. For a binary logit model, the choice probabilities of the two modes are:

$$P(\text{bus}) = \frac{exp(V_{bus})}{exp(V_{bus}) + exp(V_{car})} \quad \& \quad P(\text{car}) = 1 - P(\text{bus}), \quad (6)$$

where V indicates the observed utility.

3.2 Road traffic flow simulation model

The traffic flow simulation is an aggregation of all agents' movements on the road network. The main idea of the treatment for a single agent is progressive renewal. To be specific, the studied time period and road space are equally divided, with a hypothesis that vehicles running on the same subsection have the same speed, and one vehicle keeps its speed constant during a sub-time period. Then, given the original state of a car driver (with known speed, location and time), the speed is calculated by using the modified BPR function or the queueing model. Then, the commuter's location and time can be updated, which are transferred to the next subperiod. This process is repeated until the commuter reaches the destination. Then, they will leave the system with their travel time recorded. Details of how to calculate different road traffic speeds and additional time experienced by bus passengers are illustrated in the remainder of the section.

3.2.1 Speed for road traffic without severe congestion

The Bureau of Public Roads (BPR) function is one of the most widely used models for speed calculation; however, the measurement of variables in its formula is time-consuming, which is not suitable for the dynamic iterations required in our simulation. We modify the traditional BPR function based on Kucharski and Drabicki (2017)'s method to calculate the speed of road traffic without severe congestion.

In the traditional BPR function, the length of travel time t is estimated as

$$t = t_{free}[1+a\left(\frac{V}{K}\right)^{b}] \tag{7}$$

where t_{free} is the travel time in free flow conditions, V denotes the volume in vehicles per hour, K refers to the capacity of the road; a and b, two impedance parameters, are typically assumed to be 0.15 and 4, respectively. Suppose that the length of a road is L, then the average speed of one vehicle traveling on this road is:

$$v = \frac{L}{t} = v_{free} * \frac{1}{[1+a\left(\frac{V}{K}\right)^{b}]}. \tag{8}$$

Following Kucharski and Drabicki (2017), we divide V and K by the average distance of the vehicle traveling in an hour, and the modified BPR function becomes:

$$v = v_{free} * \frac{1}{[1+a\left(\frac{\rho^0}{K_r^0}\right)^{b}]}, \tag{9}$$

where ρ^0 represents the density of the road, and K_r^0 is the density at capacity. Finally, ρ^0 and K_r^0 are multiplied by the length of one road segment without congestion to obtain the speed traveling on the road segment:

$$v = v_{free} * \frac{1}{[1+a\left(\frac{\rho}{K_r}\right)^b]}, \tag{10}$$

where ρ denotes the number of vehicles on the road segment, and K_r is the capacity of the road segment.

3.2.2 Speed for hypercongested road traffic

Assume that the length of each subperiod and each road segment are Δt and Δl respectively. The state set of a commuter is S=$\{l, v, t^`, s\}$, where $l, v, t^`, s$ denote the location, speed, point of time, and segment of the road, respectively. To accommodate hypercongestion in some extreme situations, we employ a queueing model. Given the congestion period $[t^`_0, t^`_1]$, the arrival rate at the segment is *b*(*t*) and the release rate is *o*; and for a commuter reaching the segment at $t^` \in [t^`_0, t^`_1]$, the length of the queue she has to wait in is

$$D(t^`) = \int_{t^`_0}^{t^`} [b(t) - o]dt, \tag{11}$$

with the corresponding time

$$t^{hyper} = \frac{D(t^`)}{o} = \frac{\int_{t^`_0}^{t^`} [b(t)-o]dt}{o}, \tag{12}$$

where the speed is ‘0’ during $[t^`, \ t^`+t^{hyper}]$.

