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Exploring the relationship between life events, mode preferences and mode use of young adults: A 3-year cross-lagged panel analysis in the Netherlands

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ABSTRACT

This paper examines the impact of life events on transport mode preferences and the frequency of mode use of young adults in the Netherlands, using data from three waves (2014, 2015 and 2016) of the Netherlands Mobility Panel. The database used for this paper contains 1,180 young adults (18–39 years) who participated in all three waves. Cross-lagged structural equation panel models were estimated to examine the longitudinal relationship between life events (childbirth, moving home or a new job) and travel behaviour. We investigated the relationship between frequency of mode use and mode preference over time, and the impact of life events on mode preference and frequency of mode use. Young adults showed very stable behaviour over time: frequency of mode use and mode preference are good predictors of frequency of mode use and mode preference in the future. The results show that changes in the frequency of mode use have a stronger effect on changes in mode preferences than vice versa. In addition, young adults subjected to life events are more likely to change travel behaviour. Car use and car preference are found to increase significantly after childbirth. Bicycle use and preference for the bicycle were more likely to increase for young adults who moved home. Changing jobs showed a negative association with bicycle use. These life-changing moments could offer a window of opportunity for policymakers and other parties to create more awareness of alternative, more sustainable, modes of transport.

1. Introduction

Many governments across the globe try to achieve mode shifts from car use to public transport, cycling, and walking to reduce congestion and the environmental impacts of transport. In the development and implementation of policies and measures to facilitate these mode shifts, it is essential to understand when people consider changes in travel behaviour. People may change their daily routines, including their mode use, as they move through different stages of life (Bamberg and Schmidt, 2003). Major life events, such as moving home or getting a new job, may force changes in daily routines, also called the habit-discontinuity hypothesis (Verplanken et al., 2008). Several studies show that people are more often aware of possible changes in their behaviour when faced with these life events (e.g., Herde, 2007; Bamberg, 2006; Klockner, 2005). There is a clear link between the stress and tension caused by life events and changes in travel behaviour, either in the short- or long-term (Clark et al., 2016). Therefore, life events provide new opportunities for policymakers (Schäfer et al., 2012), for example providing alternative means of transport, and offering different mobility services on an individual level. These windows of opportunity provided by life events have also become the subject of many studies by travel behaviour researchers. Among them are several studies using the mobility biographies (or life course) approach (Müggenburg et al., 2015).

This paper examines the influence of life events on mode preference and mode use of people aged between 18 and 39 years in the Netherlands. According to Erikson's stages of human development this group are referred to as "young adults" (Erikson, 1998). Data was used from the Netherlands Mobility Panel, the most extensive ongoing mobility panel in the world, to explore the causal directions between life events, sociodemographic factors, mode preference and mode use, and to examine whether life events are indeed triggers for changes in mode choice behaviour. Kroesen et al. (2017) found there is a bidirectional relationship between mode use and the attitude towards using that mode between two time-points. In line with this study, we examine the relationship between mode use and attitude. However, the main objective of our research is to analyse the impact of life events on mode preference and frequency of mode use of young adults. Our focus was on young adults as they experience life events more frequently than other age

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groups. Furthermore, several studies have indicated that young adults in industrialised countries develop less car-oriented travel preferences (Delbosc and Currie, 2013; Kuhnimhof et al., 2012). However, these studies are mostly based on cross-sectional data and do not take life events into account. In this paper, we applied three-wave cross-lagged panel models to estimate the impact of life events and other travel behaviour related changes on mode preference and mode use of young adults simultaneously.

Although previous studies examined the impact of life events and an individual's preference of transport modes on travel behaviour (e.g., Clark et al., 2016; Chatterjee and Scheiner, 2015; Zhang et al., 2014; Susilo et al., 2019), most of these studies assume that mode preferences have not simultaneously changed during the life event. However, mode preferences may also change over time, and these changes may affect travel behaviour as well (Susilo et al., 2019). Furthermore, based on cognitive theory, we might expect that life events affect travel behaviour through influencing preferences (Andersen and Chen, 2002). Therefore, in this paper, we aim to examine the bidirectional feedback effects between mode use and mode preferences over time, as well as the mediating effects of mode preference between life events and mode use, and mode use between life events and mode preference.

