Activity-travel pattern choice modeling within space-time prisms

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SHORT SUMMARY

Route choice set generation and route choice modeling have been studied for years, but most focus on the trip level and rarely address activity-travel patterns (ATPs) in activity-based scheduling frameworks. This study proposes an integrated framework to generate ATP choice sets under space-time constraints and model ATP choices while considering overlapping among alternatives. The model framework generates ATP choice sets with flexible activity sequences using a link penalty approach and defined ATP utility functions of MNL and MNL-modification models to account for the spatial and temporal overlapping. Utilizing GPS trajectories, the simulation and estimation results of the ATP choice set generation and ATP choice modeling demonstrate the validity of the model framework. The ATP choice model comparison reveals the goodness-of-fit of capturing the correlations among the alternatives and individual heterogeneity.

Keywords: activity-travel patterns; multi-state supernetwork; space-time prism; choice set generation; discrete choice model

1. INTRODUCTION

Route choice behavior modeling is a fundamental issue in transportation research. The simplest route choice models assume travelers minimize a single criterion (e.g., travel time) with complete network knowledge, referred to as the "shortest path problem". To address the limitations of deterministic all-or-nothing assignment, stochastic assignment methods, mostly relying on the multinomial logit (MNL) model, were introduced to distribute travelers across a set of feasible routes with choice probabilities. Since the parameter estimation depends heavily on the choice set composition, most studies adopted an explicit path generation prior to model estimation, compared to the implicit method that simultaneously performs a choice-set generation and route choice computation (e.g., Dial 1971).

The existing route set generation approaches can be categorized into deterministic and stochastic methods based on the generation process and outputs. Deterministic methods use repeated shortest path searches for an OD pair, including K-shortest paths, labeled paths (Ben-Akiva et al. 1984), link elimination (Azevedo et al. 1993), and link penalty (Barra et al. 1993). Stochastic methods incorporate randomness into the generation process using techniques like Monte Carlo simulation that generate routes by sampling link attributes from probability distributions. Probabilistic methods further model how travelers form choice sets based on the paradigm proposed by Manski (1977), such as the Implicit Availability/Perception (IAP) model (Cascetta and Papola 2001). Furthermore, the quality of generated choice sets is crucial for model estimation, as large sets often include correlated routes. To address this, advanced models like MNL-modifications (e.g., C-Logit, Path-Size Logit, Path-Size Correction Logit) introduce correction terms to account for overlap among alternatives, while GEV models (e.g., Cross-Nested Logit) explicitly capture correlations through error term assumptions.

However, all these choice set generation methods and choice models are dominantly used at the trip level for routes and rarely applied in activity-based scheduling (ATS) for activity-travel pattern (ATP). For ATP choice set generation, Liao and van Wee (2016) used link elimination mechanisms to find K-shortest paths for activity programs (APs) under constraints. For ATP choice modeling, Västberg et al. (2019) proposed a nested-logit-type dynamic discrete choice model. Liao (2016) and MATSim (Feil et al. 2009) employ optimization models to identify the ATS for individuals with the lack of error terms, making the approach more suitable for recommendation system rather than for travel demand forecasting. Nevertheless, these methods have not considered ATP choice set generation under space-time constraints and ATP choice modeling accounting for correlations among alternatives.

Therefore, the aim of this study is to propose a model framework of ATP choice set generation within STP and ATP choice modeling. A comparison analysis is conducted to examine the goodness-of-fit of ATP choice models with different correction terms to capture the effects of the overlapping among alternatives and individual heterogeneity. The remainder of the paper is organized as follows. Section 2 proposes the methods of ATP choice set generation and ATP choice modeling within space–time constraints. Section 3 validates the proposed framework using GPS trajectory data. The paper is completed with conclusions in Section 4.

2. METHODOLOGY

The methods involves three steps: (1) construct the activity-based space–time prism (STP) of an AP based on multi-state supernetworks (*SNK*); (2) generate ATP choice set for APs within the STP using a link penalty approach; (3) define ATP utility functions for MNL and the MNL-modifications with a correction term to account for overlapping in space and time. The framework is shown in Figure 1.

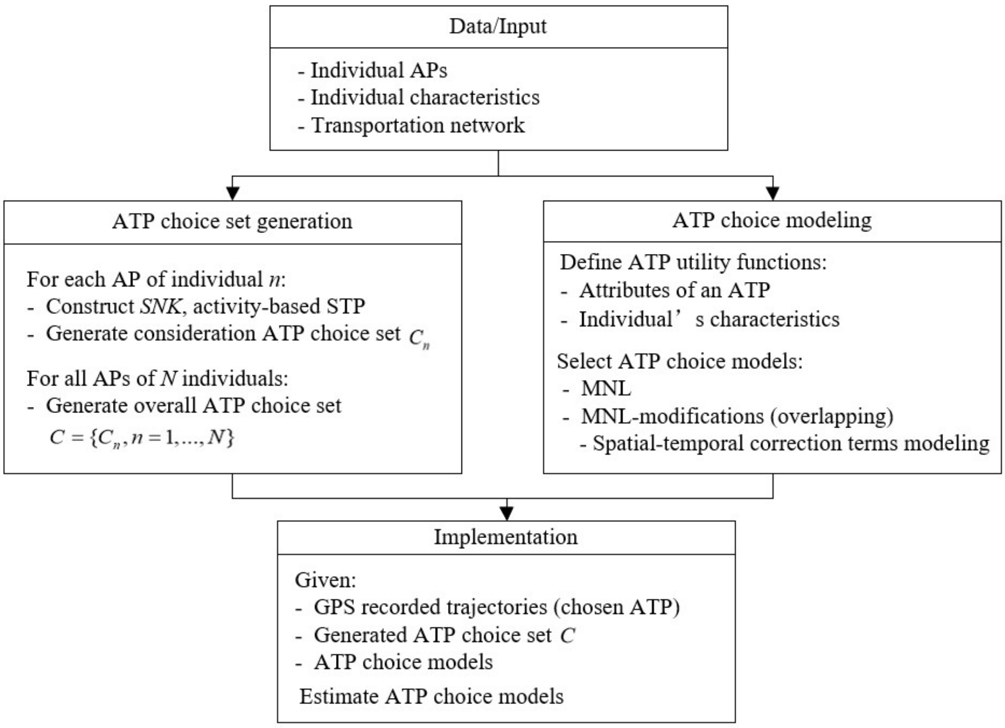


Figure 1. The framework of this study.

