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A dynamic discrete choice modelling approach for forward-looking travel mode choices

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ABSTRACT

In this paper, we present a systematic approach based on dynamic discrete choice models (DDCM) to investigate individuals' forward-looking mode choice behaviours in daily travel tours with multiple destinations. We propose a novel network transformation model that encompasses the entire decision space of all feasible mode combinations for every observed trip/tour in the dataset. By applying the well-established Recursive Logit model structure commonly used in path choice modelling, we address the tour mode choice problem effectively and quantify forward looking considerations in the mode choice process.

The proposed model captures the complex considerations individuals take into account when making mode choices. The network transformation incorporates downstream mode limitations into the preceding mode choice options, enabling us to model individuals' forward-looking behaviour and gain insights into how considerations of future trips such as a shopping in the evening, or school pick-up trip influence previous mode choice decisions earlier in the day. Uncovering and quantifying these hidden forward-looking factors can help modellers better explain the private car usage usually observed for the entire sequences of daily trips, even in presence of competitive alternative modes. The proposed network transformation also enables us to measure the effect of the requirement/preference to return private vehicles (car, motorcycle, and bicycle) home on mode choices in home-bound trips, and subsequently, on the entire daily mode choice decisions.

To validate the proposed model, we utilise the VISTA household travel survey data from the Melbourne Metropolitan area in Australia. The model is compared against baseline models, demonstrating its statistical advantages. Additionally, intuitive illustrations using the data showcase the model's efficacy.

From transport planning and policy perspective, tour-based mode choice modelling provides a more comprehensive and precise understanding of travel behaviour by considering the sequence of trips made by an individual. This can help capture the interactions and dependencies between different trips, which trip-based models may overlook. The proposed model is more suitable for analysing the effects of policy interventions like congestion pricing, public transport investments, or new mobility initiatives, as they can better represent the cascading effects of such policies across multiple trips.

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1. Introduction

Travel mode choices available to individuals may vary throughout the day. Modes available for a given trip depend on mode choices made earlier in the day, and choices of the present affect available options later. Trip-based models generally assume that factors affecting the individual's mode choice decisions have a spatial and temporal independence. A common assumption is that trip mode choice decisions are made purely based on the alternatives presented to the chooser for a given trip, and the utility provided by each mode between the origin and destination of that particular trip. In reality, however, mode choice decisions may often encompass a chain of trips starting from, and concluding at a single location (usually home), commonly referred to as a "tour". Accordingly, spatial and temporal limitations may arise from preceding mode decisions that affect the viability of mode options for succeeding trips. This is particularly relevant when preceding trip modes are among "public/walk modes" (public transport, taxi, etc.) or walking, which would consequently result in limitations of access to "private vehicle modes" (private car, motorcycle, bicycle) at every successive trip of a tour.

For instance, when individuals opt for public transport as their mode of travel to work, it restricts their access to their personal vehicles for subsequent trips until they return home, or in case of park-n-ride, to the station where they left their car (Nassir et al., 2012; Khani et al., 2012; Sharma et al., 2019). This limitation becomes particularly consequential if the individuals have additional visits or errands to make in the proximity to their workplace. Under such circumstances, they are compelled to rely on public modes of transport or walking for these intermediate trips. The availability, convenience, and quality of public transport options (and other public modes or walking) for these subsequent shorter trips can significantly shape their decision to choose public transport for their work commute. However, such factors are generally overlooked in trip-based mode choice modelling.

Consider another illustrative scenario where an individual drives their own vehicle to a public transport station to ride to work. Then at the end of the workday, they are required to revisit the same station to retrieve their car for the subsequent trip back home. However, complications arise if the public transport service does not adequately cater to the return trip or operates during inconvenient time intervals. In such cases, retrieving their private vehicle becomes a challenge, potentially causing inconvenience and disruptions to their overall travel plans.

These examples underscore the complexities associated with mode availability and highlight critical factors often overlooked or oversimplified in mode choice modelling. These considerations are particularly important in transport planning and policy-making, especially when evaluating new and emerging mobility options and strategies aimed at promoting multi-modality and reducing reliance on private cars as the dominant mode of travel. In a comprehensive survey analysis of Londoners attitudes towards car ownership and Mobility-as-a-Service (MaaS) as an alternative, Kamargianni et al. (2018) concluded that MaaS has the potential to impact travel behaviours and reduce private car dependency significantly. Recent research in this space acknowledge the significance of tour-based modelling when evaluating the advantages that MaaS can offer in filling the mobility gaps in the network (Song et al., 2021). In order to realise the true effect of such mobility alternatives, it is necessary to first understand the tour-level dependencies among mode choice decisions that may prohibit inter-modal combinations and usually lead to dominance of private car usage for all daily trips. This is identified in the literature by single-mode inertia usually towards private cars (Jabbari et al., 2023). Kim et al. (2021) showed that tourist's travel time considerations when making mode choices are more likely to be associated with entire tours, compared to the single-trip travel times of mode alternatives. Another recent example is a MaaS journey planning platform developed by Song et al. (2021) in which they adopt a multi-modal path finding model to identify the optimal recommendations for sequences of modes/services in daily tours. Earlier models of park-and-ride journey planning also considered round-trip travel times for the choice of park-and-ride station (Nassir et al., 2012). These research efforts demonstrate the significance of understanding and quantifying forward-looking behaviours and tour-based considerations associated with mode choice decisions, which is the topic of interest in this paper.

The concept of forward-looking mode choice models has been explored in recent years. Dynamic Discrete Choice Modelling (DDCM) approach presents a systematic modelling structure to address this gap. Prior to the recursive logit formulation proposed by Fosgerau et al. (2013) (which is based on the DDCM initially developed by Rust (1987)), there had been limited development of DDCMs in travel demand modelling domain (Cirillo and Xu, 2011). In the past few years, several papers have utilised the DDCM methodology for demand modelling. Västberg et al. (2020) utilises a novel DDCM for the purpose of developing and calibrating an activity-based travel demand forecasting model. They propose a Markov Decision Process (MDP) model that incorporates mode choices (among 4 elementary options) into the action set. However, their model is mainly focusing on activity partaking/duration decisions and destination choices; mode choice decisions and tour-based considerations are simplified in their method. More specifically, considerations around returning private vehicle to home, or temporal availability of private vehicles at sub-tour bases (e.g. parking at work) are generally ignored. Hasnine and Nurul Habib (2020) details several applications of DDCM studies that have been proposed within the last decade, the majority of which utilise the Random Utility Maximisation (RUM) principle and dynamic programming (Västberg et al., 2020; Hasnine and Habib, 2018) to model tour based mode choices.

Activity-Based Models (ABMs) also often utilise tour-based representations of household travel demands in micro-simulation environments. The notion of tours in the majority of ABM literature often relies on simplifications to the mode choice decisions, mainly based on a "primary" single mode representing the entire sequence of trip modes (Hasnine and Nurul Habib, 2020). As identified in Hasnine and Habib (2018), a significant gap exists in ABM literature, where insights into tour-based mode selections could benefit the development of existing and future transport infrastructure and services. This is particularly relevant considering the globally emerging policy shifts towards promoting inter-modal and multi-modal travel options (as opposed to car-dominated travel habits), shared and micro-mobility options, and MaaS.

While research into tour-based mode choice modelling has progressed in recent years, Hasnine and Nurul Habib (2020) states there still exists a gap in the development of an 'adequate methodological structure'. This is consistent with our review of the literature reported in Section 2; there is a clear gap in the methodology for understanding mode choices in daily tours and this gap pertains specifically to two dimensions: (1) systematic and comprehensive considerations of the hidden dependencies of all types among sequential modes in daily tours, and (2) effective and exhaustive representation of decision space which is the combinatorial combinations of all mode options throughout the day.

In this paper we propose a novel DDCM technique to model travel mode choices with incorporation of the entire tour-level combinations, considerations and limitations. We formulate the sequential trip mode choice decisions using a transformation network that represents the entire decision space of viable modal sequences for every observed tour in the data. The proposed network structure is a systematic approach that also allows for reflecting (and hypothesis testing) of any possible dependency among mode alternatives, or any tour-based consideration, such as returning the private vehicle home. This is achieved systematically by adjusting node connectivity in the proposed network and link costs (utility). We utilise the Recursive Logit model with a maximum likelihood estimation procedure to estimate the utility parameters and evaluate the extents of forward-looking considerations.

In terms of policy implications and applications in transport planning, the proposed model has the advantage to identify the mobility gaps in transport systems from the user perspectives, and contributes to the growing body of mode choice modelling literature that aims to highlight hidden mode choice factors such as mode inertia (Mo et al., 2021; Ambi Ramakrishnan et al., 2021), user lifestyles, habits and attitudes (Prato et al., 2017), cultural and social value systems (Moody and Zhao, 2019), and others latent factors and inter-dependencies (Schwanen and Mokhtarian, 2005; Mehdizadeh and Ermagun, 2020; Pinjari et al., 2011) influencing mode choice decisions.

2. Literature review

2.1. Recursive logit

Dynamic discrete choice models help to reduce the limitation of static discrete choice models, by incorporating past and future states (and decisions) into the choice decision framework, often through a Markov Decision Process (MDP). The recursive logit (RL) model corresponds to a dynamic discrete choice model where the path choice problem is formulated as a sequence of link choices (Fosgerau et al., 2013). Because recursive logit minimises computational complexity for large networks implementations, simplifications of the mode choice sequences for tours are not required. This addresses one of the key issues cited by Hasnine and Nurul Habib (2020) in tour-based mode choice modelling wherein simplified choice models may not accurately capture the dynamics of the decision process in reality.