3.2.3 The travel time of a car driver

The total travel time for a car user consists of the running time and hypercongested time, which is estimated with a dynamic iteration model. Ignoring traffic lights and road accidents, the travel time driving from zone s_0 to zone s_d is given as follows:

Step 1: Assign the initial values: $t^` = t^`_0, l = l_0, s = s_0, t^`_{wait} = t^`_0$.
Step 2: If the traffic flow on road segment *s* is larger than the hypercongestion critical value, use equation (12) to calculate t^{hyper}. Let the end point of time under hypercongestion be: $t^`_{wait} = t^` + t^{hyper}$. If $t^` \leq t^`_{wait}$, then $v = 0$. Otherwise, go to step 3 to obtain the value of speed *v*.
Step 3: If the traffic flow of *s* is smaller than the critical value of hypercongestion or $t^` > t^`_{wait}$, apply equation (10) to calculate *v*.
Step 4: Update the parameters:
$l = l + v * \Delta t, t^` = t^` + \Delta t, s = [\frac{l}{\Delta l}], t^`_{wait} = t^`_0$.
Step 5: Stop condition: If $l > s_d * \Delta l$, the iteration stops. The total travel time is $t^` - t^`_0$.

3.2.4 The travel time of a bus passenger

In addition to the running time and hypercongested time, the total travel time of a bus passenger who leaves from station s_1 to station s_2 also includes the waiting time for bus arrival, delay time of accelerating and decelerating, dwell time at bus stations and the walking time spent on the journey from home to the station and from the station to the office.

- *The waiting time for the bus arrival*

When a current bus is over-loaded, passengers need to wait for the next bus. The first step in calculating a bus passenger's waiting time is to count the number of extra buses someone has to wait for. Suppose that the schedule of bus arrivals at station s_1 is $[T_{s_1}^{bus,1} \dots T_{s_1}^{bus,M-1}, T_{s_1}^{bus,M}]$, and the length of the queue after bus *i* leaves station s_1 is given as follows.

If $s_1 > 0$,

$$H_{s_1}^{bus,i} = \begin{cases} max\{0, n_{board,s_1}^{bus,i} - n_{alight,s_1}^{bus,i} - n_{remain,s_1-1}^{bus,i}\}, i = 1 \\ max\{0, H_{s_1}^{bus,i-1} + n_{board,s_1}^{bus,i} - n_{alight,s_1}^{bus,i} - n_{remain,s_1-1}^{bus,i}\}, i = 2,3,\dots \end{cases}, \quad (13)$$

where $n_{board,s_1}^{bus,i} = \int_{T_{s_1}^{bus,i-1}}^{T_{s_1}^{bus,i}} b_{arrive,s_1}^{bus}(\mathrm{t})dt$, $b_{arrive,s_1}^{bus}(t)$ is the arrival rate of passengers at stop s_1, $n_{alight,s_1}^{bus,i}$ denotes the number of people getting off bus *i* at station s_1, and $n_{remain,s_1}^{bus,i}$ present the residual capacity of bus *i* after it leaves station s_1.

If $s_1 = 0$,

$$H_{s_1}^{bus,i} = \begin{cases} max\{0, n_{board,s_1}^{bus,i} - n_{alight,s_1}^{bus,i} - C^{bus}\}, i = 1 \\ max\{0, H_{s_1}^{bus,i-1} + n_{board,s_1}^{bus,i} - n_{alight,s_1}^{bus,i} - C^{bus}\}, i = 2,3,\dots \end{cases}, \quad (14)$$

where C^{bus} is the bus capacity.

Assume that a passenger arrives at the stop at $DEP \epsilon [T_{s_1}^{bus,z-1}, T_{s_1}^{bus,z}]$. If $H_{s_1}^{bus,z-1} + \int_{T_{s_1}^{bus,z-1}}^{DEP} b_{arrive,s_1}^{bus}(t)dt - n_{alight,s_1}^{bus,z}$ is less than the residual capacity of bus *z*, the passenger can use this bus. Otherwise, they have to wait for the next bus. Having estimated the total number of buses that a person needs to wait for (*h*), the corresponding waiting time for a bus service is

$$t_{arrive,s_1}^{bus} = T_{s_1}^{bus,z+h} - DEP. \quad (15)$$

- *The delay time associated with the accelerating and decelerating of a bus*

The delay time of accelerating and decelerating is another non-negligible time component. Referring to Tirachini et al. (2014), the delay time of a bus at speed v^{bus} is

$$t_{ac}^{bus} = \frac{v^{bus}}{2}\left(\frac{1}{a_0} + \frac{1}{a_1}\right) * (s_2 - s_1 - 1), \quad (16)$$

where a_0 and a_1 are the acceleration rate and the deceleration rate of the bus, respectively.