2.1 Multi-state supernetwork (SNK) and activity-based STP

Multi-state supernetworks are capable of representing the ATP space for conducting an individual's AP. A copy of the transportation network G is assigned to each possible activity state specifies which activities have been conducted. The link that interconnects the same activity location at two different reachable activity states is considered an "activity link", representing the participation of an activity at a location. Denote the multi-state supernetwork as $SNK(N, E)$, where node set N includes road intersections, activity locations, and parking locations, and link set E includes travel links of road segments and transaction links, a daily AP's implementation is a path choice through SNK. For example, the ATP in Figure 2 expressed by the interconnected bold links indicating that an individual leaves home (H_0) to conduct activity A_1 and then A_2 before returning home (H_1).

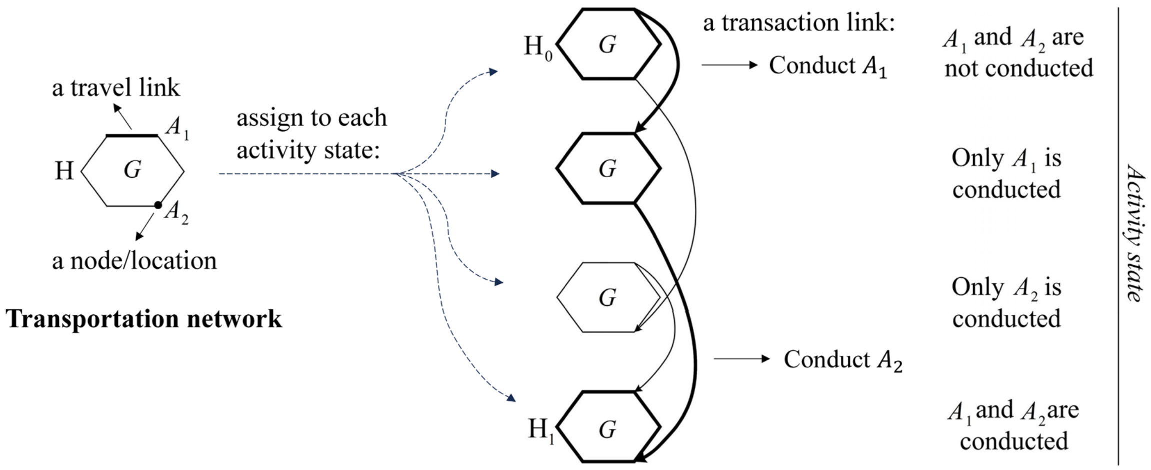


Figure 2. SNK representation with a single mode (travel links are bi-directed).

Suppose H_0 and H_1 are two anchors with the a time budget window $[t_{\mathrm{H}_0}, t_{\mathrm{H}_1}]$. An individual conducts activity α from an activity set A at one location with a minimum duration d_α. The temporal feasibility for a node in *SNK* in the STP and PPA is formulated as

$$\min\{g(\mathrm{H}_0, n|_s) + g(n|_s, \mathrm{H}_1)\} \leq t_{\mathrm{H}_1} - t_{\mathrm{H}_0} \tag{1}$$

where $n|_s$ denote node n at activity state s in *SNK*, $g(\mathrm{H}_0, n|_s)$ and $g(n|_s, \mathrm{H}_1)$ represent the actual activity-travel times of two sub-paths from H_0 to $n|_s$ and $n|_s$ to H_1, respectively. the exact STP all $n|_s \in SNK$ that satisfy Eq. (1) at time range $\left[t_{\mathrm{H}_0} + \min g(\mathrm{H}_0, n|_s), t_{\mathrm{H}_1} - \min g(n|_s, \mathrm{H}_1)\right]$.

2.2 ATP choice set generation within STP

Since travelers consider only attractive ATPs based on their preferences, a well-sampled consideration set should be priorly generated as a subset of the universal set. We apply the link penalty approach to generate a choice set of exact ATPs as the master (or consideration) set C_n of an AP based on the *SNK* within the STP, due to its advantages in efficiently generating diverse and attractive ATPs by applying constraints and adjustable penalty factors. The framework for generating an ATP choice set for a single AP is shown in Figure 3.