Fosgerau et al. (2013) proposed the initial recursive logit formulation citing its similarity to the original dynamic discrete choice model developed in Rust (1987). The recursive logit model is applied to directed graph networks with applications for modelling the path choice problem. The objective was to formulate an econometric model for the path choice problem where path choice was conditional on origins and destinations. One key advantage of utilising this method, is that it does not require the enumeration of all path possibilities — substantially reducing the model complexity and thus computational requirements. Maximal downstream utilities are captured through a node value function, which is computed using dynamic programming through the Bellman Equation (Bellman, 1958).

Modelling correlation between alternatives has been one of the subjects for further developments in the recursive logit literature. Mai et al. (2015) proposed a path choice model that utilises link specific, scalable error parameters to relax the proportional substitution characteristic of the IIA, inherent in the logit formulation. In doing so, the RL model draws similarities to the nested logit formulation, particularly in networks where nesting naturally occurs. Similarly, Zimmermann et al. (2018) adapts the original recursive logit to relax the IIA by allowing for correlation patterns between both paths and link choices, addressing one of the key limitations of the original recursive logit method defined by Fosgerau et al. (2013). As in Mai et al. (2015), this approach draws analogies to existing static logit models. Specifically, the probability calculations are analogous to those seen in mixed logit literature (Hensher and Greene, 2003; McFadden and Train, 2000).

Mai et al. (2018) further develops the methodology by providing a technique for reducing the number of linear systems solved in RL models, allowing for large RL based models to be more efficiently estimated. The decomposition method proposed allows for more efficient calculation of value functions - a substantial computation in the RL formulation — by allowing value functions to be computed using a single system of linear equations.

Since the conception of Fosgerau et al. (2013), several applications of recursive logit have emerged in the transport modelling research space. In line with the original application, path choice models utilising link-based (rather than path-based approach) have been proposed. Mai et al. (2015), de Moraes Ramos et al. (2020), and Oyama and Hato (2017) all utilise developments on the original recursive logit formulation to apply the dynamic choice model to the route choice problem. Additionally, applications outside path choice modelling have been evident in the literature. Specifically, Nassir et al. (2019) applied a recursive logit model to the transit strategy choice problem, utilising smart card data to produce a dynamic model for transit load assignment. In this paper they take advantage of a link-based formulation to avoid the enumeration of all possible path sequences. Meyer de Freitas et al. (2019) applied a recursive logit model to determine the factors influencing inter-modal travel behaviour using household travel survey data while, Zimmermann et al. (2018) estimated a novel mixed recursive logit model to produce a combined activity, location, timing and mode choice model to analyse the choice paths in an activity network.

One key advantage of the recursive logit model is that path sequences need not be enumerated. In applications where static models produce restrictive choice sets – such as in the examples highlighted – the recursive logit model allows for the choice set to be constructed as an enumeration of links, reducing the combinatorial nature of the choice possibilities. However, akin to aforementioned examples, the representation of the choices is crucial to the effective utilisation of the model. In this paper, we highlight an effective network transformation for the tour-level mode choice problem in Section 3 which formulates the choice problem for estimation with recursive logit models.

2.2. Tour-based mode choice models

Tour-based mode choice models are commonly used in conjunction with activity-based models. In this paper, we define a tour as a chain of trips where the individual starts and ends at the same location (Ben-Akiva and Bowman, 1998; Hasnine and Habib, 2020). However, in the presented model we restrict this definition to tours occurring within a 24 h period.

Dynamic models have been used in tour mode choice literature, for example Hasnine and Habib (2018, 2020) as well as activity based modelling (Västberg et al., 2020). These typically model the decisions made in a tour as a Markov Decision Process. Västberg et al. (2020) states, some work has been made to utilise Markov chains to analyse the sequential dependence of chained activities. They utilise the daily travel patterns as a Markov Decision Process (through the DDCM formulation) and acknowledges time dependence within their model. However, they expand the framework to an activity-based model, where mode choices in trip chains are simplified and analysed in conjunction with activity-based factors.

Vovsha and Hicks (2017) proposes a tour-based combinatorial choice model that utilises a method similar to the recursive logit for utility estimation. Mode choice options are presented as a sequence of modes and car availability states. This model represents states as a combination of mode choices made and the location of the car, and estimates the utility based on the observed mode usage and data from the Household Travel Survey (HTS) travel diary data set. Of all the tour-based mode choice models available in the literature, the methodology presented in Vovsha and Hicks (2017), most closely resembles the idea and estimation procedure presented in this paper, albeit with some distinct differences.

Hasnine and Habib (2018) proposes a Dynamic Discrete Choice Model (DDCM) for tour-based mode choice modelling with the objective of capturing the dynamics of multimodal behaviour in a tour setting. The forward-looking nature of the RUM-based model presented in this paper, emphasises the importance of state dependence — mode choices can have subsequent effects pertaining to the availability of modes at future stages. This methodology uses a combination of a the Dynamic Generalised Extreme Value (DGEV) formulation developed by Swait et al. (2004) to apply the RUM concept, and the forward looking dynamic discrete choice method detailed in Rust (1987).

Hasnine and Habib (2020) demonstrates the tour-based, dynamic RUM mode choice model proposed in Hasnine and Habib (2018), using the Transportation Tomorrow Survey 2016 of household travel in the Southern Ontario, Canada. Their proposed model demonstrated the significance of ‘‘un-simplified’’ tour-based mode choice modelling by evaluating accurate utility of transfers in tour mode choice combinations and associated fare changes. This finding highlights some of the policy implications that can be made with such models, as well as pricing considerations for MaaS and other upcoming mobility services.

Paleti et al. (2017) proposes a method that utilises a modified rank-ordered logit (ROL) framework for activity-based tour modelling. Tours are decomposed in this method by the activity sequencing and location. The model estimation involves the placement of trip utility components to incorporate these activity sequencing and location effects.

2.3. Identified gaps and paper contribution

While research into tour-based mode choice modelling has progressed in recent years, a large number of tour-based models presented in the literature utilise an enumeration of either activities or links, resulting in exponentially increasing model complexity with longer tours. Another issue is that existing models often fall short in completely representing the sequential dependencies and multi-modal dynamics inherent in real-world travel behaviour. Current tour-based mode choice models tend to simplify the decision-making process, potentially overlooking critical factors like intermediate trip choices and their subsequent impact on mode availability and utility. Therefore, a significant gap remains in fully capturing the intricacies of tour-based mode choice modelling. This gap specifically pertains to two critical dimensions: (1) systematic and comprehensive considerations of the hidden dependencies among sequential modes in daily tours, and (2) effective and exhaustive representation of the decision space, which encompasses the combinatorial combinations of all mode options throughout the day.

To address this gap, we propose a novel network transformation technique to model travel mode choices, incorporating the entire tour-level combinations, considerations, and limitations. We utilise the Recursive Logit model with a maximum likelihood estimation procedure to estimate the utility parameters and evaluate the extents of forward-looking considerations. This methodology aims to enhance the accuracy and comprehensiveness of tour-based mode choice modelling, thereby improving the precision in transport planning and policy-making efforts in promoting sustainable and efficient multi-modal transport systems.

Table 1
Notation and definitions.

Notation	Definition
M^{PRV}	Set of all private vehicle modes (car, motorcycle, bicycle)
M^{PBL}	Set of all public modes (public transport, taxi, etc.) and walking mode
M	Set of all travel modes of transport available such that $\{M^{PRV}, M^{PBL}\} = M$
m and q	indices of single mode of transport where, $m, q \in M$
k	Index of an observed tour from data where, K is a set of tours
S_k	Vector of tour stages (trips) in tour k
I_k	Length of tour k, or cardinality $\|S_k\|$
$s_{k,i}$	A single tour stage of index i in the vector of tour stages S_k
G_k	Transformation network associated with tour k
N_k	Set of all nodes in transformation network G_k
$N_{k,i}$	Set of nodes transformation network G_k associated with tour stage s_i
$n^m_{k,i}$	Node in transformation network G_k associated with tour stage s_i and with mode m
$L^m_{k,i}$	Set of outgoing links available at node $n^m_{k,i}$
$u^m_{k,i}$	Utility value at node $n^m_{k,i}$ (recursive value function from stage i to end of tour)
γ	Node Coefficient (Forward-looking Coefficient)
$l^{q,m}_{k,i}$	Link from node $n^q_{k,i}$ to node $n^m_{k,i+1}$ where m is the mode utilised
$a(m\|n^q_{k,i})$	Systematic utility of link from node $n^q_{k,i}$ to $n^m_{k,i+1}$ via mode m

3. Methodology

This paper proposes a novel approach to modelling the mode choice decisions in tours of trips, which allows the use of DDCMs to estimate the underlying functional parameters. This is accomplished by employing a network transformation that accurately represents the mode choice alternatives available to individuals as a function of their past decisions. The notation for the proposed model is presented in Table 1.

The proposed approach is therefore based on the assumption that individuals make decisions about the destinations visited in a day, independent of their mode choices. We acknowledge that this is not always the case, however integration of activity/destination locations and mode choices would add significant complexities to choice structure and is beyond the scope of this research. As shown in Västberg et al. (2020), incorporation of these considerations greatly increases the complexity and computational requirements of the model.

3.1. Proposed network transformation

We propose the adoption of a directed, acyclic network transformation denoted as G_k for every observed tour k within the dataset, based on the chronological sequence of visited locations. This transformation network provides a comprehensive representation of choice attributes, encompassing not only the availability, accessibility, travel time, and other relevant travel attributes associated with each mode, but also chooser attributes, including socio-economic characteristics of the traveller.

Within this transformation network, nodes are created to capture the dynamic states of the decision maker prior to making mode selections at the beginning of each travel stage, taking into account the available mode options. The states of these nodes reflect factors such as the presence or absence of a private vehicle at that particular stage. In essence, nodes serve as indicators of the available mode choices. Conversely, links represent the specific attribute values mode options, such as travel time, cost, etc, regardless of the previous mode selections. It is the configuration of nodes and links in the transformation network that provides the complete representation of all possible mode combinations with their specific characteristics when connecting the individuals to their array of destinations for every observed tour.