- *The dwell time of a bus*

The relationship between the speed of boarding and alighting the bus and passenger density in the bus has been studied empirically (Fernández, 2011), as follows.

$$v_{board} = \begin{cases} 0.89, 0 \le \rho < 1 \\ 1.13, 1 \le \rho < 2 \\ 1.37 \ \ 2 \le \rho < 3 \\ 1.67 \ \ 3 \le \rho < 4 \\ 2.03 \ \ 4 \le \rho < 6 \end{cases} \text{ and } \quad v_{alight} = \begin{cases} 0.59, 0 \le \rho < 1 \\ 0.92, 1 \le \rho < 2 \\ 1.11 \ \ 2 \le \rho < 3, \\ 1.89 \ \ 3 \le \rho < 4 \\ 5.92 \ \ 4 \le \rho < 6 \end{cases} \quad (17)$$

where ρ presents the density of standing passengers in the bus, which can be calculated by Tirachini's method (Tirachini et al., 2014). With the obtained v_{board} and v_{alight}, the time for passengers who get on and off bus *j* at station *k* can be estimated as

$$t_{load\&unload,k}^{bus,j} = max\left\{\frac{n_{alight,k}^{bus,j}}{v_{alight}(\rho_{k-1}^{bus,j})}, \frac{n_{board,k}^{bus,j}}{v_{board}(\rho_{k-1}^{bus,j})}\right\}, \quad (18)$$

where $\rho_k^{bus,j}$ is the density of standing passengers in the bus *j* after it leaves stop k. Moreover, the passenger's total dwell time from stop s_1 to stop s_2 is

$$t_{dwell}^{bus} = \sum_{k=s_1}^{s_2-1}(t_{load\&unload,k}^{bus,z+h} + c_o + c_c), \quad (19)$$

where c_o *and* c_c denote the time for a bus to open and close its doors.

- Walking time

Assuming that individuals walk at a constant speed, the time spent walking during the bus journey is

$$t_{walking}^{bus} = \frac{L_{home,station}}{v_{walking}} + \frac{L_{work,station}}{v_{walking}}, \quad (20)$$

where $L_{home,station}$ and $L_{work,station}$ are the distance from home to the station and the distance from work to the station, respectively. $v_{walking}$ is the commuter's walking speed, which is supposed to be constant.

4. Computational experiments

4.1 Simulation setup

As an illustrative case study, the proposed model is applied to a 5-km transport corridor, divided into 10 zones, a section of Parramatta Road, Sydney's Inner West (see Figure 1 in which the red dots represent the actual bus stops along this corridor), and where the travel demand figures are constructed based on real-market evidence of Sydney.