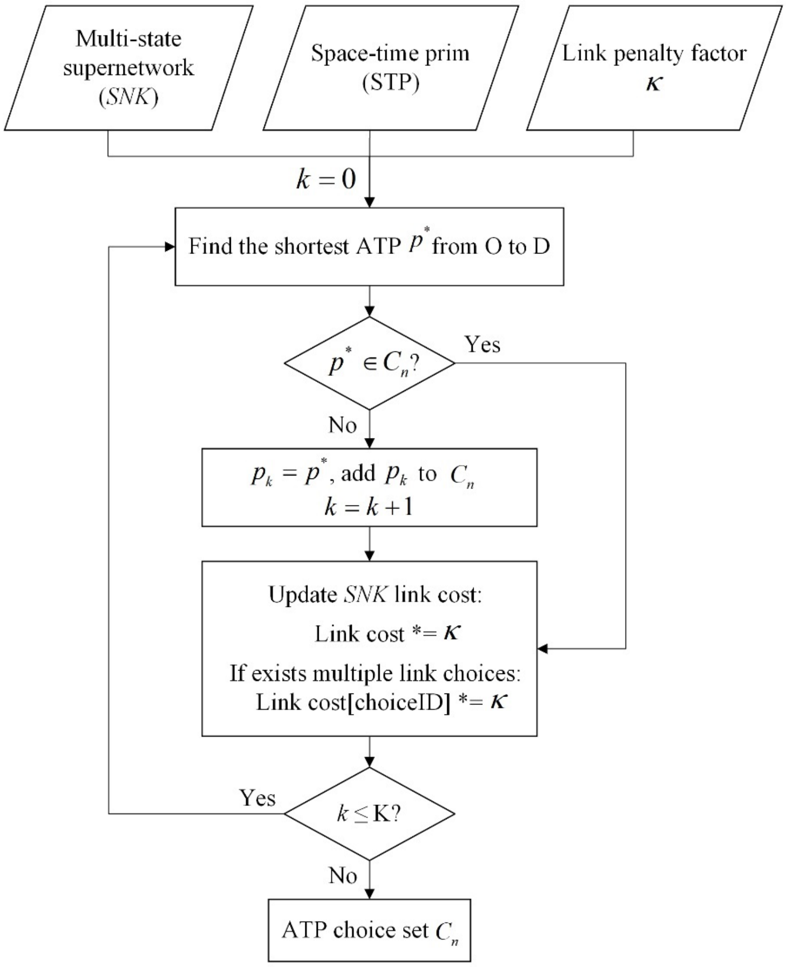


Figure 3. Framework of ATP choice set generation using link penalty method.

Algorithm 1: Link penalty approach of generating ATP choice set of all APs

Initialization: Load transportation network, pre-specify link penalty factor as κ, $|C_n| = 0$

For individual $n = 1,2, \dots, N$.

Step 1: Construnct *SNK* of individual n's AP; Construct activity-based STP.

Step 2: Find the first least dis-utility ATP p_1 of the AP using Dijkstra algorithm within the STP.

Step 3: **If** $p_1 \notin C_n$:

add p_1 to C_n, for $\forall l_{ij|ss'} \in p_1$, $disU(l_{ij|ss'}) =* \kappa$.

$k = k + 1$.

If $|C_n| = K$, add observed GPS ATP trajectory to C_n if not included, **return** C_n for n.

else:

$disU(l_{ij|ss'}) =* \kappa$ (simple way to continue penalizing the current ATP)

Step 4: If $n > N$, stop process. Choice sets of all APs are generated, $\mathcal{C} = \{C_n, n = 1, \dots, N\}$.

Specifically, we re-define the "link" from node $i|_s$ to node $j|_{s'}$ as $l_{ij|ss'} = (i|_s, j|_{s'})$ for $\forall s, s'$ in *SNK*. The time expense on the travel link ($i \neq j$, $s = s'$) and the activity link ($i = j$, $s \neq s'$) is travel time and activity duration d_α, respectively. When penalizing links on the current ATP, the disutility (i.e., time expense) on $l_{ij|ss'}$ is increased by multiplying the link penalty factor. To incorporate duration choice, multiple duration choices are considered and only the activity link with the chosen duration is penalized. For N individuals' APs, an overall ATP choice set is generated as $\mathcal{C} = \{C_n, n = 1, \dots, N\}$, following the pseudo-code described in Algorithm 1. Each C_n has the size of $K + 1$ if the observed chosen ATP is not replicated by generated ATPs, otherwise the size is K.

2.3 ATP choice modeling

MNL-modification models

The MNL can be applied to ATP choice due to its simplicity. ATP choice is sensitive not only to route travel time but also to activity duration and activity locations' attractiveness. Therefore, the deterministic utility functions can be formulated as

$$V_{kn} = \beta_{ASC} + \beta_{TT} \cdot TT_k + \beta_{\Delta D_{\alpha k}} \cdot \Delta D_{\alpha k} + \beta_{LA_{\alpha_m}} \cdot LA_{\alpha_m,k} \quad (2)$$

where β_{ASC} is the constant, TT_k is the total travel time on ATP k, $\Delta D_{\alpha k}$ is the deviation of the chosen duration $D_{\alpha k}$ for conducting activity α on ATP k from the individual's "ideal" duration $D^*_{\alpha k}$ to capture the disutility caused by deviations from the preferred duration:

$$\Delta D_{\alpha k} = |D_{\alpha k} - D^*_{\alpha k}| + \xi \quad (3)$$

where ξ is a random term to capture unobserved heterogeneity. $LA_{\alpha_m,k}$ is the attractiveness of location m for conducting α on ATP k. To incorporate the heterogeneity effects, individuals' socio-demographic variables can be added to Eq. (2).

To consider the correlations among alternatives, several MNL-modifications have been proposed to account for route overlap by adding a deterministic correction as follows

$$V_{kn} = f(\beta, X_{kn}) + \beta_\Delta \cdot g(\Delta_{kn}) \quad (4)$$

where $f(\beta, X_{kn})$ is system utility part representing alternative attributes and travelers' background; $g(\Delta_{kn})$ is a transformation of the overlapping correction term Δ_{kn} and β_Δ is the corresponding parameter to be estimated.

C-Logit Model

C-logit model is proposed as the modification of the MNL, in which a commonality factor CF_{kn} measures the degree or percentage of the route length that route k shares with other routes in the choice set C_n. We select the following formulation (Ramming 2001) to be examined:

$$CF_{kn} = \ln \sum_{a \in \Gamma_k} \left(\frac{L_a}{L_k} \sum_{l \in C_n} \delta_{al} \right)$$

where L_k, L_l, L_a are the length of route k and l, and link a, respectively. Γ_k is the set of links belonging to route k. δ_{al} is the link-path incidence variable, equal to 1 if route l uses links a and 0 otherwise. Since the "activity link" in *SNK* does not have spatial length, L_k, L_l, L_a are replaced with their link time expense T. The re-defined CF_{kn} is

$$CF_{kn} = \ln \sum_{a \in \Gamma_k} \left(\frac{T_a}{T_k} \sum_{l \in C_n} \delta_{al} \right) \quad (5)$$

The coefficient β_{CF} is typically negative because larger overlap makes a path less attractive.

Path Size Logit Model (PSL)

Ben-Akiva and Bierlaire (1999) presented the PSL model, in which the path size PS_{kn} accounts for the proportion of the path that does not overlap with others. This study applies the PS_{kn} formulation and similarly re-defined PS_{kn} using "link time length" as

$$PS_{kn} = \sum_{a \in \Gamma_k} \frac{T_a}{T_k} \left(\frac{1}{\sum_{l \in C_n} \delta_{al}} \right) \tag{6}$$

The coefficient β_{PS} is typically positive as greater uniqueness increases the attractiveness of the ATP.