In the proposed network G_k, the set of nodes N_k comprises multiple copies of nodes where each copy is associated, on the one hand, with the trip stage $s_{k,0}, s_{k,1}, \dots, s_{k,i}$, and on the other hand, with the modes m available at the respected trip stage. Consequently, for every trip stage $s_{k,i}$, the node set $N_{k,i} \in N_k$ encompasses multiple replicas of nodes $n^{drive}_{k,i}, n^{walk}_{k,i}, \dots, n^m_{k,i}$, with each replica representing a specific mode m (mode taken to arrive to stage i).

Links in the transformation network represent an actual travel movement from one stage to the next, and are denoted as $l^{q,m}_{k,i}$ where the starting node is $n^q_{k,i}$ and the ending node is $n^m_{k,i+1}$. The mode utilised in link $l^{q,m}_{k,i}$ is the mode associated with downstream node (m) which must be available at stage i given the previous mode taken q to get to stage i. Feasibility of mode sequences can be guaranteed in the transformation network through availability of links. Links representing nonviable mode sequences are eliminated (not created) during network generation process.

When creating the link set for standard tours (without sub-tours), for every stage $i < I$, a link $l^{q,q}_{k,i}$ is generated from all nodes $n^q_{k,i}$ to node $n^q_{k,i+1}$. This guarantees that every chosen mode q is viable for subsequent trips. Then in the next step, for every stage $i < I$, a link $l^{q,m}_{k,i}$, ($q \neq m$), is generated from all nodes $n^q_{k,i}$ to node $n^m_{k,i+1}$ unless $m \in M^{PRV}$. This way, utilising private vehicle modes will depend on utilising the same mode in previous stage. Fig. 1 illustrates the network notation. For the remainder of the paper, the index k which represents a specific tour is removed from the notation for simplicity and ease of reading.

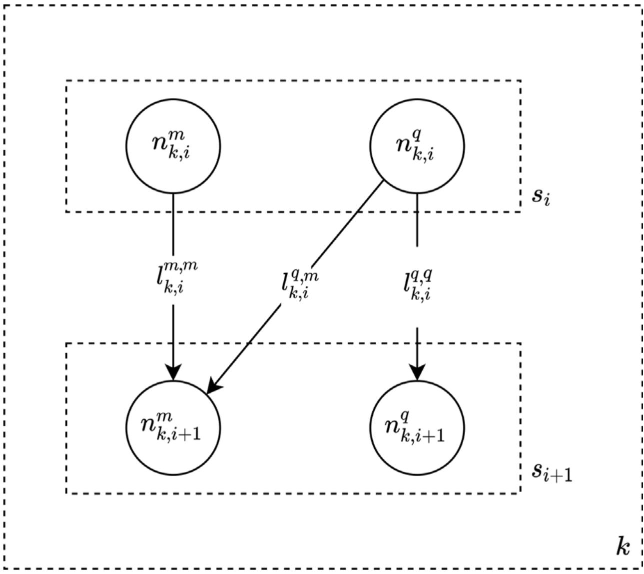


Fig. 1. Example network notation with $m \in M^{PBL}$ and $q \in M^{PRV}$.

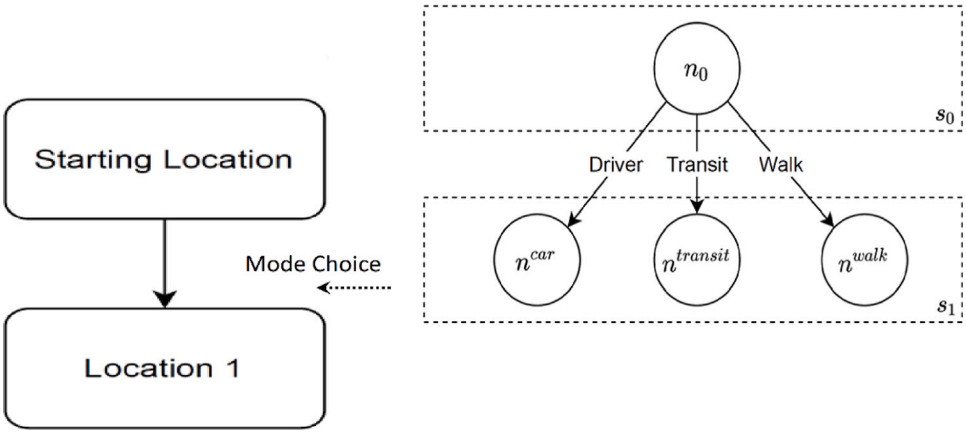


Fig. 2. Start of tour.

3.1.1. Illustrative examples

For the first trip in any tour, we assume that an individual has access to all modes that they have the option to utilise, according to the information recorded in the travel diary data. For example an individual who owns a car and has a driving licence would have access to the "drive" mode from home, in addition to all public/walk modes.

In Fig. 2, for the sake of simplicity in illustrations, we assume that the set of private vehicle consists of a single mode only, car driver, and the public/walk mode set consists of public transit and walking. For the first stage of any tour, links are created linking the starting node with all nodes in stage s_0. This represents the ability for individuals to choose any mode for the first trip in a trip chain and assumes that the starting, home location of the individual contains access to all private vehicle (if owned by the household).

At all stages s_i where $i > 0$ in the network (with the exception of sub-tours presented in 3.3) links and nodes are generated uniformly. A single node for each mode available in the dataset is created within each identified tour stage. Links are subsequently generated using a set of rules on the basis of a link's adjacent nodes. The rationale behind this approach for the link generation process, is based on the notion that individual's are not able to access modes that they are not in possession of. For public modes, we assume that there is little or no restriction on the ability to utilise the mode. Therefore, the choice set available to an individual at any public node in a tour – irrespective of their prior choices – is always inclusive of these modes. On the other hand, private modes such as car, requires that the mode itself is present with the individual and is thus included in the set of choices available to them. As such, the network's links are constructed such that choice options are restrictive on the availability of private modes $m \in M^{PRV}$ (see Fig. 3).

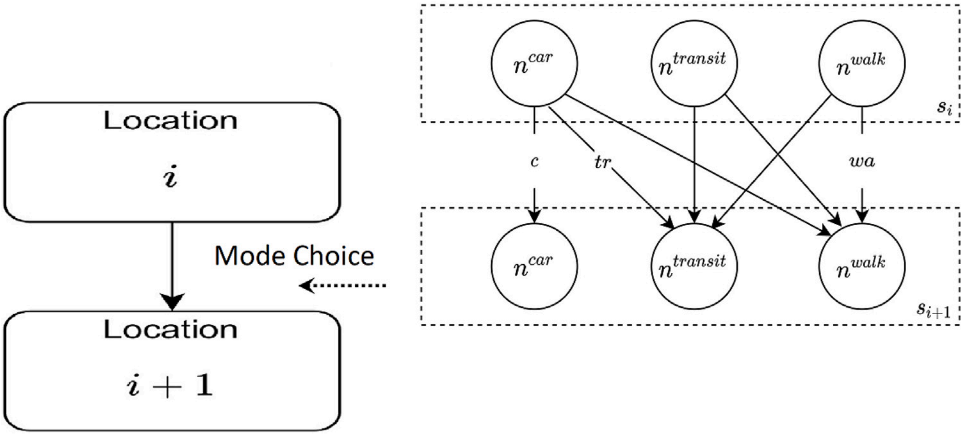


Fig. 3. Standard node structure.

