Heterogeneity in habitual active travel choices over the life course

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SHORT SUMMARY

Focusing on life trajectories and exploring heterogeneity is critical in developing targeted-specific and lifelong interventions for active travel. This study estimated mixed logit models to explore determinants of habitual active travel from a life-course perspective and capture potential heterogeneity in the decision-making process. The effects of trip purposes, life transitions, neighborhood attributes, and socio-demographic characteristics were captured. Based on retrospective longitudinal data collected in the Netherlands from a representative panel of 627 adults via a web-based survey, results indicate the importance of travel purposes, key life transitions, living environments, health conditions, and some socio-demographic characteristics in influencing active travel choices. Besides, results show that determinants, including school commuting, work commuting, shopping for daily needs, marital status change, school change, distance, having a partner, and having motorized vehicles, have random effects, suggesting the existence of heterogeneity. Their heterogeneities can be captured by age, education level, working hours, and having children.

Keywords: cycling and walking behaviour and design, habitual active travel, heterogeneity, life course

1. INTRODUCTION

As a part of daily physical activity, regular active travel (e.g., walking and cycling) is thought to bring significant health, environmental, and economic benefits (Prince et al., 2022). However, reliance on passive transportation modes remains prevalent today. Data showed that in 2019, about 65% of Dutch commuters habitually drove to work, while only about 29% cycled (I&O Research, 2019). Therefore, to develop targeted interventions, a deeper understanding of habitual active travel decisions is necessary.

Although previous studies have shown that active travel behavior is determined by the combined interplay of personal (e.g., age, gender, employment, car ownership, etc.), social (e.g., social support from peers and family), and environmental (e.g., distance, infrastructure, safety, etc.) characteristics (Aziz et al., 2018; Eldeeb et al., 2021), there are still some limitations in explaining habitual active travel decisions. Firstly, most relevant studies assume that one determinant has a homogeneous influence on active travel, ignoring the existence of possible heterogeneity. Among existing studies, spatial heterogeneity is the main focus (e.g., Eldeeb et al., 2021; Wu et al., 2023). It's necessary to capture other heterogeneities in the decision-making process to formulate target-specific strategies. Secondly, previous research has been primarily cross-sectional and has ignored the dynamics of active travel choices in life. According to the habit discontinuity hypothesis, individuals are more likely to reconsider their habitual travel behavior when life transitions occur (Verplanken et al., 2008). Understanding determinants of habitual active travel decisions from a life course perspective is important to support active travel as a lifelong practice. Currently, only a few studies have considered life transitions, but they specifically focus on their effects on car ownership, car use, or multimodality (e.g., Beige and Axhausen, 2012; Clark et al., 2016), which provides indirect evidence for active travel. Finally, compared to the numerous studies on school and work commutes, shopping trips are often overlooked despite stores being highly frequented destinations in daily life (Wiese et al., 2015). Considering shopping travel behavior is crucial to further exploring habitual active travel.

To contribute to the current literature, this study has collected retrospective longitudinal data including individuals' life trajectories, school and work commuting behaviors, and daily and non-daily shopping travel behaviors. Specifically, the aims of this study are twofold: 1) Understand the drivers of habitual active travel choices over the life course, focusing comprehensively on trip purposes, life transitions, neighborhood attributes, and sociodemographic characteristics. 2) Capture heterogeneity that may exist in the decision-making process. Mixed logit models are formulated to achieve these objectives. The findings may help develop targeted-specific and lifelong interventions for active travel promotion.

2. METHODOLOGY

Model specification and analysis process

This study applied mixed logit models (Hensher and Greene, 2015) to estimate random parameters to account for heterogeneity. Assume that an individual q (q=1, …, Q) faces a choice among two alternatives (j=1, completely active modes; j=2, other modes.) in each of T choice situations (t=1, …, T). This study treats every life transition and every change in habitual travel behavior of an individual as a choice situation. Individuals are assumed to make the choice that provides the greatest overall utility after evaluating all available factors in a choice situation (De Dios Ortúzar and Willumsen, 2011). Then, the mixed logit model can be expressed as:

$$U_{q,j,t} = \boldsymbol{\beta}'_q \boldsymbol{X}_{q,j,t} + \varepsilon_{q,j,t} \tag{1}$$

where, $\boldsymbol{X}_{q,j,t}$ is the full vector of explanatory variables. $\boldsymbol{\beta}'_q$ is the coefficient vector of explanatory variables representing individual preferences, which can be fixed or random. If β_{kq} is a random coefficient for the kth explanatory variable faced by individual q, $\boldsymbol{z}_q$ is a set of individual-specific characteristics, $\boldsymbol{\delta}'_k$ is a vector of coefficients of $\boldsymbol{z}_q$, assume β_{kq} follows normal distribution, then β_{kq} can be written as:

$$\beta_{kq} = \bar{\beta}_k + \boldsymbol{\delta}'_k \boldsymbol{z}_q + \sigma_k \tag{2}$$

where, $\bar{\beta}_k$ is the population mean, $\boldsymbol{\delta}'_k \boldsymbol{z}_q$ refers to observed heterogeneity around the mean, and σ_k is the standard deviation of the distribution β_{kq}. If β_{kq} is fixed, $\beta_{kq} = \beta_{kq}$. Additionally, the unobserved term $\varepsilon_{q,j,t}$ is assumed to be distributed IID extreme value. Collect the structural parameters ($\boldsymbol{\beta}'_q, \boldsymbol{\delta}'_k$) in a parameter set $\boldsymbol{\Omega}$. For a give value of β_q, the conditional probability for choice j in choice situation t is in logit form:

$$L_{q,j,t} = P_{q,t}\left[j|\boldsymbol{X}_{q,t}, \boldsymbol{\Omega}, \boldsymbol{z}_q\right] = \frac{exp(\boldsymbol{\beta}_q' \boldsymbol{X}_{q,j,t})}{\sum_{j=1}^{J} exp(\boldsymbol{\beta}_q' \boldsymbol{X}_{q,j,t})} \tag{3}$$

The unconditional choice probability for alternative j of individual q is:

$$P_{q,j,t}(\boldsymbol{X}_{q,t}, \boldsymbol{\Omega}, \boldsymbol{z}_q) = \int_{\boldsymbol{\beta}_q} L_{q,j,t}(\boldsymbol{\beta}_q|\boldsymbol{X}_{q,t}, \boldsymbol{\Omega}, \boldsymbol{z}_q)\, f(\boldsymbol{\beta}_q|\boldsymbol{\Omega}, \boldsymbol{z}_q) d\boldsymbol{\beta}_q \tag{4}$$

Considering the panel effects due to the repeated measurement nature of the data, the full log likelihood is:

$$\log L(\boldsymbol{\Omega}) = \sum_{q=1}^{Q} log \int_{\boldsymbol{\beta}_q} \prod_{t=1}^{T_q} L_{q,j,t}(\boldsymbol{\beta}_q|\boldsymbol{X}_{q,t}, \boldsymbol{\Omega}, \boldsymbol{z}_q) f(\boldsymbol{\beta}_q|\boldsymbol{\Omega}, \boldsymbol{z}_q) d\boldsymbol{\beta}_q \tag{5}$$

The analysis process started from the univariate analysis and multinomial logit model, then built the base mixed logit model with random parameters, continuously deepened and optimized it, and finally formed a mixed logit model with observed heterogeneity around the mean of random parameters (Figure 1). During the analysis, the utility of other transport modes (j=2) was taken as the reference. Effect coding was used to represent all categorical variables. Models were estimated using Nlogit 6 software.

Data collection and observations generation

The retrospective longitudinal data were collected in the Netherlands in September-October 2020 in collaboration with a national survey company Panelclix. A web-based retrospective survey was designed to collect three types of longitudinal data from one's birth year to the survey date: life trajectory, commuting behavior, and regular shopping behavior (Figure 2). 'Regular' means at least once a week for more than six months.