We address the following two research questions:

1. How do life events affect mode preferences and mode use of young adults over time?
2. How do mode preferences of young adults mediate the effects of life events on mode use and vice versa?

The rest of the paper is structured as follows. Section 2 reviews research on the relationship between life events, mode preference, and mode use and describes the contribution of this paper. Section 3 comprises the methodology and theoretical framework used for modelling the relationship between life events, mode preference, and mode us. Section 4 describes the data and variables used, followed by the results of the analysis in section 5. Finally, section 6 discusses the results, describes policy implications, and makes recommendations for further research.

2. Literature review

In previous years, several studies have been undertaken to examine the impact of life events on travel behaviour and to improve our understanding of travel behaviour changes (Müggenburg et al., 2015). In this study, we focus on the relationship between life events, mode preference, and mode use.

2.1. Life events, mode preferences and mode use

In recent years, the impact of life events on travel behaviour has received increasing attention. Various studies reveal that important events in someone's life course can provide the trigger for changes in travel behaviour (e.g., Haas et al., 2016; Axhausen et al., 2006; Lanzendorf, 2010). Previous research shows that life events such as the birth of a child, entering the labour market, moving home or changing jobs increase the chance of changing mode choice behaviour (e.g., Clark et al., 2016; Scheiner, 2016; Rau and Manton, 2016). Also, to understand the relationship between life events and mode choice behaviour, it is essential to have insight into the personal values and experiences regarding different transport modes. 'Personal values, feelings, preference and social norms mainly predict individual mode choices', as argued by Steg and Kalfs (2000). Mode preferences may also change over time, and these changes may also affect travel behaviour (Susilo et al., 2019). As mentioned before, cognitive theory might lead us to expect mode preferences to play a mediating role between life events and mode choice behaviour.

Janke and Handy (2019) found that having children, meeting a new partner, and residential relocation (to a bicycle-friendly community) changed bicycling behaviour and attitudes through a causal mechanism of social norms, latent demand and alteration of interests. Also, from previous research, we know there is a strong correlation between mode preference and frequency of mode choice (Harms et al., 2007). In general, people who use the car, public transport or bicycle are more likely to prefer these transport modes relative to less frequent users. Social and spatial differences, such as age and residential location, do not seem to impact their preferences (Olde Kalter et al., 2015). In a recent study, Olde Kalter et al. (2020) showed that changes in attitudes towards the car did not significantly affect the frequency of mode use. However, younger adults turned out to show a more positive attitude towards the car after facing life events, such as moving home, starting a new job or the birth of a child. These results suggest that personal values and mode preferences play a mediating role between life events and mode choice behaviour.

2.2. Research gaps and the contribution made by our study

Although the relationship between life events and changes in travel behaviour has been the subject of many studies, we need a better understanding of these changes because policy interventions may be more effective during times of transition (Thompson et al., 2011). Previous research showed that various life events increase the likelihood of behavioural changes, such as frequency of mode use, car ownership and commuting mode choice (e.g., Clark et al., 2014, 2016; Oakil, 2016). However, there is little evidence on how changes in mode preferences affect travel behaviour at the time of life events. Moreover, there is also a lack of longitudinal studies examining these relationships in the Netherlands. Most longitudinal studies are conducted in Germany and Great Britain. Research from the Netherlands mostly used retrospective surveys (Oakil et al., 2014; Oakil, 2016), longitudinal data from the eighties (Kroesen, 2014) or qualitative studies (Schwanen, 2011). The Netherlands is an interesting case study area to examine changes in mode preferences given the quality and role of alternatives to the car. In particular, the Netherlands is well known for good quality cycling and public transport infrastructure, and a significant portion of the Dutch population prefers cycling and/or public transport over the car as commuting mode (Olde Kalter et al., 2015).