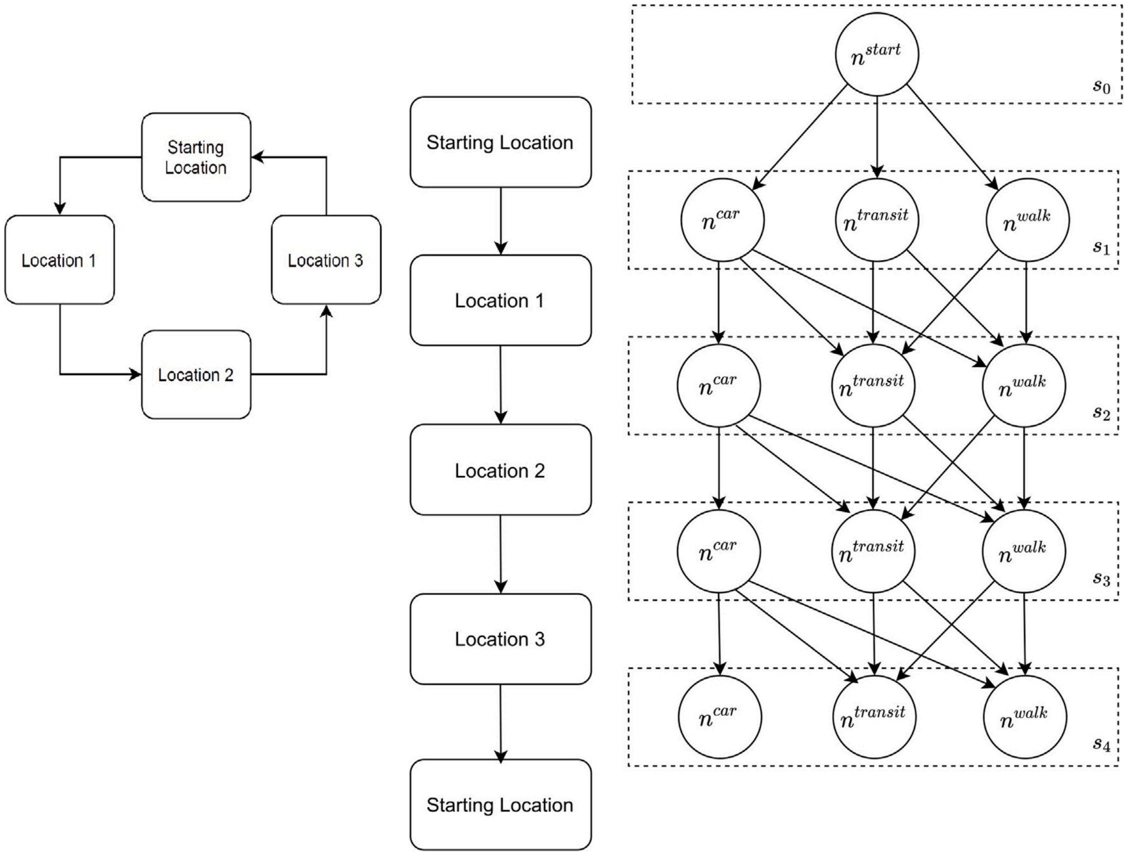
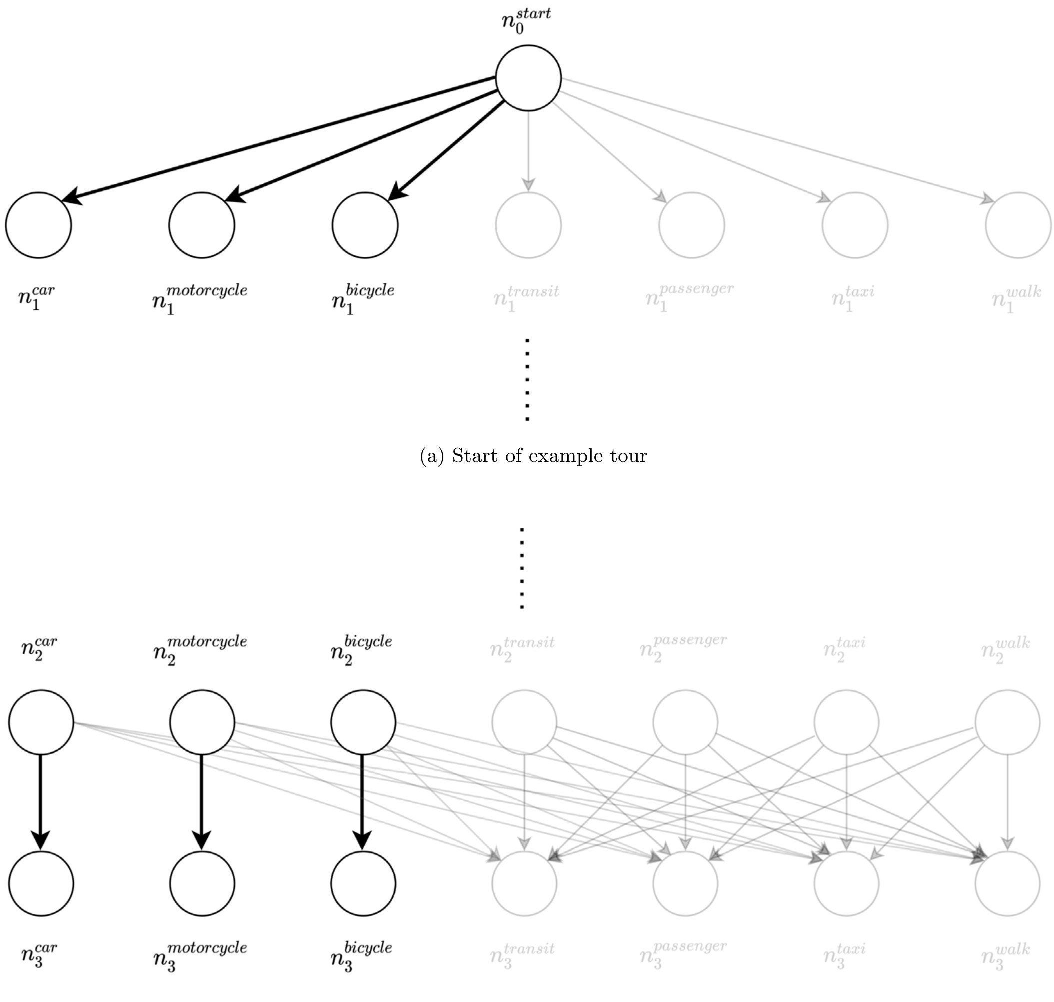


Fig. 4. Complete example tour network structure.

For a sample tour assumed for illustration, the created network transformation is shown in Fig. 4. In this figure, the mode choice associated with links can be deduced from the ending node mode annotations. The mode of the node at the end of a link is always the same as the mode used in the link.

This directed graph structure ensures a dynamic dependence of modal availability at any given node within the network. As a result, the model contains a forward-looking mechanism to restrict not only the availability of private vehicle at future states, but also the potential access to downstream utilities (logsums) which these modes may provide (as in Nassir et al. (2016)).



(a) Start of example tour

(b) End of example tour

Fig. 5. Illustrative example for deposit constants.

One of the key differences in the network structure that differentiates the proposed network layout from that seen in Vovsha and Hicks (2017), is the representation of the nodes within the network. As shown in Fig. 4, nodes signify the choice set restriction available at a specific stage s_i. Node representation also enables us to quantify the significance of returning home of private vehicles. This is done using soft constraints in the proposed model and is discussed in Section 3.2

3.2. Utility functions and vehicle deposit penalty/credit

A systematic utility function, $a(m|n_{k,i}^{q})$, is defined for every link $l_{k,i}^{q,m}$ which incorporates the level-of-service variables such as travel time, cost, etc, specific to mode m and measured for the origin–destination pair observed in the travel stage i of tour k (plus chooser attributes). This way, link utilities are computed individually and independently, forming the building blocks for utility computation for the entire transformation network. Node utilities are computed recursively based on downstream node utilities and link utilities. Precise calculation of link and node utilities are presented in Section 3.4.

In addition to utilities specified for links and nodes in the transformation network, utility deposit constants (to be estimated) will be placed at initial (penalty) and final links (credit) of private vehicle modes: car driver, motorcycle and bicycle. The rationale behind this is to estimate the cost or burden of having to return private vehicles back home. This constant is applied independently for every private vehicle mode through a deposit utility constant which is paid at the start of the trip chain if checking out the private vehicle, and returned (as positive utility) to the individual at the end of the trip chain, if the vehicle is returned back. The value of this constant is estimated for every private vehicle mode, using the estimation procedure presented in Section 3.4.

In addition to evaluating and quantifying the deposit constant for every private vehicle mode, the proposed vehicle deposit mechanism helps us capture the effect of private vehicle mode choice inertia for daily tours (Jabbari et al., 2023), which is a

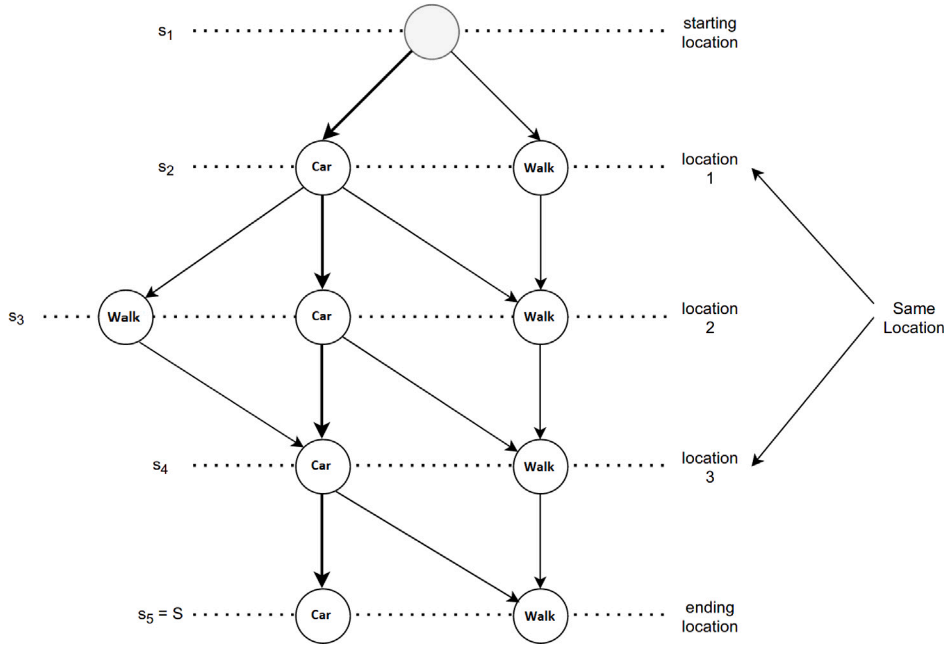


Fig. 6. Simplified sub-tour example.

desirable and novel feature of the proposed model. For example, by selecting to drive for the first trip of the day, the individual is more likely to drive the rest/majority of remaining trips in that day, otherwise they may have difficulty in returning the car back home. This type of behaviour can be modelled and quantified by the proposed deposit penalty mechanism.

For illustration of the deposit coefficient, consider a sample tour where the individual travels from home to work to shopping centre and then back home. Using the private vehicle and public/walk modes, the first two tour stages can be seen in Fig. 5(a). The three links highlighted correspond to private vehicle mode choice alternatives between stages s_0 and s_1 and contain the deposit coefficient. Fig. 5(b) shows the final two stages of the tour. At these highlighted links, the deposit coefficient provided is returned.

Using the proposed deposit utility mechanism, we test the hypothesis that individuals who utilise their private vehicle modes, have an obligation/preference to return vehicles to the origin destination; i.e. the individuals are charged a deposit at a price that is calibrated specific to the vehicle type (car, motorcycle, or bicycle) in the estimation process, and are only refunded this deposit upon return of the vehicle to the original location thereby reducing the utility of paths which prevent return of vehicle. The only exception to this rule occurs in sub-tours, where one may leave their vehicle at a location other than home, but comes back later to pick it for the remainder of tour back home. Sub-tours are treated especially in the proposed network transformation and presented in Section 3.3.