The survey collected life trajectory information from the following eight aspects: education, employment, residence and associated neighborhood characteristics, marital status, childbirth, diseases, living with physically active people, and vehicles ownership. For each life trajectory, individuals were first asked to indicate whether they had experienced the event (or current status). If yes, they were asked to provide a detailed chronological description from birth to the survey date. Commuting behavior data involved school commuting and work commuting. Based on respondents' answers to education and employment, for each school and work experience, initial commute information and subsequent changes were asked. Also, regular shopping behavior involved two types: shopping for daily necessities and shopping for non-daily items. Respondents were first asked to indicate whether they had had experienced the activity. If so, they were asked to describe their experiences in chronological order. For each experience, the required information included time period, frequency, transportation modes, travel time, and weekly shopping hours.

Although retrospective surveys, in which information is collected from memories or records, are widely used in life-course research today, the risk of recall bias is probably unavoidable (Moschis, 2019). To minimize the possible biases, this survey inserted numerous error-checking functions from three aspects: 1) temporal logic check, 2) event logic check, and 3) consistency check. A total of 627 panelists provided valid responses.

To simultaneously evaluate changes in the choices of transportation modes and associated life transitions, habitual travel behavior data were integrated with the life trajectory data. That is, for an individual, the choices of transportation modes for school commuting, work commuting, daily shopping, and non-daily shopping were repeatedly measured at different time points in life.