Path Size Correction Logit (PSCL)

The path size correction PSC_{kn} weighs the length of the common links by the logarithm of the number of routes using these common links (Bovy et al. 2008). The re-defined PSC_{kn} is as follows

$$PSC_{kn} = -\sum_{a \in \Gamma_k} \left(\frac{T_a}{T_k} \ln \sum_{l \in C_n} \delta_{al} \right) \tag{7}$$

Similar to PSL, the coefficient β_{PSC} is typically positive.

Spatial-temporal correction term extensions

Previous correction terms focus only on the spatial level, we extend them to include temporal overlap, to account for the discounting effect when the spatially overlapped links are temporally distant in two ATPs. When link a is spatially overlapped by ATP k and l ($\delta_{ak} = \delta_{al} = 1$), a temporal overlap ratio r_{akl} and a temporal correction value ρ_{akl} are modeled. The spatial-temporal correction terms are obtained by multiplying ρ_{akl} as a temporal discount to the link-path incidence dummy, changing δ_{al} to $\delta_{al} \cdot \rho_{akl}$ in Eqs. (5-7), obtaining $CF_{kn,T}$, $PS_{kn,T}$ and $PSC_{kn,T}$:

$$CF_{kn,T} = ln \sum_{a \in \Gamma_k} \left(\frac{T_a}{T_k} \sum_{l \in C_n} \delta_{al} \cdot \rho_{alk} \right) \tag{8}$$

$$PS_{kn,T} = \sum_{a \in \Gamma_k} \frac{T_a}{T_k} \left(\frac{1}{\sum_{l \in C_n} \delta_{al} \cdot \rho_{alk}} \right) \tag{9}$$

$$PSC_{kn,T} = -\sum_{a \in \Gamma_k} \left(\frac{T_a}{T_k} \ln \sum_{l \in C_n} \delta_{al} \cdot \rho_{alk} \right) \tag{10}$$

Given no correction term and six correction terms of Eqs. (5-7) and Eqs. (8-10), seven ATP choice models are estimated:

1) MNL(no $g(\Delta_{kn})$)
2) C-logit ($g(\Delta_{kn}) = CF_{kn}$)
3) C-logit-T ($g(\Delta_{kn}) = CF_{kn,T}$)

4) PSL (PSL) ($g(\Delta_{kn}) = PS_{kn}$)
5) PSL-T ($g(\Delta_{kn}) = PS_{kn,T}$)
6) PSCL ($g(\Delta_{kn}) = PSC_{kn}$)
7) PSCL-T ($g(\Delta_{kn}) = PSC_{kn,T}$)

3. EXPERIMENTAL RESULTS

To illustrate the proposed framework, we consider the North-Brabant Province, the Netherlands as the experimental study area (Figure 4). 312 individuals' trajectories with working at a fixed workplace, shopping at a flexible location, and car as the transportation mode are extracted from a GPS dataset. Detailed settings are as follows.

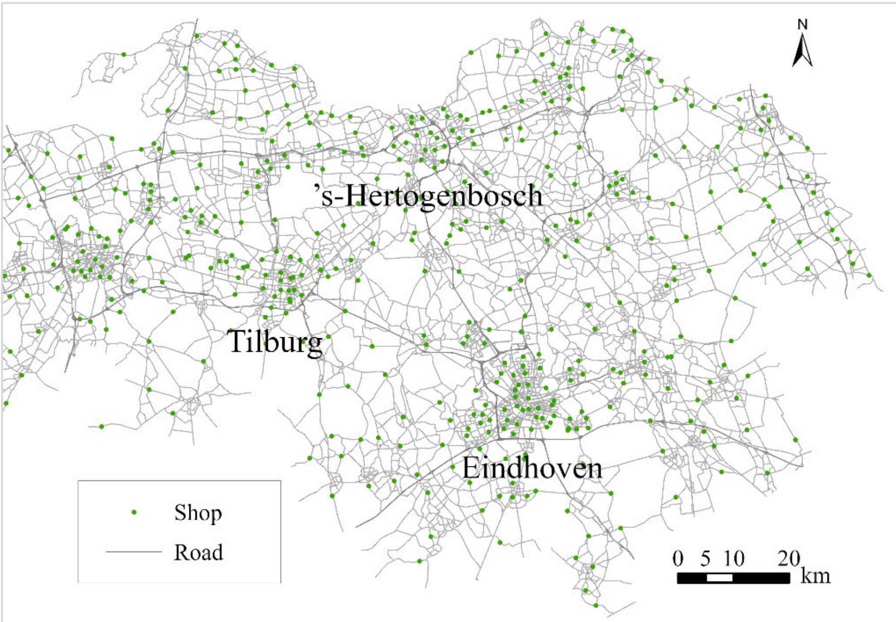


Figure 4. Study area and the transportation network.

1. The road network has 47,901 nodes and 100,581 directed links categorized into <motorways, provincial roads, local roads>. The maximum car speeds for peak hours ([7:00, 9:00] and [16:30, 19:00]) and non-peak hours are set to <70, 50, 30> and <100, 80, 50> km/h, respectively.

2. For constructing STP, the start time uses the AP's recorded departure time, and the time budget is set with a 20% extra over the out-of-home time expense in the GPS trajectory.