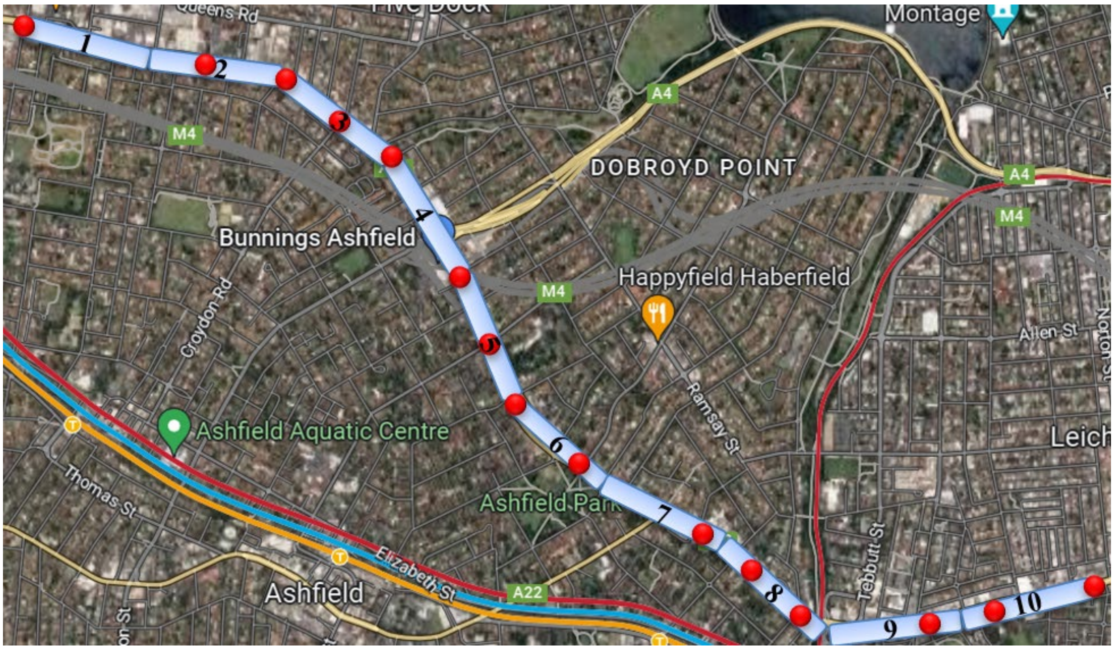

Figure 1. The case corridor

Given that the majority of walking trips are within the zoom distance defined in our simulation (500 meters per zoom), we only consider car and bus for the between-zone travel activities. In total, there 8,625 trips during a morning peak (7.30 a.m. to 8.30 a.m.), where Zones 3, 6 & 8 are the destination stops for the majority of analyzed individuals. We assign each traveler a unique travel trajectory in terms of departure time and risk attitude (see Figure 2 for the departure time distribution and Table 3 for the risk attitude distribution) using the random assignment method. The value of ambiguity seeking for the initial traffic flow during the first two months is set to be 3.328, according to the average number of bus trips of the sampled commuters in Li et al. (2022). After that, individuals' ambiguity attitudes are updated on a daily basis, depending on their mode choice outcomes. With the aid of the morning-peak modal split provided by the Household Travel Survey Report, Transport NSW, the numbers of car trips and bus trips on the first day of iteration are 7,073 and 1,552, respectively.

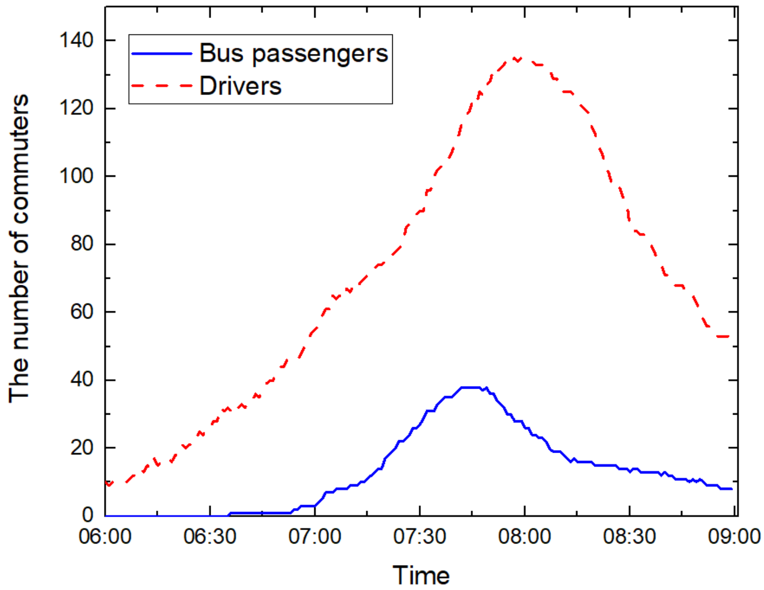

Figure 2. Departure time distributions across individuals

Following Tirachini et al. (2014), other settings for bus are provided in Table 2.