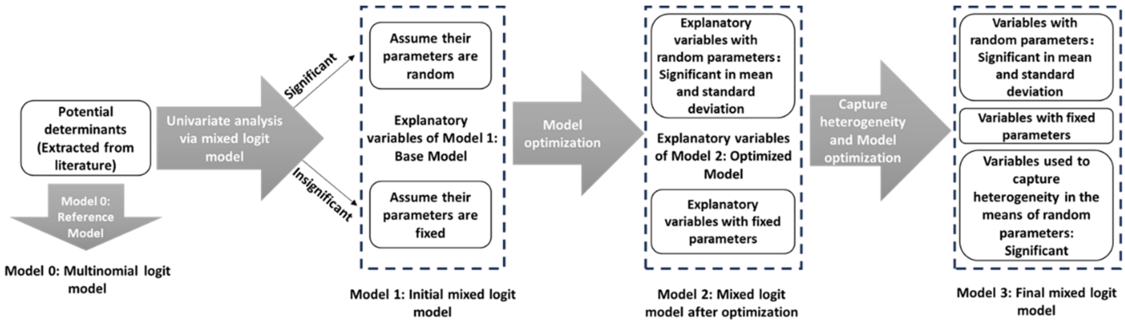

Figure 1: Analysis process

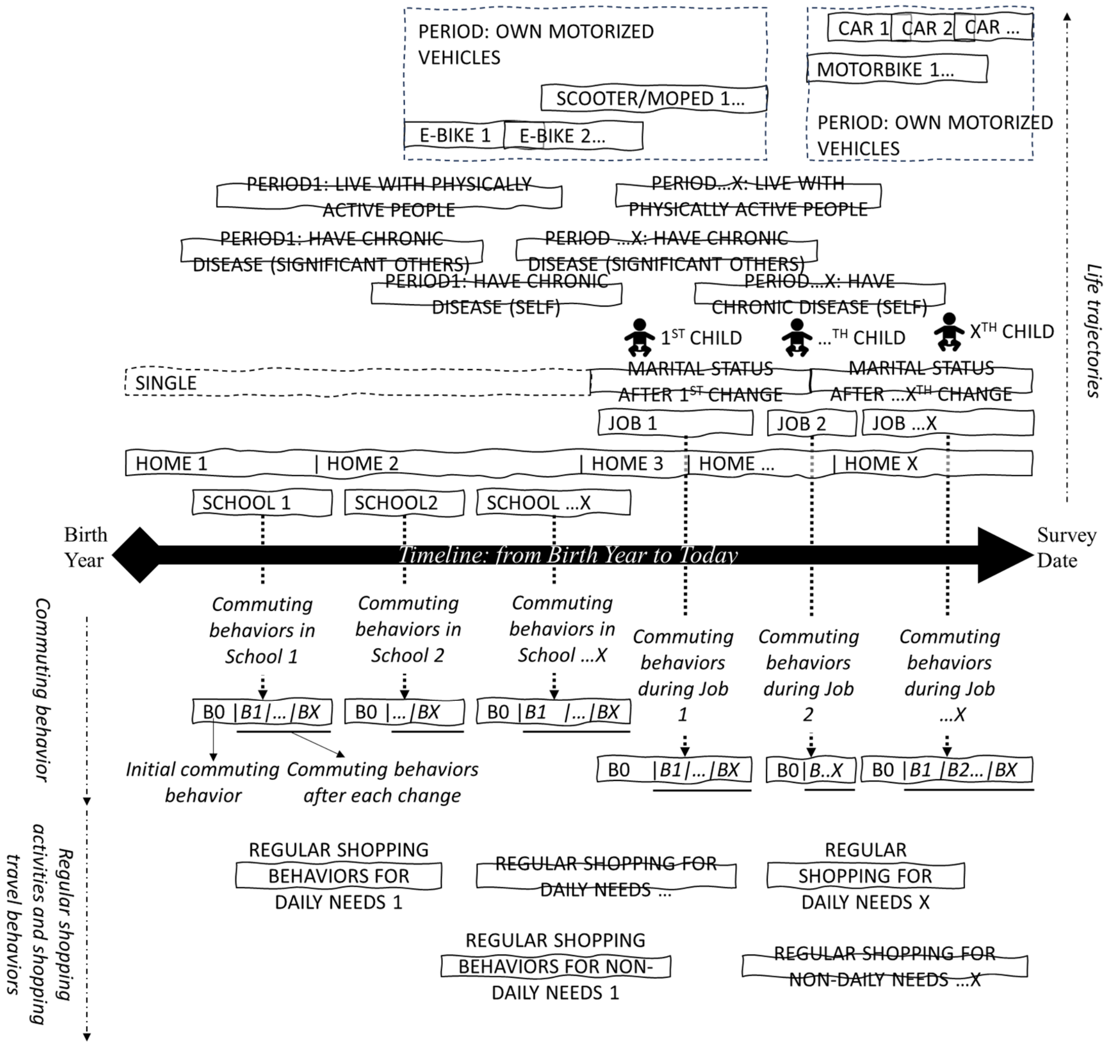

Figure 2: Information collected in survey

Specifically, observations generation had three main steps: 1) Generate observations at time points when life transitions occurred. Possible delays in the impact of life transitions were considered. 2) Generate additional observations at time points when habitual travel behavior changed. 3) Add outcome variables (active transportation modes or others) for the generated observations. If, at a certain time point, the respondent's transportation choices for different travel purposes were inconsistent, for example, active transportation modes for school commuting but passive modes for daily shopping, multiple observations would be generated. 4) Remove observations with no commuting behavior or unreliable information. A total of 8051 observations were generated for further analysis, of which active transportation modes accounted for 52.60%.

Descriptive statistics of explanatory variables

Figure 3 presents the descriptive statistics of explanatory variables. As shown, the proportion of people who habitually choose active travel was higher among those who were under 17, had primary-level education, worked less than 20h/w, owned no motorized vehicle, and had no partner or child. Additionally, active travel was more likely to be chosen for school commutes and daily shopping trips. It was also likely to happen when changing schools. Unsurprisingly, the data indicated that the shorter the travel distance, the higher the rate of active modes use.

3. RESULTS AND DISCUSSION

As shown in Table 1, the final mixed logit model with characteristics capturing heterogeneity (Model-3), which increases the log-likelihood to -21995.088, improves the *R*-squared to 0.64249, and decreases the AIC to 4092.2, has a better fit. Table 2 lists the results of the final model.

Results indicate that for school commuting and daily shopping, people are more likely to choose walking and cycling, but for work commuting, people prefer other modes. It's consistent with the previous reports showing that a large proportion of trips to work is made by private motor vehicles (I&O Research, 2019). Age and education are statistically significant sources of influence on preference heterogeneity for active school commuting, implying people under 17 or in primary education are more likely to walk or bike to school. It's consistent with statistics from Statistics Netherlands, reporting that the 18-25-year-old group averagely makes fewer walking and cycling trips than the 6-12- and 12-18-year-old groups (CBS, 2022). Also, primary education is an important source of preference heterogeneity for active shopping trips for daily needs, indicating primary school students are less likely to actively travel for daily shopping. It may be because children's shopping behavior often overlaps with their parents'. Additionally, age and working hours are statistically significant sources of preference heterogeneity in active commuting to work. It suggests that the likelihood of active work commuting increases when people are under 17 or work part-time. It may be related to their poor economic status.