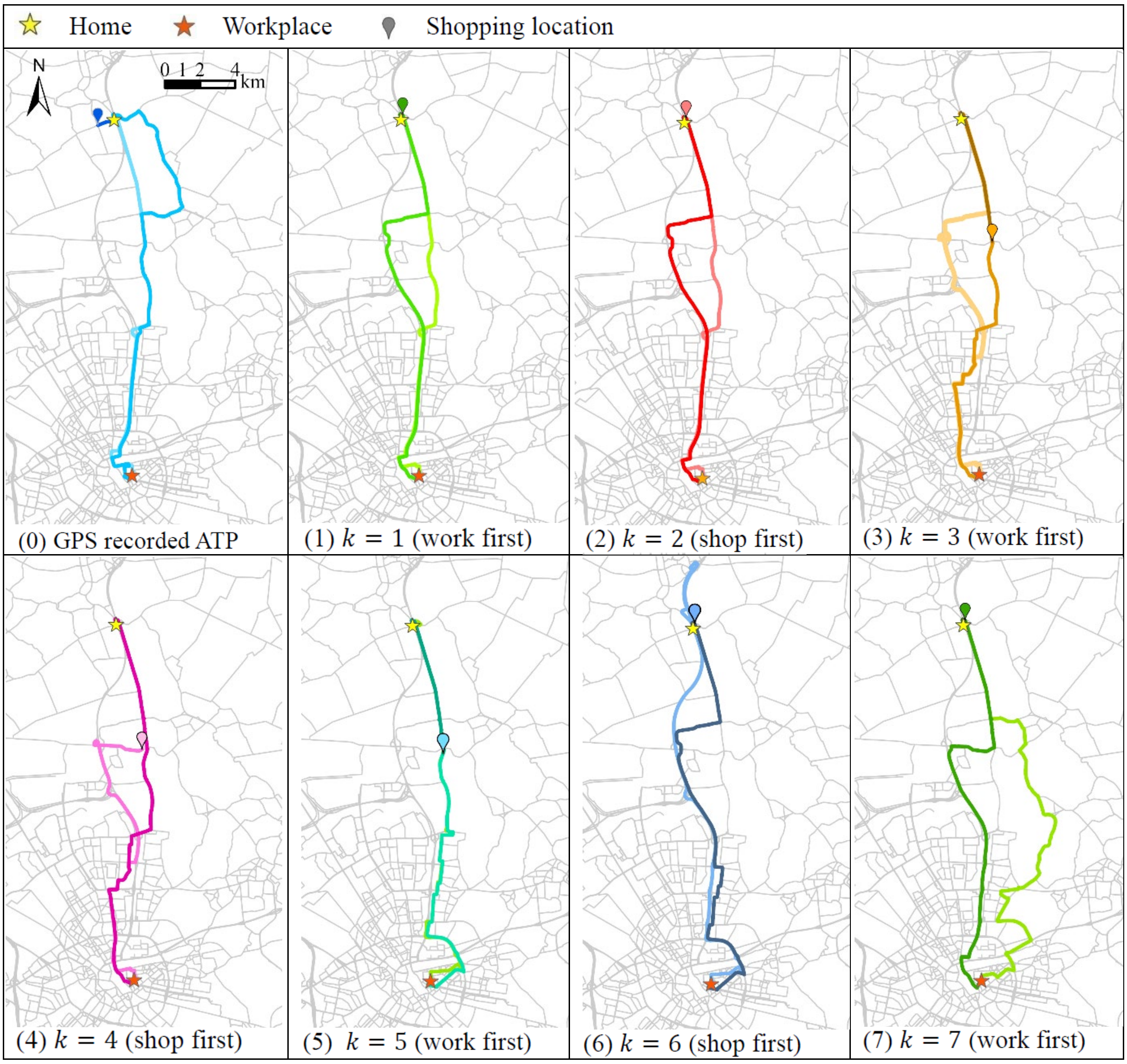
3. Alternative flexible activity locations consist of 518 locations selected from the OpenStreetMap for each 4-digit postcode area (PC4) and 312 locations recorded in the GPS trajectories.

4. For ATP utility functions, $D^*_{\alpha k}$ are extracted from GPS trajectories and $LA_{\alpha_m,k}$ is represented by the floor space of the PC4 (4-digit postcode area) where the location is situated. To account for the heterogeneity, individual n's gender and age are incorporated to Eq.(2) as the second utility function, where G_n and A_n represent the gender and age dummy variables, respectively. $G_n = 1$ if n is female given base level is male, $A_n = 1$ if n's age is $\leqslant$50 as young given base level is >50. Considering the interactive effects on travel time and location attractiveness, $\beta^{G_n}_{TT}$ and $\beta^{A_n}_{TT}$, $\beta^{G_n}_{LA}$ and $\beta^{A_n}_{LA}$ are the coefficients for the interactive effects of n being female and young on TT_k and $LA_{\alpha_m,k}$.

5. ATPs are generated with three duration choices: $D^*_{\alpha k}$, a 50% increase, and a 50% decrease.

3.1 ATP choice set generation results

Following the methods in Figure 2 and Algorithm 1, we generate the overall ATP choice set $\mathcal{C} = \{C_n, n = 1, \dots N\}$ for $N = 312$ individual APs, with pre-defined choice set size K and link penalty factor κ. The experiment tests $K = 5, 7, 10, 15$ with $\kappa = 1$, using a specific AP in Eindhoven area to illustrate the results in Figure 5. Sub-figure (0) is the GPS-recorded ATP (shop after work). Sub-figures (1−5) show the ATPs belonging to choice set C_n for $K = 5$. As K increases, more ATPs are generated by repeatly penalizing the links of previous-identified ATPs and are subsequently added to C_n. Sub-figures (1−7), (1−10), (1−15) illustrate the ATP choice sets for $K = 7, 10, 15$ respectively. Each ATP consists of 3 trips, illustrated by color gradients from light to dark.