3.3. Sub-tours

One peculiarity that is present in the tour formulation is the presence of "sub-tours" within the tour structure. These structures are based on the occurrence of tours, within an existing tour. One example of a sub-tours occurs when an individual makes trips from work. Any round trips from the work location (or any other intermediate destinations) are considered sub-tours. These greatly increase the complexity of the network, as the network must include path options that represent future, but not present availability of private vehicle modes (e.g. car left at parking at workplace).

Fig. 6 shows a simplified example of a sub-tour. In this example, the sub-tour occurs between stages s_2 and s_4 where these two stages (locations) would represent identical locations. It can be seen that at location 1, the individual at node n_2^m where $m \in M^{PRV}$, has the option to take either the private vehicle mode (car) or public mode (or walk) with future access to the private vehicle mode. This choice set differs from those at other nodes with private vehicle, as the public link option for the trip from location 1 to location 2 results in future access to the abandoned private vehicle, without access within the sub-tour (at s_3). This is highlighted at the proceeding node where the individual is presented with the option to return to their previously abandoned private vehicle, or completely abandon this vehicle for the remainder of the tour. While there exists the possibility of sub-tours within sub-tours using the network generation, in our experience these are highly unlikely and non-existent in the case study data set.

3.4. Model specification and estimation: Recursive logit

This section presents the methodology associated with the specification and estimation of utility coefficients for the proposed transformation network structure. Estimation of link, node and choice probabilities is largely analogous to the dynamic path choice models (Fosgerau et al., 2013; Mai et al., 2015; Zimmermann et al., 2018) and utilises the recursive logit path choice model equations presented in Zimmermann and Frejinger (2020) and Fosgerau et al. (2013), as a framework for the estimation of mode choices probabilities of links.

The journey of the individual through a tour is presented as a stochastic Markov Decision Process. Errors are assumed to be present in the data set, and are represented within the logit error term, ϵ. This error represents the heterogeneity of preferences and subjectivity of traveller perceptions. In logit models, it is assumed that the errors are randomly distributed and is scaled uniformly via the scaling term μ. Individuals are also assumed to be utility maximising, resulting in the instantaneous link utility function, defined in Eq. (1), where the link choice is dependent on the mode of transport m available at the originating node n. It should be noted that in the presented recursive logit methodology, we refer to the formulation provided in Fosgerau et al. (2013) in which the scaling term μ is uniform across all links.

$$v(m|n_i^q;\beta) = a(m|n_i^q;\beta) + \mu\epsilon \tag{1}$$

where,

$$a(m|n_i^q;\beta) = \boldsymbol{\beta}^m \cdot \mathbf{X}^m + \boldsymbol{\beta}^m \cdot \mathbf{Y}^m \tag{2}$$

The $\mathbf{X}^m$ represents a vector of utility variables whose values are derived using the trip stage memory data (trip OD locations, departure time) and journey planning databases (tripgo API). The $\mathbf{Y}^m$ term corresponds to chooser specific explanatory variables, present in the travel diary data.

As described in Zimmermann and Frejinger (2020), from the perspective of the modeller the inverse traversal of the nodes is akin to a stochastic shortest path problem, where the optimal solution to the node utilities is provided by solving the expected value $E_{\mu\epsilon}$ of each node through the error-parameterised Bellman Equation. It is assumed that the individual seeks to maximise the instantaneous (link) and downstream (node) utilities (multiplied by a coefficient γ), respectively given by Eqs. (2) and (3).

$$u_i^q = \begin{cases} 0 & i = I \\ \mathbb{E}[\max_{l_i^{qm}\in L_i^q}\{a(m|n_i^q) + \gamma \cdot u_{i+1}^m + \mu\epsilon\}] & \forall i < I \end{cases} \tag{3}$$

Assuming that all error terms are i.i.d Extreme Value Type I, the expected value function in Eq. (3) for nodes at stages $i < I$, can be represented as the logsum of instantaneous and node value utilities.

$$u_i^q = \mu ln \sum_{l_i^{qm}\in L_i^q} e^{\frac{1}{\mu}(a(m|n_i^q)+\gamma\cdot u_{i+1}^m)} \tag{4}$$

This results in the following node value functions

$$u_i^q = \begin{cases} 0 & i = I \\ \mu ln \sum_{l_i^{qm}\in L_i^q} e^{\frac{1}{\mu}(a(m|n_i^q)+\gamma\cdot u_{i+1}^m)} & \forall i < I \end{cases} \tag{5}$$

Akin to the multinomial logit probability equation, the probability of choosing a single link is dependent the originating state or node of the link:

$$P(l_i^{qm}|n_i^q;\beta) = \frac{e^{\frac{1}{\mu}(a(m|n_i^q)+\gamma\cdot u_{i+1}^m)}}{\sum_{l_i^{qp}\in L_i^q} e^{\frac{1}{\mu}(a(p|n_i^q)+\gamma\cdot u_{i+1}^p)}} \tag{6}$$

and the probability of choosing a particular sequence of modes $\mathbf{V} = \{v_i \in M | i \in I_k\}$ for all trips i in tour k is equal to the product of all intra-tour mode selections.

$$P(\mathbf{V}|k;\beta) = \prod_{i=1}^{I_k} P(l_i^{v_{i-1},v_i}|n_i^{v_{i-1}};\beta) \tag{7}$$

The resulting likelihood for all tours in the data set $k \in K$ with $\delta^c \in \{0,1\}$ being a binary variable indicating chosen modes, is therefore:

$$P(K_c|\boldsymbol{\beta}) = \prod_{k\in K}\prod_{i=1}^{I_k} \delta_{k,i}^m \left(\frac{e^{\frac{1}{\mu}(a(m|n_i^q)+\gamma\cdot u_{i+1}^m)}}{\sum_{l_i^{qp}\in L_i^q} e^{\frac{1}{\mu}(a(p|n_i^q)+\gamma\cdot u_{i+1}^p)}}\right) \tag{8}$$

While these equations define the mathematical logic of link and tour probabilities, due to numerical overflow, log probabilities and overall log likelihood is used for model estimation.

The formulation of the node value function as a system of linear equations in Fosgerau et al. (2013) provides an efficient method for solving node values. While the equations described above are sufficient for the calculation of the likelihoods used in

Table 2
Mode simplifications used.

VISTA modes	Model modes	Mode type
Vehicle driver	Car driver	Private (PRV)
Motorcycle	Motorcycle	
Bicycle	Bicycle	
Vehicle passenger	Car passenger	Public (PBL)
Taxi	Taxi	
Other	(excluded)	
Public bus School bus Train Tram	Transit	
Walking	Walking	

model estimation, the matrix formulation of these equations is the method used in implementation due to the inherent efficiency improvements. We refer the reader to this paper for the specifics of the formulation.

As proven in Fosgerau et al. (2013), the recursive logit method retains the IIA condition based on the proportional substitution of paths. Due to the nesting structure evident in private vehicle mode nodes, use of nested recursive logit (Mai et al., 2015) would aid in producing more reliable parameter estimates. This has been noted as a point of future development as stated in Section 5.

3.5. Maximum likelihood estimation

Eq. (8) defines the objective function used for Maximum Likelihood Estimation. Using the predefined optimisation framework we take the negative of overall log likelihood and find the optimal minimum value. Rust (1987) detail a two stage optimisation process (NFXP), involving an inner loop to compute the value functions within the network, and a second utilising an optimisation algorithm to solve for optimal coefficient estimates. While the value functions computed at each estimator increment are solved via Eq. (5) in the estimated model, estimators are optimised using the Sequential Least Squares Quadratic Programming (SLSQP) algorithm.

We refer the reader to Fosgerau et al. (2013) for a formal definition of the analytical gradient calculation process and its details. In the method implemented, numerical gradients are utilised wherein partial derivatives respective to the log-likelihood are estimated through the optimisation algorithm. We use numerical optimisation as opposed to the more efficient closed-form solutions, due to the estimation of a value function coefficient.

The justification for utilising the SLSQP algorithm over other optimisation algorithms available in Python, is due to the observation that the SLSQP algorithm is able to achieve an optimal solution with the fewer function iterations. Due to the increase in likelihood function evaluations required for numerical optimisation, this makes the method preferable.

3.6. Confidence intervals

To obtain the statistical significance required to accept or reject the estimated coefficients, we utilise the bootstrapping method. Using this method, generated networks are sampled with replacement and each sample has their parameters optimised using maximum likelihood estimation process. This provides us with a sample of coefficient estimates to calculate the sample mean, variance and standard deviation used to determine parameter significance. In total, the sampling procedure was undertaken 30 times and resulting sample mean, variance and standard deviation was calculated for each of the estimated coefficients.

4. Case study implementation

4.1. Data sets

Data used for tours, stages, nodes and links was generated from the ongoing Victorian Integrated Survey of Travel and Activity (VISTA) travel diary data set. Specifically, the data sets corresponding to the travel diaries between 2012 and 2016 have been used, due to the location information provided within these data sets which are no longer available from the Victorian Government. The data is generated from households completing a travel diary for a single day. From this diary, detailed information about the household, person, trip and stop is provided. In this example, we use the proposed methodology to generate the mode choice sequences (networks) for each identified tour in the data set.

Several simplifications to the modes detailed in the survey have been made according to the level of specificity of alternative mode choice information. Table 2 displays a summary of the simplifications made to the set of mode options seen in the VISTA data set.

Generation of alternative mode information requires location data. While the VISTA data set provides location data for each trip, this is provided at a Statistical Area 1 (ASGS) level of accuracy. To convert this data into meaningful location data – for the

Table 3
Characteristics of generated tour set.