Estimates of life transitions indicate that people are more likely to choose active modes when changing marital status, changing schools, and starting work. Usually, these transitions occur with changes in travel distance, duration, cost and environment, affecting the reconsideration of transportation modes. Another explanation for changing schools is related to age. Mostly, school transfers occur under 18, a very active life stage for walking and cycling (Aziz et al., 2018). The result for starting work is consistent with previous evidence that young adults are prompted to start cycling when they begin to work due to the lack of other options (Chatterjee et al., 2013).

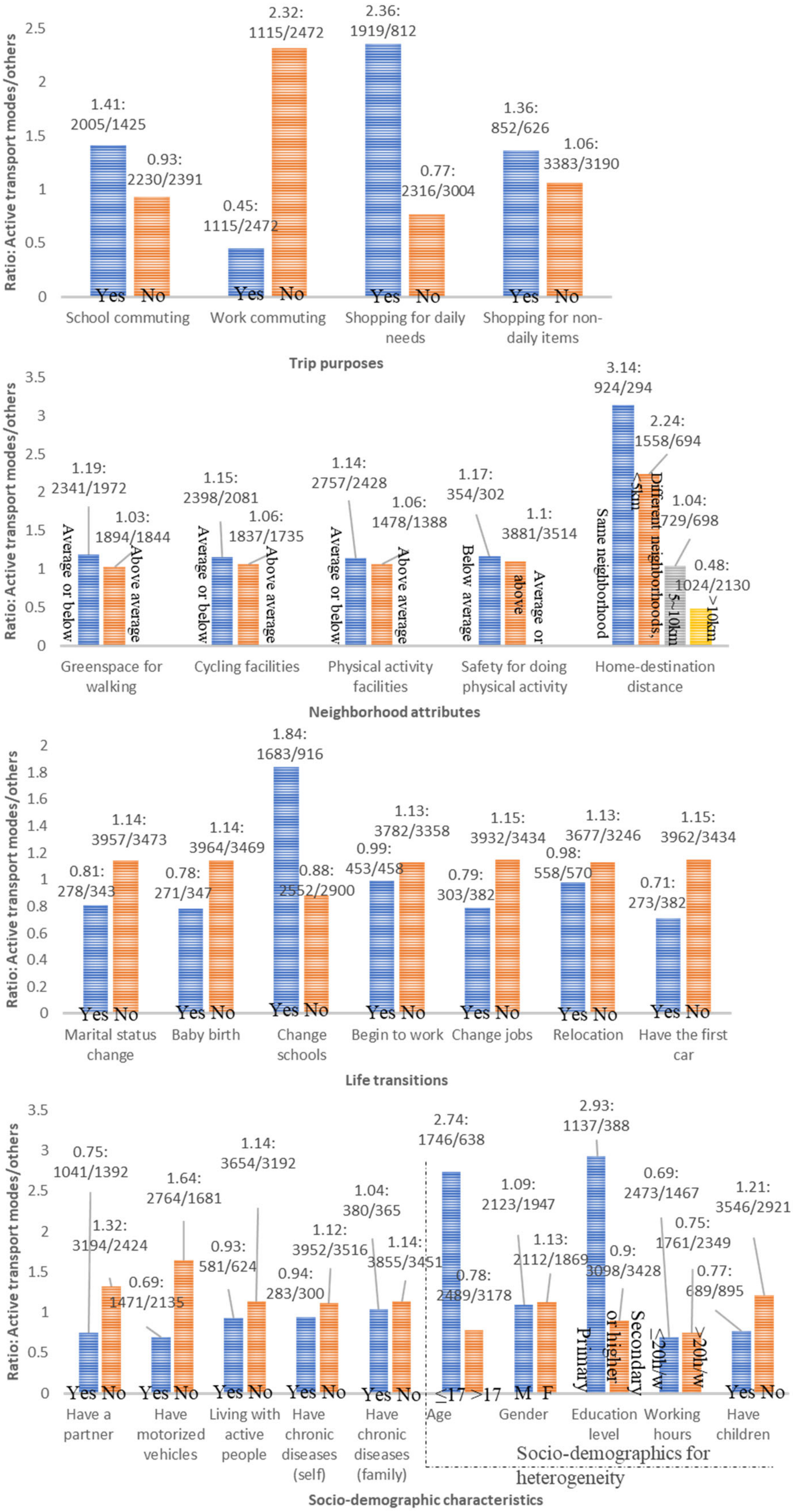

Figure 3: Descriptive statistics of explanatory variables (N=8051)

Table 1: Results of model comparisons

Models	Log-likelihood (*LL*)	df	Chi-squared	Chi-squared *p*-value	*R*-squared	AIC
Model-0	- 3897.31184	23	3344.61625	0.0000***	0.3003	7842.6
Model-1	-2228.97472	39	6703.10647	0.0000***	0.6006	4535.9
Model-2	-2250.66302	34	6659.72986	0.0000***	0.59669	4569.3
Model-3	**-1995.08800**	**51**	**7170.87990**	**0.0000*** **	**0.64249**	**4092.2**

As expected, the closer the neighborhood distance between home and destination, the more likely people are to take active trips. Especially when the distance is less than 5km, the likelihood of active travel is higher. Age, education, and working hours are statistically significant sources of preference heterogeneity influencing distance-related active travel choices. Estimates for age≤17 suggest that it increases the likelihood of active travel when the destination is in the same neighborhood as the residence, but has an opposite effect when the residence and destination are in different neighborhoods (neighborhood distance≤5 km). Moreover, for cases where residence and destination are within the same neighborhood, the effect of primary education is negative, indicating increasing marginal disutility. It may be associated with parents escorting their children to and from primary school. While, when the neighborhood distance between residence and destination is 5-10km, the effect of working hours≤20h/ is positive, indicating an increase in marginal utility.

Besides, estimates suggest neighborhoods with adequate greenspace or adequate physical activity facilities encourage residents to travel actively. Results also show that people living in unsafe neighborhoods have a higher likelihood of active travel. The reasons behind this may be related to the socioeconomic level of the neighborhood. Generally, unsafe neighborhoods are those with lower socioeconomic status and whose residents have less access to cars.

Furthermore, results indicate that people with a partner, a motorized vehicle, or a chronic disease are less likely to travel actively, consistent with many previous studies (e.g., Scheiner and Holz-Rau, 2013; Eldeeb et al. 2021). Having a partner and owning motor vehicles have random effects, and their heterogeneities can be captured by age, education and having children. The results imply that among those who own motorized vehicles, being less educated or having children increases the likelihood of active travel. Somewhat surprisingly, living with physically active people is also negative. Given the earlier finding that having a partner decreases the likelihood of active travel decisions, who is the active person you live with (e.g., partner, parents, friends, etc.) may be a factor worth looking into.

4. CONCLUSIONS

Based on retrospective longitudinal data on life trajectories, commuting behaviors, and regular shopping travel behaviors collected in the Netherlands, this study has applied mixed logit models to explore determinants of habitual active travel from a life-trajectory perspective and capture potential heterogeneity in the decision-making process. According to the estimated model, trip purposes (incl. school commuting, work commuting, and shopping for daily needs), life transitions (incl. marital status change, school change, and start employment), neighborhood attributes (incl. distance, greenspace, physical activity facilities, and safety), and socio-demographics (incl. having a partner, having motorized vehicles, having chronic diseases, and living with physically active people) show significant effects.