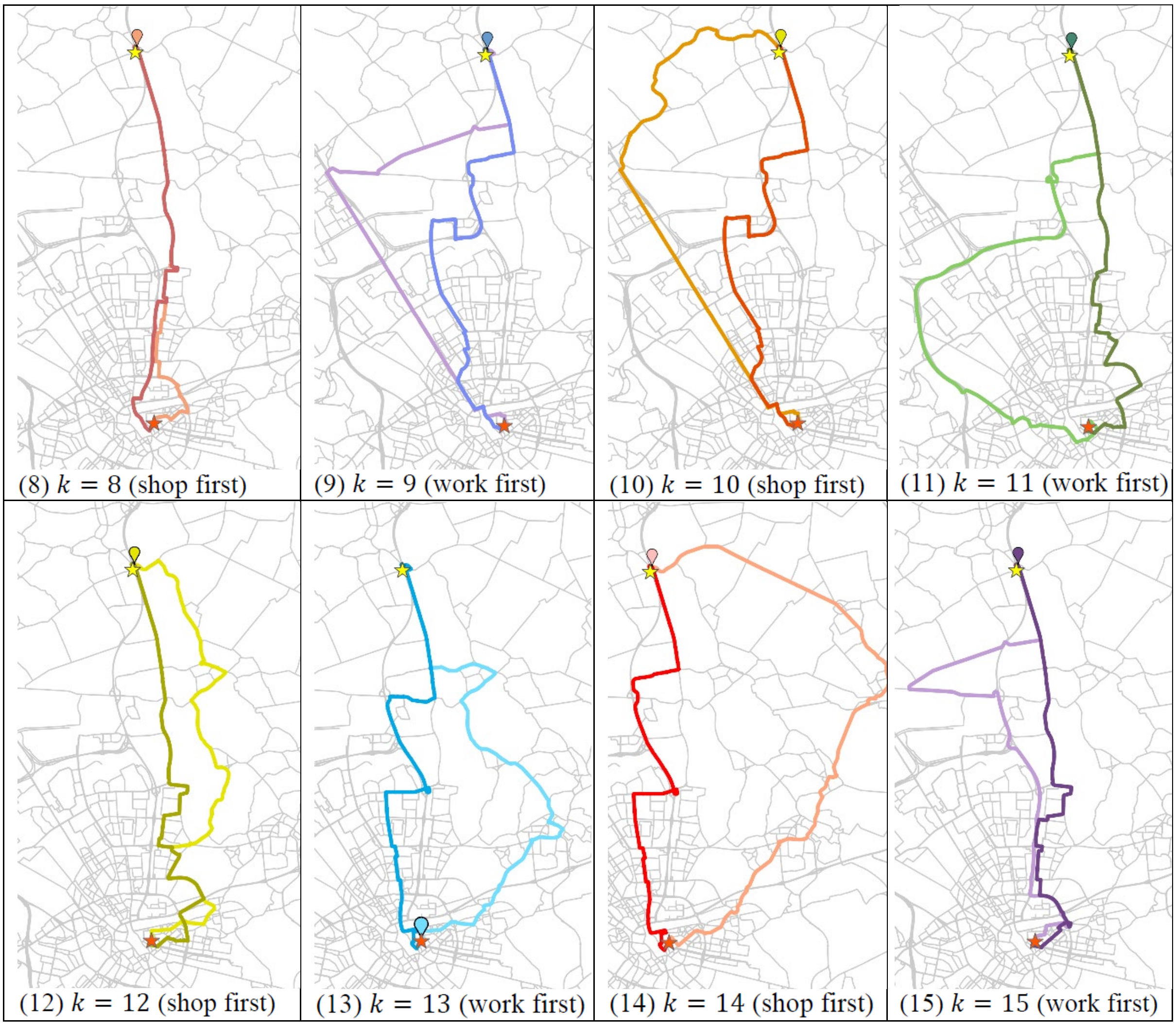


Figure 5. ATP choice set generation results of an AP with $K = 5, 7, 10, 15$.

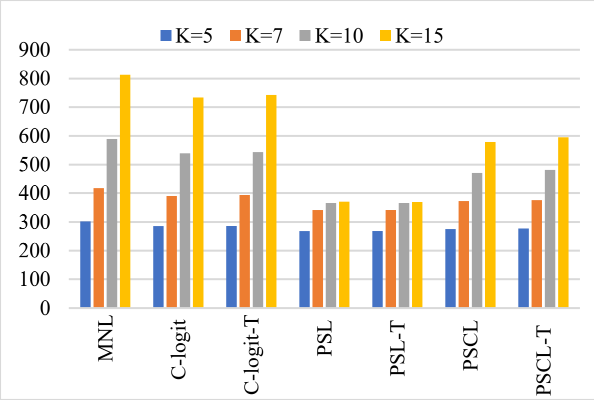
Unlike k-different route generation, the dissimilarity in ATP can be reflected in the variations of activity sequences and location choice, even with similar routes (i.e., (2–5) for $K = 5$). Table 1 shows the link penalty approach's effectiveness via overlapping percentages among alternatives. For travel links only, the percentage across different K ranges from 20%-25%. If activity links overlap (same locations and sequence) is also considered, the percentage ranges from 42%-43%. At $K = 10$, the whole ATP overlapping percentage reaches the minimum.

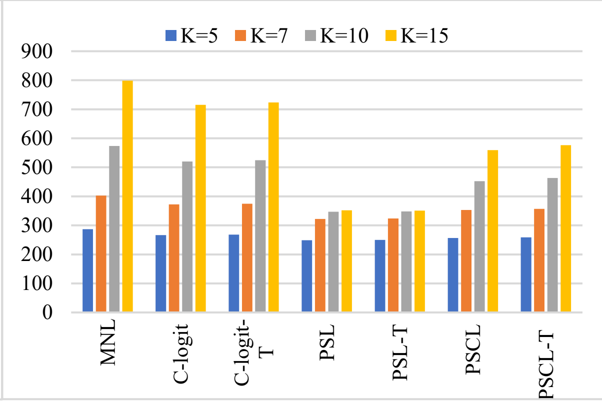
Table.1. ATP choice set overlapping percentages

Overlapping attributes	$K = 5$	$K = 7$	$K = 10$	$K = 15$
ATP travel time	24.05%	20.51%	21.78%	25.40%
Whole ATP (incl. $\sum_{\alpha \in A} d_\alpha$)	43.27%	43.14%	42.12%	43.95%