Table 2. Bus setups

Parameter	Value
h^{bus}	3min
$rate_{seat}^{bus}$	0.6
A^{bus}	$25.025m^2$
a_{stand}^{bus}	$0.15m^2$
a_{seat}^{bus}	$0.5m^2$
c_o, c_c	1s
a_0, a_1	$1.2\text{m}/s^2$

With respect to the monetary costs, the variable cost for car is Au$0.15 per kilometer, and the fixed cost is Au$6 for parking. The specific bus fares are formulated as:

$$f^{bus} = \begin{cases} \text{Au\$3.20, distance} < 3\text{km} \\ \text{Au\$3.93, distance} \geq 3\text{km} \end{cases}. \tag{21}$$

As for the behavioral parameters of Sydney commuters, we use the empirical results of Model 4 in Li et al. (2022) where a normal distribution is used to represent heterogeneous risk attitudes at the individual level, summarized in Table 3. β_{IS} is set to be 0.5, and the speed of walking is 5km/h.

Table 3 Commuters' behavioral parameters in the context of mode choice, obtained from Li et al. (2022)

α	ψ	θ^0	θ_{trip}	$const_{Car}$	β_{Cost}	β_t
N(0.454,0.281)	0.467	1.361	0.281	3.127	-0.303	-0.574

4.2 Simulation experiment

To demonstrate the gain of embedding travelers' behavioral parameters estimated from uncertain choices into a traffic simulation, we compare it (Model 1: Full, equation 22) with two partial models: Model 2: Assuming ambiguity neutrality while allowing risk attitudes (equation 23) and Model 3: Assuming ambiguity neutrality and risk neutrality (equation 24). In Sydney, between 7:30 and 8:30, the bus mode accounts for 18.0% of road travel demand. According to the Australian Automobile Association (2019), the average speed during morning rush hours is 57.0km/h in Sydney. The comparison is summarized in Table 4, and an important observation is that the ignorance of ambiguity seeking resulted in a biased modal split and average speed at equilibrium; while, ignoring both ambiguity and risk attitudes would lead to even worse performance. In the loss domain with uncertain travel time outcomes, commuters would prefer irregularity of frequencies (Kemel & Paraschiv, 2013; Li et al., 2022), for example, in our case the probability distribution associated with bus trips tends to be more volatile than that of car travel. In our model specification, it is the relative ambiguity-seeking parameter which captures this preference and which exists in the decision-making process under uncertainty (Kocher et al., 2018; Xu et al., 2018; Bouchouicha et al., 2017) but is largely ignored in the transport simulation literature. The improved behavioral realism at the micro-level is associated with a gain in describing traffic system behavior. This finding can also be linked to the role of ambiguity seeking in stimulating market entry (Gutierrez et al., 2020), and this study adds some evidence on this important topic from a new perspective, that is, sustainable mobility driven by an important behavioral mechanism, namely ambiguity seeking. The iteration paths of the three models with regard to modal split are depicted in Figure 3, which draws some similar conclusions.

Model 1 (Full):

$$U = const + \beta_t[\beta_{IS}t^{IS} + (1-\beta_{IS})\sum_{k=1}^{n}\omega(p_k)\frac{{t_k^{individual,e}}^{1-\alpha}}{1-\alpha}] + \beta_{cost}tc\ + \varepsilon, \qquad (22)$$

Model 2 (Ambiguity neutral):

$$U = const + \beta_t[\beta_{IS}t^{IS} + (1-\beta_{IS})\frac{{t^{individual,e}}^{1-\alpha}}{1-\alpha}] + \beta_{cost}tc\ + \varepsilon, \qquad (23)$$