Description	Example tour set
Total number of tours estimated	1000
Average tour length	3.184 (stages)
Maximum tour length	8 (stages)
Total number of tours with a Sub-tour	22

Table 4
Estimated model fit.

Description	Value
Number of independent variables	44
Number of links generated	45 060
Number of nodes generated	2823
Log-likelihood of constant only model	−8616.25
Estimated forward looking log-likelihood	−5726.38
Estimated baseline log-likelihood (node coefficient = 0)	−5870.95
Rho-square	0.335
Adjusted Rho-square	0.334
Overall accuracy (validation set)	64.74%

generation of alternative mode information – the latitude and longitude of the SA1 locations centroids has bee utilised. Using the TripGo API, mode specific trip information was queried. The TripGo API provides detailed mode specific information for each trip queried however, due to the SA1 level of location information, highly specific information such as parking cost and walking times for inter-modal trips has not been included in the estimated model. Overall, approximately 90k time-specific trips were fetched using the TripGo API, based on the trips identified over the 2012–2016 period.

To ensure that the data set is up-to-date, only the trips and tours made in the 2014–2016 period have been included in the data set used for this paper. In total, 26,296 unique tours were identified from the travel diaries provided in the VISTA within this 2014–2016 period.

As links, in the proposed transformation networks, are generated based on modal availability inferred from the tour dynamics – and not from the availability of modes determined by the characteristics of the trip or chooser – a large number of tours have been excluded from the estimation data set. In total 8728 of the 26,296 tours identified have been retained, with the primary reason for the emancipation of tours being the lack of trip information provided by the TripGo API. Additionally, whilst motorcycle mode information is provided by the TripGo API, travel time data pertaining to car driver, motorcycle and car passenger have all been assumed to be equal. Tours with trip chains that are deemed nonviable under link creation rules in network transformation were also removed. The exclusion was also applied to tours which did not have a starting and ending point at the same location, and tours which exceeded a period of 24 h.

4.2. Model estimation

A subset of the tours generated from the VISTA data set have been used with the proposed network choice structure and estimated using the recursive logit model. In total, 1000 out of 8841 available tours have been randomly sampled to generate the estimation set and an extra 200 tours were sampled for out-of-sample validation. As the motorcycle mode naturally occurs at a lower frequency to other modes (not at all in the validation set), the proportion of tours wherein motorcycle has been chosen was matched to the proportion seen in the complete data set. This has had the benefit of improving optimised results while maintaining the inherent propensity for individuals to utilise this mode, in the VISTA data set (see Table 3).

Fig. 7 shows the distribution of each unique, non-sequential combinations of modes used. As can be seen, in the randomly sampled tour set, the majority of tours consist of single mode transport usage. As expected, car driver has a relatively low proportion of multi-modal choices in tours, while car passenger and transit show relatively high multi-modal choices. In this example, we consider a trip between two destinations to be inclusive of any transfers made (linked trips). For example, in Fig. 7 transit shows a relatively high proportion of tours where transit is the sole mode used however, transit is often compounded with walking for purposes such as transfers and short trips to destinations in a tour. As such, public modes such as transit, wherein the individual's trip is compounded into a series of transfers, may introduce inaccuracies into the data. Whilst VISTA provides a higher degree of trip descriptiveness in the stop-level data set, in many cases location information is not accurate enough to approximate unique trip starting and ending locations.

4.3. Results and discussion

In this section, the model specified in Section 4.2 has been estimated using the estimation procedure detailed in Section 3.4. The model has been estimated with 44 utility parameters and achieved a McFadden rho-square value of 0.335. The mode choice simplifications specified in Table 2 have been used in the network assembly with the final results displayed in Table 5.

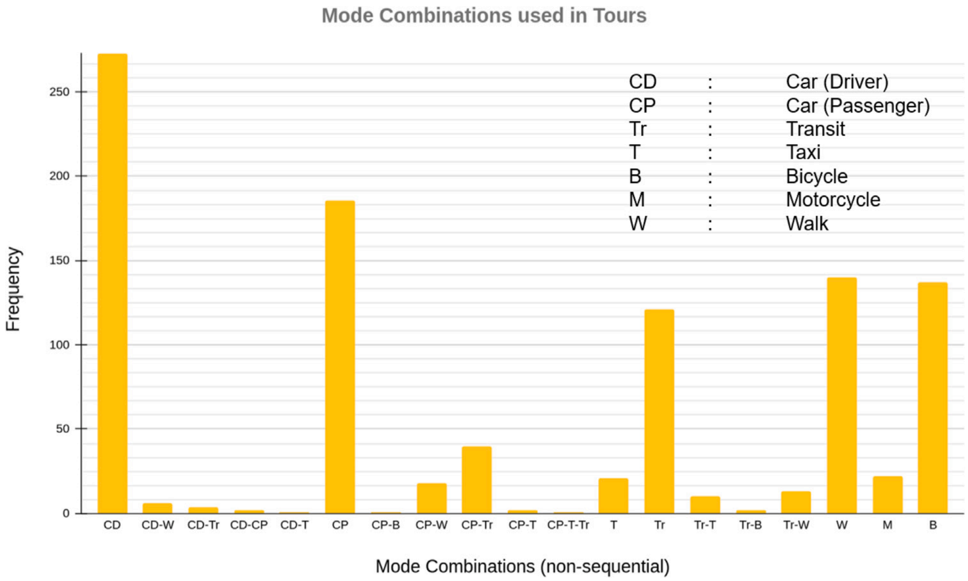


Fig. 7. Frequency of mode utilisation in example tour-set.

Table 4 shows the estimation results for the fitted model. Goodness-of-fit has been calculated by estimating the model log-likelihood with ASC's only, and compared with the model estimated with all 44 mode specific utility parameters. This models achieved a McFadden goodness-of-fit equal to 0.335.

The estimated node coefficient in Table 5 is the forward-looking coefficient, placed on the $u(m)_{k,i+1}$ term in Eq. (5). The idea behind the estimation of the forward looking coefficient is to quantify the validity of tour level effects on mode choices. In recursive logit application to path choice modelling, Fosgerau et al. use a node coefficient equal to 1, carrying downstream path utilities directly to upstream link choices. On the other hand, the majority of research in dynamic programming use diminishing coefficients ($0 < \Gamma < 1$) assuming that the future rewards/utilities should be discounted because of uncertainties involved in dynamic process outcomes. In our model, however, we allow the estimation procedure to evaluate the node coefficient as a measure of forward-looking considerations.

The calculated node coefficient of 1.31 implies that future utilities carry slightly more weight than current link utilities. While this might initially seem contrary to conventional dynamic discrete choice models, it presents an intriguing and enlightening perspective. It could point towards characteristics such as risk aversion and forward-thinking decision-making in the context of observed tour mode choices. In essence, our data indicates that travellers are inclined to place more emphasis on planning for their return trips, which is a rational behaviour in the context of daily mode selection. For instance, if a traveller anticipates post-work shopping plans, expects fatigue after an active day, or simply envisions a late-night return home, they may proactively make choices earlier in the day to allow for greater flexibility towards the end of their daily tours. To investigate the heterogeneity of this behaviour among different demographics. We developed and investigated different models and segmentations. We observed a significant difference among working-age (18–65 years) vs non-working age groups (below 18 or above 65 years) in their forward-looking behaviour. We conducted bootstrapping (30 iterations) to test for stability and significance of these findings. We realised that node-coefficient for working-age group is significant at value of 1.47, and for non-working group it is not statistically different from 1. This is an interesting observation and indicates that the population in the workforce have a very strong forward-looking behaviour and in-fact they value future utilities (perhaps for trips after work or errands on return trip) much more heavily than immediate options, whereas the rest of population have a uniform utility perception for future and immediate choices.

The estimated log-likelihood value for the baseline model represents the log-likelihood calculated when the model is optimised with the forward-looking coefficient (node coefficient) set to zero. This configuration resembles an MNL model with a choice set restricted for non-viable trip sequences, but without forward-looking utilities. It should also be noted that for the ASC-only model, the node coefficient is set to 1 indicating equal weighting to present and the logsum of future mode choice decisions.

Table 5 presents the parameter estimates of the recursive logit model. This is contrasted with the MNL model where node coefficients are disabled (set to zero), providing a baseline for the analysis in Section 4.4. This model has been estimated using the same methodology as presented in Section 3.4, as well as the same optimiser.

The proposed network RL model demonstrates a significant performance advantage over the baseline model (with a node coefficient set to zero) in terms of model goodness-of-fit, with rho-square values of 0.335 compared to 0.319. In the results of this case study, the majority of estimated parameters were found to be statistically significant at a 0.95 confidence level through bootstrapping. However, some exceptions include the coefficients related to ASC coefficients for bicycle, taxi and tram. When setting ASC for car driver to zero, for other modes outstanding values are large negative ASC for motorcycles (−15.669) and large positive ASC value for walking (4.880).

Table 5
Model results.