3.2 ATP choice model estimation results

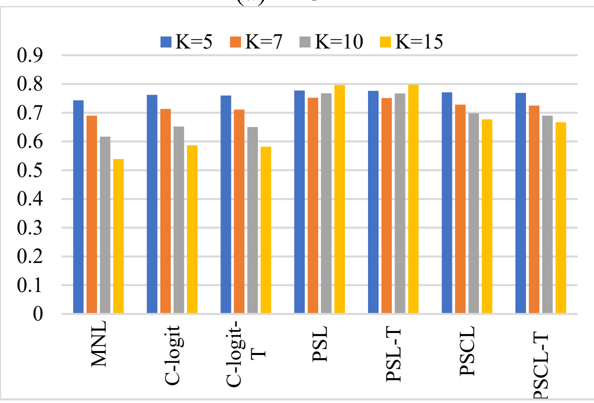
Given the results of $\mathcal{C}$, parameter estimation is conducted using Biogeme 3.2.13 (Python). Pre-estimation shows individual's gender has no significant effect on ATP choice, leading to modified utility functions V_{kn}^1 and V_{kn}^2 by removing the G_n-related terms. V_{kn}^1 follows Eq.(2) and V_{kn}^2 considers the interactive effect of age given $\left(\beta_{TT} + \beta_{TT}^{A_n} \cdot A_n\right)$ and $\left(\beta_{LA} + \beta_{LA}^{A_n} \cdot A_n\right)$ as the parameters of TT_k and $LA_{\alpha_m,k}$, respectively. Parameter $\lambda = 0.5$ in ρ_{akl} is set for $CF_{kn,T}$, $PS_{kn,T}$, and $PSC_{kn,T}$. Figures 6 and 7 present a comparison of the choice models' performance for different K based on statistics.

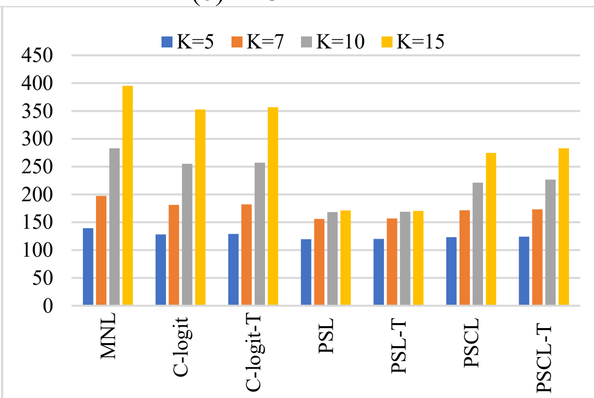




(a) BIC

(b) AIC

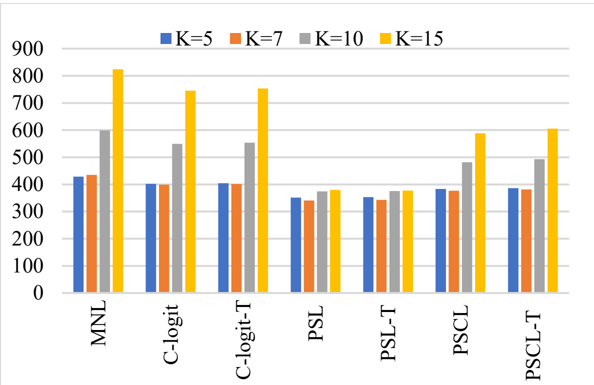


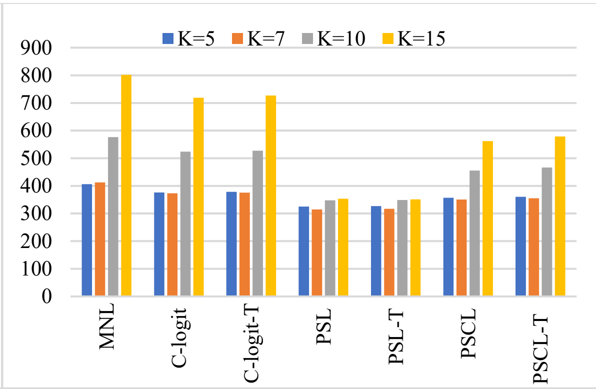


(c) $\overline{\rho}^2$

(d) -log-likelihood

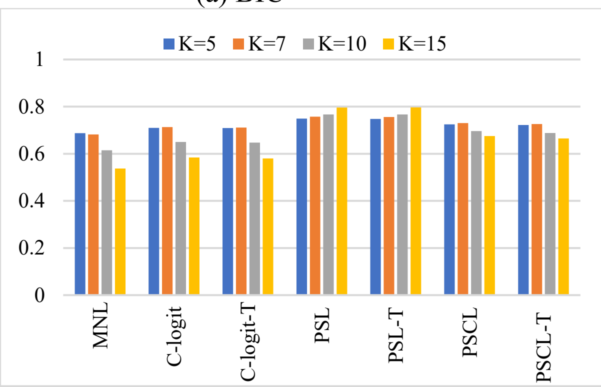
Figure 6. Models estimates – statistics (V_{kn}^1)

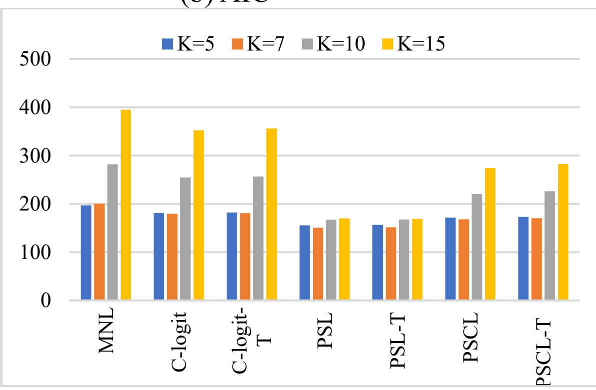




(a) BIC

(b) AIC





(c) $\overline{\rho}^2$

(d) -log-likelihood

Figure 7. Models estimates – statistics (V_{kn}^2)

The choice set size K should be pre-defined to own a better fit for explaining the ATP choice behavior. In Figure 6 (V_{kn}^1), BIC, AIC, rho-square-bar ($\overline{\rho}^2$), and loglikelihood (negative log-likelihood) are presented as histograms. Following that lower BIC/AIC and higher the log-likelihood / $\overline{\rho}^2$ indicate a better goodness-of-fit, considering all K as a whole, the results follow an order of MNL < C-logit < PSCL < PSL, which is consistent with Figure 7 (V_{kn}^2). Models with $CF_{kn,T}$, $PS_{kn,T}$, $PSC_{kn,T}$ ($\lambda = 0.5$) do not show a significant improvement, except PSL-T outperforms PSL at $K = 15$.