Model 3: (Ambiguity neutral & risk neutral)

$$U = const + \beta_t[\beta_{IS}t^{IS} + (1-\beta_{IS})t^{individual,e}] + \beta_{cost}tc \ +\varepsilon. \quad (24)$$

Table 4: Model comparison

	Model 1	Model 2	Model 3
Bus modal split at equilibrium	17.87%	7.23%	4.84%
Average speed at equilibrium (km/h)	58.76	51.47	50.08

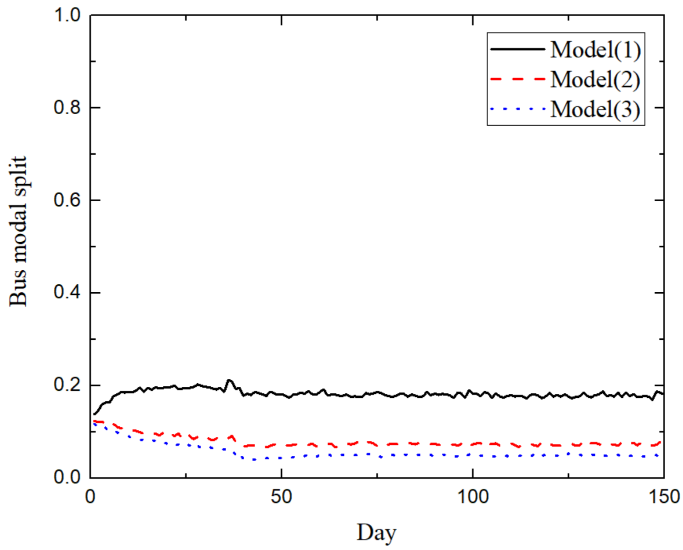

Figure 3 The iteration paths of the three models

The evidence presented in the previous paragraph reinforces the rationality of using an extended list of behavioral characteristics from both economic and psychological perspectives which together characterize the nonlinear utility specification of Model 1, where ambiguity seeking plays the most crucial role among them. To further demonstrate its significance, a sensitivity test is conducted, and three different values representing a growing extent of ambiguity seeking (from '2' to '6') at the beginning of iteration are chosen, under which different model outputs are summarized in Table 5, holding all other factors constant. This test suggests, even under a - utility specification that can depict choice behavior under uncertainty, the value of its key parameter cannot be simply assumed; otherwise, unrealistic results may be obtained. According to our simulation, the average ambiguity attitude is 3.090 at equilibrium (see Figure 4), close to our initial average ambiguity attitude being 3.238 based on the empirical estimation from commuters' daily choices in Sydney, under which the outputs of Model 1 are credible. This evidence highlights the important role of context-dependent elicitation using local survey data (Li, 2020; Gangadharan et al., 2019) in simulation analysis. Moreover, this study establishes a connection between individual choice at the micro-level and system behavior at the macro-level through, primarily, the aggregated role of ambiguity attitudes.

Table 5: Sensitivity test on ambiguity seeking

	θ=2	θ=4	θ=6
Bus modal split at equilibrium	13.20%	19.83%	22.81%
Average speed at equilibrium (km/h)	54.99	60.10	61.52

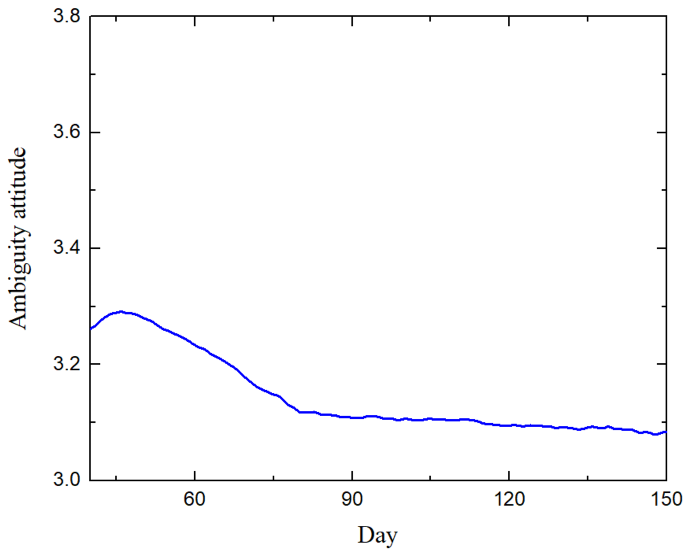

Figure 4 The average ambiguity attitude of Model (1)