Table 2: Estimation results of the finial model

Variable-Level	Coef.(P-value)
Random parameters	
School commuting-Yes	0.72948(0. 0118*)
Work commuting-Yes	-2.17010(0.0000***)
Daily Shopping-Yes	3.49465(0.0000***)
Marital status change-Yes	0.84469(0.0007***)
Change school-Yes	0.93804(0.0005***)
Distance (home-destination)-Same neighborhood	4.46238(0.0000***)
Distance (home-destination)-Different neighborhood(<5km)	2.02327(0.0000***)
Distance (home-destination)-5km~10km	-1.01101(0.0000***)
Have a partner-Yes	-1.71280(0.0000***)
Have motorized vehicles	-0.63558(0.0326*)
Non-random parameters	
Non-daily shopping-Yes	0.15206(0.4628)
Baby birth-Yes	0.38801(0.1595)
Start working-Yes	0.39290(0.0338*)
Change jobs-Yes	0.39927(0.0594)
Relocation-Yes	0.16507(0.1436)
Have the first car-Yes	0.29965(0.0552)
Greenspace for walking-Average or below	0.35837(0.0209*)
Cycling facilities-Average or below	-0.03524(0.8163)
Physical activity facilities-Average or below	-0.41265(0.0051**)
Safety for doing PA-Below average	0.56019(0.0169*)
Have chronic diseases(self)-Yes	-0.65894(0.0137*)
Have chronic diseases(family)-Yes	0.12729(0.5855)
Live with active people-Yes	-0.58218(0.0046**)
Constant: Other modes	-2.77436(0.0005***)
Heterogeneity around the means of random parameters	
School commuting-Age(≤17)	1.42155(0.0000***)
School commuting-Education(Primary)	0.77807(0.0014**)
Work commuting-Age(≤17)	0.96155(0.0000***)
Work commuting-Gender(Male)	-0.09532(0.5374)
Work commuting-Working hours(≤20h/w)	1.36059(0.0000***)
Daily shopping-Education(Primary)	-0.75061(0.0030**)
Change school-Education(Primary)	-0.24062(0.1232)
Change school-Have children(Yes)	0.31765(0.1159)
Distance(Same neighborhood)-Age(≤17)	0.80663(0.0022**)
Distance(Same neighborhood)-Education(Primary)	-0.7504(0.0011**)
Distance(Different neighborhood<5km)-Age(≤17)	-0.57268(0.0085**)
Distance(Different neighborhood<5km)-Workinghours(≤20h/w)	0.14731(0.5054)
Distance(5km~10km)-Workinghours(≤20h/w)	0.61220(0.0029**)
Have a partner-Age(≤17)	-0.97814(0.0000***)
Have motorized vehicles-Age(≤17)	-0.90483(0.0000***)
Have motorized vehicles- Education(Primary)	1.00734 (0.0001***)
Have motorized vehicles-Have children(Yes)	0.74954 (0.0000***)
Standard deviation of random parameters	
School commuting-Yes	3.12727(0.0000***)
Work commuting-Yes	4.40145(0.0000***)
Daily Shopping-Yes	6.44471(0.0000***)
Marital status change-Yes	2.67781(0.0000***)
Change school-Yes	0.96972(0.0000***)
Distance (home-destination)-Same neighborhood	3.70504(0.0000***)
Distance (home-destination)-Different neighborhood(<5km)	2.87659(0.0000***)
Distance (home-destination)-5km~10km	1.29082(0.0000***)
Have a partner-Yes	0.83996(0.0001***)
Have motorized vehicles	1.49461(0.0000***)

***, **, * means significance at 0.1%, 1%, and 5% level. Estimates are based on 200 Halton draws.

Judging from these results, people's choices for active travel are dynamic and complex throughout life, varying with travel purposes, key time points in life, living arrangement and related environments, health conditions, and socioeconomic levels. It indicates that dynamic and lifelong strategies are necessary for promoting and maintaining habitual active travel. Moreover, results find that heterogeneity in determinants (incl. school commuting, work commuting, shopping for daily needs, school change, marital status change, distance, having a partner, and having motorized vehicles) exist. Their heterogeneities can be captured by age, education level, working hours, and having children. This suggests that strategies to promote habitual active travel should shift from general to specific, refined, and personalized. Although some interdependencies have been captured by this study, more possibilities could exist due to the complexity of the decision-making process. The findings of this study can be used as preliminary research to propose hypotheses for further research and help policymakers establish a more optimized policy system.

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