Given the PSL as the best fitting model, a comparison between K shows that $K = 5$ has better statistics but yields unrealistic estimates (e.g., positive β_{TT}), similarly, $K = 7$ yields negative but insignificant β_{TT} for PSL, both indicate an inappropriate choice set or overfitting, possibly due to the small size failing to capture sufficient heterogeneity and realistic alternatives, resulting in unstable parameter estimates. Although $K = 15$ has a higher $\overline{\rho}^2$, $K = 10$ achieves lower BIC, which is considered more robust for model selection. Moreover, $K = 10$ provides smaller ATP overlapping (Table 1) and individuals are unlikely to consider large ATP sets, making $K = 10$ the most suitable for model estimation.

Based on $K = 10$, Tables 2 and 3 present parameter estimates for the utility functions. For V_{kn}^1, results show the individual prefers ATPs with less travel time and shopping at attractive locations with ideal duration. Coefficient estimates of all the correction terms are reasonable, demonstrating the importance of addressing overlapping among the alternative ATPs. For V_{kn}^2, results suggest that individuals exhibit an aversion to travel time and consistently prefer attractive locations. The estimated $\beta_{TT}^{A_n}$ in Table 3 indicate that younger individuals may exhibit slightly stronger travel time aversion in PSL compared to those aged over 50, while $\beta_{LA}^{A_n}$ shows no significant differences in preferences for attractiveness between the two age groups.

Table 2. Models estimation results – parameters (V_{kn}^1, $K = 10$)

Variables	ATP chocie models						
	MNL	C-logit	C-logit-T	PSL	PSL-T	PSCL	PSCL-T
Constant							
β_{ASC}	10.2 ***	9.89 ***	9.91 ***	9.08 ***	9.09 ***	9.45 ***	9.53 ***
ATP							
β_{TT}	-0.0333 **	-0.0381 ***	-0.0372 ***	-0.15 ***	-0.153 ***	-0.0792 ***	-0.0768 ***
$\beta_{\Delta D_{\alpha k}}$	-0.166 ***	-0.168 ***	-0.167 ***	-0.217 ***	-0.217 ***	-0.195 ***	-0.192 ***
$\beta_{LA_{\alpha_m}}$	0.299 ***	0.294 ***	0.296 ***	0.202 ***	0.201 ***	0.258 ***	0.265 ***
$\boldsymbol{g(\Delta_{kn})}$							
CF_{kn}		-0.0148 ***					
$CF_{kn,T}$			-0.0121***				
PS_{kn}				0.297 ***			
$PS_{kn,T}$					0.304 ***		
PSC_{kn}						0.0507 ***	
$PSC_{kn,T}$							0.048 ***
Statistics							
Parameter number	4	5	5	5	5	5	5
Log-likelihood	-282.9046	-255.1381	-257.1317	-168.3716	-168.9784	-221.0896	-226.63
Likelihood ratio	930.4775	986.0105	982.0232	1159.543	1158.33	1054.107	1043.027
$\overline{\rho}^2$	0.617	0.652	0.65	0.768	0.767	0.698	0.69
AIC	573.8092	520.2762	524.2635	346.7432	347.9568	452.1793	463.2601
BIC	588.7812	538.9912	542.9785	365.4582	366.6718	470.8943	481.9751

Note: *** significant at α=0.01, ** significant at α=0.05, * significant at α=0.1.

Table 3. Models estimation results – parameters (V_{kn}^2, $K = 10$)

Variables	ATP chocie models						
	MNL	C-logit	C-logit-T	PSL	PSL-T	PSCL	PSCL-T
Constant							
β_{ASC}	10.3***	13.2 ***	9.97 ***	8.88 ***	8.9 ***	12.7 ***	9.49 ***
Socio-demographic interactions with ATP attributes							
β_{TT}	-0.0293	-0.0346 *	-0.0338 *	-0.141 ***	-0.144 ***	-0.0742 ***	-0.072 ***
$\beta_{TT}^{A_n}$	-0.0349	-0.028	-0.0282	-0.0727 *	-0.0731 *	-0.0351	-0.0336
β_{LA}	0.327 ***	0.311 ***	0.316 ***	0.189 **	0.187 **	0.252 ***	0.262 ***
$\beta_{LA}^{A_n}$	-0.113	-0.0746	-0.0801	0.0659	0.0693	0.014	0.00379
$\beta_{\Delta D_{\alpha k}}$	-0.167 ***	-0.169 ***	-0.168 ***	-0.219 ***	-0.219 ***	-0.196 ***	-0.192 ***
$\boldsymbol{g(\Delta_{kn})}$							
CF_{kn}		-0.0147 ***					
$CF_{kn,T}$			-0.012 ***				
PS_{kn}				0.303 ***			
$PS_{kn,T}$					0.311 ***		
PSC_{kn}						0.0512 ***	
$PSC_{kn,T}$							0.0484 ***
Statistics							
Parameter number	6	7	7	7	7	7	7
Log-likelihood	-282.2544	-254.7714	-256.7444	-167.0137	-167.5959	-220.6485	-226.2238
Likelihood ratio	931.7779	986.7438	982.7978	1162.259	1161.095	1054.99	1043.839
$\overline{\rho}^2$	0.615	0.65	0.647	0.767	0.767	0.696	0.688
AIC	576.5087	523.5428	527.4889	348.0274	349.1919	455.297	466.4477
BIC	598.9667	549.7439	553.6899	374.2284	375.3929	481.498	492.6487

4. CONCLUSIONS

This study proposes a model framework for ATP choice set generation within STP and ATP choice modeling. The link penalty approach effectively generates appropriate ATP choice sets with less similarity. Comparing the goodness-of-fit among seven ATP choice models, results indicate that including correction terms can better address interdependence among alternatives, with the statistics consistently following the order of PSL > PSCL > C-logit > MNL. Parameter estimation reflects individuals' ATP choice behavior within constraints and the impact of socio-demographic factors on ATP choice.

The following limitations should be addressed in future works. First, the evaluation of the generated ATP choice set requires further testing of different combinations of choice set size and link penalty factor. Second, the spatio-temporal correction term modeling needs deeper exploration to examine the temporal. Third, enriching the GPS dataset with more socio-demographic information to enhance ATP choice behavior analysis.

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