Parameter	Recursive logit				MNL choice set restricted[a]	Bootstrapping averages
Car	β	S.E	t-stat	p-value	β	β
ASC	0[b]	–	–	–	–	–
Travel time (minutes)	−0.051	0.002	−25.500	0.000	−0.050	−0.054
Number of cars owned (household)	0.323	0.015	21.533	0.000	0.385	0.315
Licence owned	2.875	0.518	5.550	0.000	3.052	3.510
Trip purpose (education or work)	−2.478	0.133	−18.632	0.000	−2.939	−1.863
Trip purpose (social or recreational)	−6.274	0.145	−43.269	0.000	−0.817	−0.701
Trip purpose (temporary)	−0.405	0.041	−9.878	0.000	−0.412	−0.406
Car deposit coefficient	−0.727	0.018	−40.389	0.000	−0.068	−0.707
Motorcycle						
ASC	−15.669	0.523	−29.960	0.000	−16.527	−15.697
Travel time (minutes)	−0.050	0.006	−8.333	0.000	−0.044	−0.059
Number of motorcycles owned (household)	2.052	0.206	9.961	0.000	2.674	2.495
Trip purpose (education or work)	−1.547	0.760	2.036	0.020	−1.133	0.897
Trip purpose (social or recreational)	−6.217	0.686	9.063	0.000	−0.251	1.349
Licence owned	17.463	0.437	39.961	0.000	17.501	15.460
Deposit coefficient	−0.987	0.134	−7.361	0.000	−0.004	−1.374
Bicycle						
ASC	−0.307	0.953	−0.322	0.373	−0.297	−0.389
Travel time (minutes)	−0.038	0.002	−19.021	0.000	−0.039	−0.041
Number of bicycles owned (household)	0.315	0.010	31.549	0.000	0.384	0.331
Trip purpose (education or work)	−0.230	0.133	−1.729	0.041	−0.535	0.472
Trip purpose (social or recreational)	−3.605	0.154	23.435	0.000	2.007	2.050
Deposit coefficient	−0.096	0.014	−6.855	0.000	0.211	−0.085
Car passenger						
ASC	1.934	0.979	1.973	0.020	2.149	1.881
Travel time (minutes)	−0.056	0.002	−28.356	0.000	−0.059	−0.059
Number of cars owned (household)	0.292	0.020	14.576	0.000	0.290	0.297
Has licence	0.943	0.102	9.249	0.000	0.958	0.987
Trip purpose (education or work)	−3.549	0.129	−27.552	0.000	−3.907	−2.955
Trip purpose (social or recreational)	−6.193	0.139	−44.557	0.000	−0.714	−0.651
Taxi						
ASC	1.467	0.927	1.582	0.056	1.720	1.402
Travel time (minutes)	−0.101	0.004	−25.280	0.000	−0.104	−0.103
Trip purpose (education or work)	−1.889	0.146	−12.973	0.000	−2.258	−1.062
Trip purpose (social or recreational)	−4.407	0.153	28.838	0.000	1.079	1.152
Transit						
ASC	1.739	0.844	−2.064	0.019	1.929	−1.041
Travel time (minutes)	−0.021	0.001	−21.237	0.000	−0.022	−0.023
Transfer wait time (minutes)	−0.040	0.006	−6.677	0.000	−0.040	−0.053
Train main mode (by time)	0	–	–	–	–	2.712
Tram main mode (by time)	−0.309	0.209	1.478	0.069	−0.307	2.476
Bus main mode (by time)	−1.017	0.193	5.265	0.000	−1.012	1.766
Trip purpose (education or work)	−0.647	0.153	4.216	0.000	−0.990	0.033
Trip purpose (social or recreational)	−5.286	0.161	32.229	0.000	0.183	0.360
Walking						
ASC	4.880	0.950	5.137	0.000	5.067	4.878
Travel time (minutes)	−0.058	0.001	−58.012	0.000	−0.059	−0.061
Trip purpose (education or work)	−0.623	0.126	−4.939	0.000	−1.583	−0.496
Trip purpose (social or recreational)	1.431	0.144	9.933	0.000	0.890	1.027
Node coefficient γ (for All Modes)	1.307	0.020	65.345	0.000	0.000	1.279

[a] MNL model with choice set restriction through network transformation (model 2 in Section 4.4).
[b] Set to zero to provide a baseline.

Travel time coefficients were negative and significant for all modes of transport included in the model. The travel time coefficients for car driver (−0.051) and motorcycle (−0.050) were approximately equal, which matches our expectations as both modes of transport have similar qualities in that, individuals are only able to focus on the task of driving when utilising these modes. Conversely, transit (−0.021) showed the lowest, negative utility per minute of travel time, with respect to set of mode choices. Again, this is inline with our expectations as the characteristics of transit allow an individual to partake in alternative activities

Table 6
Model accuracy comparison.

Model	Accuracy	Accuracy difference	Adj. Rho square
(1) MNL	56.65%	−8.12%	0.29
(2) MNL + restricted choice set	39.79%	−24.95%	0.314
(3) RL + network transformation	64.74%	–	0.334

whilst utilising the mode e.g. reading a book, answering emails. Transit has an additional travel time coefficient derived from the estimated waiting times present in the data fetched from the TripGo API. As expected, this value (−0.040) is greater than the travel time but lower than the travel time coefficients of private vehicle modes, car driver and motorcycle. One possible reason for this is that individuals are not required to focus on travel during this time, or may in fact factor this into their mode choice decisions ahead of time. The travel time coefficient for the taxi mode (−0.101) is the largest of the mode choice set. This is likely due to the lack of missing fare data, therefore the coefficient may serve the dual purpose of accounting for the unit of travel time and the cost per unit time as fares usually scale with the duration of travel.

The coefficients for car deposit, motorcycle deposit, and cycling deposit all exhibited significant and negative values. These findings suggest that there is a disincentive to initially opt for private vehicle modes for the first leg of a tour. Conversely, these modes offer a proportionate incentive to be used again when returning to the starting point, thereby favouring the continued use of the same private vehicle mode.

We hypothesise that the estimated deposit coefficient for cycling, which stands at −0.096, indicates a difference compared to car (−0.727) and motorcycle (−0.987). In the case of cycling, ownership can be maintained while utilising public/walk modes, such as bringing the bicycle onto a train, as well as other private vehicle modes like a car.

Trip purpose coefficients have been included specific to all modes in the model. The number of coefficients is not exhaustive of all trip purposes given in the VISTA data set, however education/work and social/recreational accounts for the majority of all trip purposes identified. All trip purpose coefficients included in the model have statistical significance at a 0.95 level of confidence, with walk mode displaying the highest utility for social/recreational trips (1.431), and bicycle (−0.230), walk (−0.623) and transit (−0.647) highest for educational/work trips.

An important observation in this model is that private Car mode (and motorcycle) displays the highest negative coefficients for education/work (−2.478) and social/recreational (−6.274) trip purposes, indicating a negative likelihood for driving to such destination, when compared to shopping and pick-up/drop-off trips (coefficient zero). Especially, given the fact that the proposed network model does rules out the effects of forward looking considerations, trip purpose coefficients and their effect on mode preferences are much more reliable because they are measures for the specific trip with forward looking considerations ruled out by the proposed network structure.

4.4. Model validation

In this section, the proposed network transformation and DDCM approach used for model estimation is compared with a standard MNL model and an MNL model with the choice set restricted by the network transformation. This comparison is conducted using simulation on 200 randomly sampled tours from VISTA dataset. In this section, we also report results of an analysis of individual tours to demonstrate model advantages in understanding complex mode choice considerations.

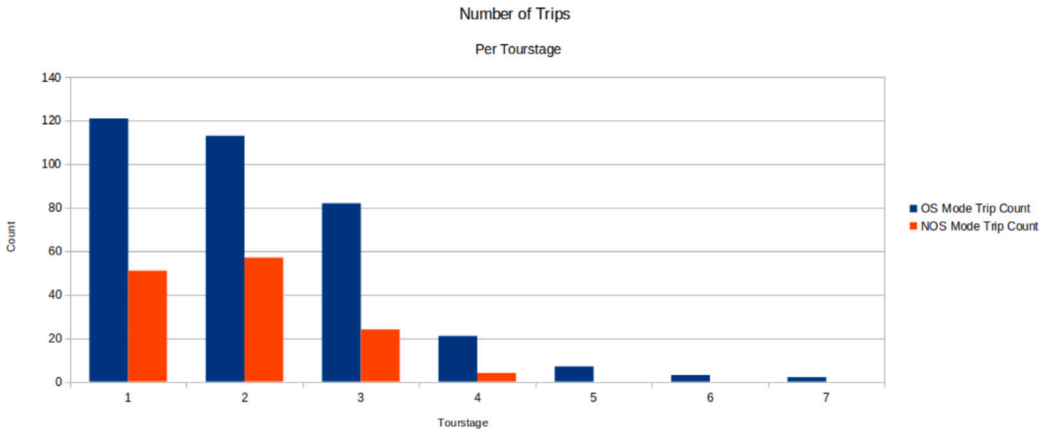
Model validation is conducted using the same randomly selected 1000 tours and with an out-of-sample dataset including 200 randomly selected tours, using three different models. These three models are:

1. MNL computed in Biogeme,
2. MNL with choice set restricted using proposed network transformation (but without forward looking component),
3. RL using network transformation proposed in this paper.

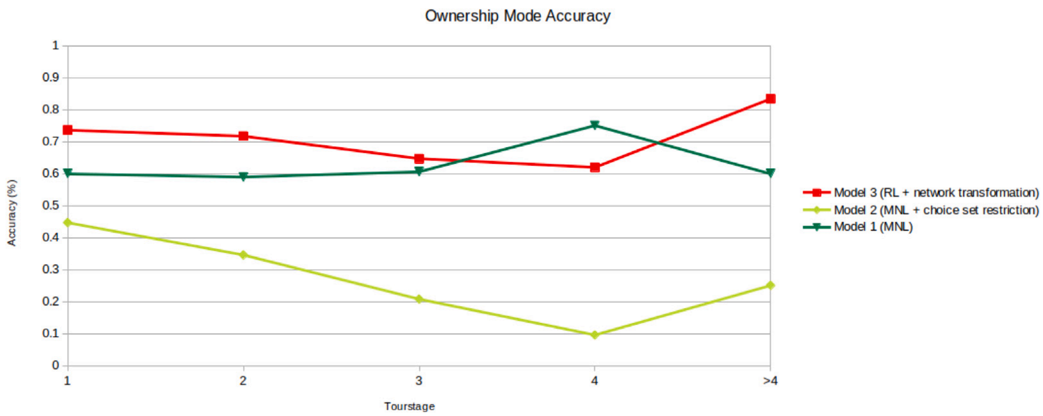
The simulation procedure involves estimating utility parameters using 1000 tours for each of the models and simulating the model predictions using the 200 tour validation set. For the proposed model (3) and model 2, the parameters shown in Table 5 were used. For model 2, node coefficient values are equated to zero but the network transformation was used to apply the choice set restrictions, akin to model proposed method. The standard model (1) was estimated in Biogeme using the same data set as models 2 and 3. Note that the same coefficients were used uniformly throughout all models with the exception of the node coefficient, which was not included on models 1 and 2, and the deposit coefficients were not included in model 1 (see Table 6).