In this study, an individual's perceived travel time is jointly determined by their experience and real-time information provided by ATIS as a reference point. The degree of trust towards information provision may be influenced by the accuracy of ATIS (Di et al. 2022; Ma & Di, 2017), the source of information (Imants et al., 2021) and traveler's inertia (Yu & Gao, 2019). However, the corresponding figure (β_{IS}) for Sydney's commuters is not available, and we assume 0.5 for our simulation. As such, the robustness of our results may be compromised by this assumption. To test this, the outputs of Model 1 under different degrees of trust (β_{IS}=0, …, 1) are identified. As shown in Table 6, the bus modal split at equilibrium varies from 23.14% to 14.12%, and the average speed varies from 61.99km/h to 55.19km/h. Considering the market evidence of 18.0% and 57.0km/h, our findings appear to be robust to alternative values of β_{IS}, except for some extreme values (e.g., '0', '1'). Across all β_{IS} values, the average bus modal split is 18.08% with a standard deviation being 3.20% and the average speed is 58.36km/h with a standard deviation being 2.73, and two means are closer to the market evidence, suggesting a better practice is to use a distribution of β_{IS}, when its true value is absent.

Table 6: The role of trust towards information provision

	β_{IS}=0	β_{IS}=0.2	β_{IS}=0.4	β_{IS}=0.5	β_{IS}=0.6	β_{IS}=0.8	β_{IS}=1
Bus modal split at equilibrium	23.14%	21.01%	18.75%	17.87%	16.52%	15.14%	14.12%
Average speed at equilibrium (km/h)	61.99	61.09	59.710	58.76	56.04	55.79	55.19

5. Conclusions

To aggregate individuals' mode choices in the presence of travel time uncertainty to obtain overall traffic behavior, we developed a dynamic traffic simulation, with three major improvements designed to increase behavioral realism: (1) A more realistic representation of travel choice behavior under travel time uncertainty with the consideration of ambiguity attitudes and risk attitudes, (2) an improved way of capturing the impact of heterogeneous and evolving choice behaviors across individuals and over time on road traffic, and (3) a treatment procedure to account for a feedback mechanism into the model in terms of the traffic pattern's influence on commuters' mode decisions. Moreover, we applied a number of empirical parameters estimated from survey data conducted in Sydney to mimic local commuters' mode choice behaviors. The improved behavioral framework and the use of context-dependent behavioral parameters led to a better understanding of traffic flow, in terms of a realistic modal split and average speed. Among the list of behavioral mechanisms, ambiguity seeking, a typical behavior in the loss domain, plays a critical role in capturing mode choice and traffic behaviors. Our simulation results show that ambiguity seeking is a key behavioral driver that encourages commuters to switch from car to public transport and vice versa. Ignoring it or misusing its value would result in biased findings and misleading policy implications such as system design and service planning.

The modeling framework illustrated in this paper can be extended in the following ways. Currently, it is applied to a Sydney corridor with two available cross-zone modes: car and bus. For future research, additional alternatives can be considered in the mode choice model. Moreover, the analysis scope can be extended to a network with the consideration of other important service/infrastructure factors such as between-mode connectivity and road conditions. Last but not least, heterogeneous behaviors across individuals need to be further investigated, so as to design personalized interventions to promote sustainable mobility, as called on by Ho et al. (2020): "Individuals are heterogeneous, so it is important to develop individual-specific theories of intervention. Since people respond to interventions differently, interventions must be customized based on individual characteristics" (p. 7).

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