In the validation data set, the observed private vehicle modes were car driver and bicycle (the random sample did not include motorcycle trips), and the public/walk modes observed were car passenger, walking and pubic transit. Fig. 8 shows accuracy results for all three modes, grouped by tour stage. For private vehicle mode trips, the proposed model showed the highest accuracy of prediction occurring at the first, second and third stages and for trips whose tour stage was greater than 4. However, when compared to model 2, showed slightly worse accuracy in predicting public/walk mode trips.

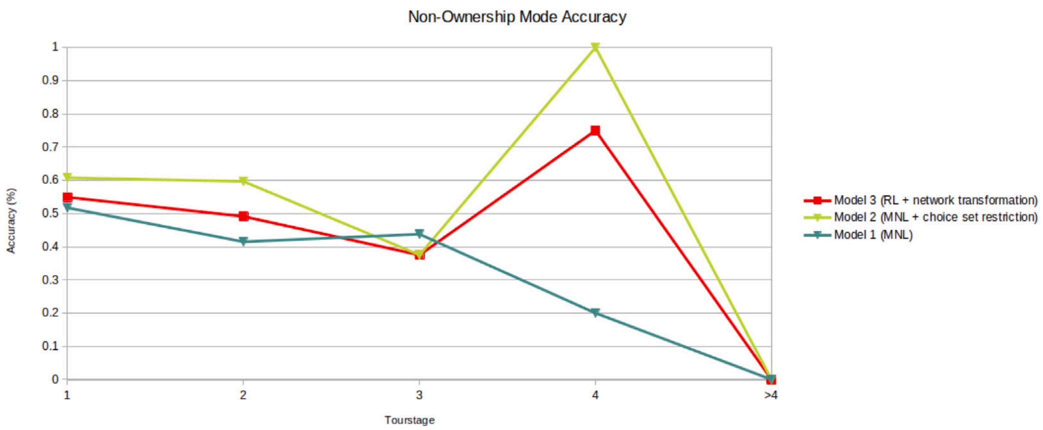
Model 2 shows significantly lower accuracy for private vehicle modes. This is likely due to the choice set restriction and highlights the requirement of the forward looking component to complement the network transformation. As the network transformation does not allow for private vehicle modes to be used once a public/walk mode is used in a tour, an incorrect simulated choice of a



(a) Number of trips per tour stage



(b) OS Mode Comparison



(c) NOS Mode Comparison

Fig. 8. Model accuracy comparison by tour stage.

public/walk mode can result in a large number of subsequent incorrect choices made by the model (prohibiting private modes). Additionally, the forward looking component is not included to incentive the utility of private vehicle modes from downstream links, resulting in a lower utility for private vehicle modes at the initial tour stages.

Overall, model 3 (proposed) showed the highest accuracy and model fit and highlights the value in including proposed transformation and forward looking components. This model could be further improved by utilising more network specific constants and providing a more detailed model specification, as highlighted in Section 5.

5. Discussions and conclusions

Tour-based mode choice modelling provides a more comprehensive and precise understanding of travel behaviour by considering the sequence of trips made by an individual. This approach helps capture the interactions and dependencies between different trips, which trip-based models may overlook. Tour-based models are often more suitable for analysing the effects of policy interventions like congestion pricing, transit investments, or urban planning changes, as they can better represent the cascading effects of such policies across multiple trips. Therefore, accurately formulating tour-based mode choice problems is of utmost importance. For example, consider a policy intervention like congestion pricing for inbound trips to a city centre. A trip-based model might evaluate the immediate impact of congestion pricing on a single trip to the city centre. However, a tour-based model can provide a deeper analysis by considering the entire sequence of trips an individual makes throughout the day and within the city. This provides a more accurate prediction of how congestion pricing can influence overall travel behaviour and mode choices, and possibilities to fail as a result of hidden factors and tour-based relationships. Another example is the impact of new transit investments. A trip-based model might simply assess how a new subway line affects travel time for a single inbound journey. In contrast, a tour-based model can evaluate how the new line influences an individual's entire travel modes. It can capture the decision to use the subway for multiple trips within a day, potentially reducing reliance on personal vehicles and thereby impacting overall traffic patterns and emissions. Urban planning projects, such as the development of a new residential area with mixed-use facilities, also benefit from tour-based modelling. A trip-based model may underestimate the change in travel patterns for commuting and sub-tour trips. However, a tour-based model can assess how the new development affects daily travel routines, including shopping, dining, and recreational trips. This helps planners understand how the new area integrates with existing urban infrastructure and supports the goal of reducing travel times and promoting sustainable transport modes. Moreover, tour-based models are most crucial for understanding the implications of emerging mobility services like ride-sharing and MaaS. A proper tour-based approach can provide insights into how individuals might integrate MaaS into their daily travel plans and how that may have extended effects of mode choice throughout the day. This also extends to considering the availability of ride-sharing options for different trip segments and their influence on the choice to use personal vehicles, public transport, or active modes like walking and cycling.

This study advances the formulation of tour-based mode choice problems through a novel network transformation based on the recursive logit model presented in Fosgerau et al. (2013). An innovative approach based on the DDCM technique is proposed and designed to model travel mode choices by taking into account tour-level considerations, utilities, and limitations. Our methodology addresses the sequential trip mode choice decisions by employing a transformation network that encompasses the entire decision space, offering viable modal sequences for each observed tour in the dataset. We apply the recursive logit model in conjunction with a maximum likelihood estimation procedure to estimate utility parameters and assess the influence of forward-looking considerations.

The model developed in this study is applied to an extensive dataset sourced from the household travel survey (VISTA dataset) conducted within the Melbourne metropolitan area of Australia. The estimation process yields commendable goodness-of-fit measures, and the derived parameter values exhibit intuitive and insightful estimates. By applying the model to the VISTA dataset and conducting additional analyses on the outputs, we have derived several valuable insights.

We observed car drivers have a very strong tendency to use single modes for entire sequence of trips, this observation was made based on a high and significant parameter estimated for "car deposit parameter". However, car passengers and transit users often make multi-modal choices. Even though transit may seem like the sole mode in some cases, it is frequently combined with walking for transfers and short trips within a tour. Our findings reveal that travellers exhibit a tendency to focus on planning the return portions of their tour trips, indicating a rational approach to mode selection within the context of these daily tours. This emphasis on return planning may suggest characteristics like risk aversion and forward-thinking decision-making. For instance, when a traveller anticipates post-work shopping, expects fatigue after a busy day, or envisions a late-night return home, they are more likely to make strategic choices earlier in the day regarding the sequence of transportation modes within their daily tours. Travel time in the model was negative and significant for all modes, with car driver and motorcycle having similar coefficients, while transit had the lowest negative utility per minute. This aligns with expectations, as private vehicle modes require the traveller's full attention, whereas transit allows for multitasking. Including trip purpose coefficients in the model provides valuable insights. Walk mode is preferred for social/recreational trips, while bicycle, walk, and transit are favoured for educational/work trips. Notably, private car mode exhibits a strong aversion for both trip purposes, highlighting the importance of trip purpose in tour-based mode choice.

There is room for enhancement in the proposed model and the accuracy of tour-based mode choice analysis. Potential avenues for future research in this domain include the following:

- Enhancing Computational Efficiency: The computational efficiency of the model can be optimised through the adoption of the decomposition method (DeC), as developed by Mai, Bastin, et al. in 2018. Additionally, implementing the network generation and estimation in a high-efficiency programming language such as C++ (in contrast to Python) can yield significant improvements. This would effectively address a critical shortcoming in model estimation, notably the computational bottleneck associated with network updates during each optimiser increment.

- Expanding Model Scope: To further enhance the insights gained from tour-level mode choice modelling, future research can explore the estimation of larger models. These expanded models should encompass a greater number of link-specific coefficients, thus fully leveraging the capabilities of the tour choice network transformation. This expansion would contribute to a more comprehensive understanding of the various factors that influence tour-level mode choice decisions. Utilising Richer Data for

- Improved Trip Descriptions: While VISTA offers a greater level of trip detail within its stop-level dataset, there are often challenges associated with the accuracy of location information, making it difficult to precisely estimate unique trip origins and destinations. There would be an opportunity to enhance location accuracy by exploring innovative methods or technologies such as the integration of GPS data, machine learning algorithms, or other geospatial techniques, to more precisely identify unique trip origins and destinations based on the available stop-level information. This would contribute to the refinement of trip descriptions and facilitate more robust analysis and modelling of travel behaviour.
- As a complex relationship exists in between link alternatives where natural nesting occurs in private vehicle modes, or links may overlap among paths in network transformation, the utilisation of the nested (Mai et al., 2015) or mixed (Zimmermann et al., 2018) recursive logit models would help to address issues inherent in the MNL model used in the presented model and aiding in the interpret ability of coefficient estimates produced by the model.

CRediT authorship contribution statement

Joseph Leong: Data curation, Formal analysis, Investigation, Methodology, Software, Writing – original draft. **Neema Nassir:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing. **Seyed Sina Mohri:** Formal analysis, Investigation, Writing – review & editing. **Majid Sarvi:** Formal analysis, Resources, Writing – review & editing.

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