This study aimed to contribute to filling this research gap. The start of the Netherlands Mobility Panel in 2013 has made longitudinal data available for the present Dutch situation, offering new opportunities to examine the relationship between life events and travel behaviour. Longitudinal modelling allows mode choice behaviour to be examined over time as well as testing the impact life events have on changes in mode preference and mode use, which is not possible with cross-sectional data (Burkholder and Harlow, 2003). Also, the availability of more than two time points allows us to model patterns of change over time (Liu, 2016) and to investigate the impact of life events on travel behaviour both at time $t+1$ and time $t-1$. Previous studies indicate the relevance of life events in understanding changes in travel behaviour. However, the direction of the relationship between life events and changes in mode preference and the frequency of mode use is not always clear and needs further investigation. Furthermore, it is obvious that life events may affect both mode preference and mode use simultaneously, whereas most studies consider only one of these measures. In our research, we assume that life events are exogenous. We do not examine the reciprocal relationship between life events and mode preference or mode use. Moreover, in this study, the relationship between life events, mode preference and mode use is explored separately for each transport mode (i.e. car, public transport and bicycle).

3. Method

We expected to find that mode preference in the past is a strong predictor for mode preference in the present situation. The same accounts for the frequency of mode use. However, we also expected people to adjust their mode preference as well as their frequency of mode use in response to life events. To examine whether these expectations were right, we developed a three-wave random-intercept cross-lagged panel model (RI-CLPM) for each transport mode separately, based on structural equation modelling (SEM). An important advantage of SEM above multivariate regressions is that within the SEM framework simultaneous equations are allowed. In panel analysis, it is essential to consider the correlation between repeated observations of the same individual (Zeger and Liang, 1992). For example, it is likely that variations in the frequency of mode use for the same individual will be less than the variation in the frequency of mode use for different individuals. Parameters' standard errors may be biased if this correlation is not included (Ghisletta and Spini, 2004). The traditional cross-lagged panel model (CLPM) does not consider this intrapersonal correlation. Within the RI-CLPM the scores of the variables of interest are split into two components: an interpersonal and an intrapersonal part (Hamaker et al., 2015).

Fig. 1 shows our conceptual framework, and this model can be expressed as follows:

$$x_{it} = \mu_t + \kappa_i + \xi_{it} \tag{1}$$

$$y_{it} = \pi_t + \omega_i + \eta_{it} \tag{2}$$

with

$$\xi_{it} = \alpha_t \xi_{i,t-1} + ß_t \eta_{i,t-1} + u_{it} \tag{3}$$

$$\eta_{it} = \delta_t \eta_{i,t-1} + \gamma_t \xi_{i,t-1} + v_{it} \tag{4}$$

where

x_{it} = mode preference of individual *i* at time *t*

y_{it} = mode use of individual *i* at time *t*

μ_t and π_t are the temporal group means for mode preference and mode use

κ_i and ω_i are the individual's trait-like deviations from these means

ξ_{it} and η_{it} are the individual temporal deviation terms

Within the model, a distinction is made between autoregressive (α and δ) and regression coefficients (ß and γ). Autoregressive effects, also stability or inertia effects, represent the association between the values of the same variable at time *t*−*1* and time *t* (Selig and Little, 2012; Yáñez and Cherchi, 2009; Cherchi et al., 2013).

The autoregressive parameters in a RI-CLPM reveal the amount of intrapersonal carry-over (Hamaker, 2012; Kuppens et al., 2010). A positive autoregressive parameter means that people who use the car more frequently than their expected frequency of car use, are also likely in following years to use the car more frequently than expected. The regression coefficients represent cross-lagged effects or the effect of a variable at time *t*−*1* on another variable at time *t*. We assumed two directions of cross-lagged effects: the impact of mode preference on mode use over time and the impact of mode use on mode preference over time. An important feature of the model is that cross-lagged effects are controlled for previous levels of the dependent variable (Selig and Little, 2012). For example, mode preference at time *t* + *1* can be predicted by the frequency of mode use at time *t* while controlling for previous levels of mode preference at time *t* (i.e., the stable portion). Life events (i.e. new job, moving home and birth of a child) affect mode use and mode preference both within and between waves (ι). Furthermore, all relationships are controlled for possible confounding effects of socio-demographic and spatial characteristics at the baseline situation. The included variables were age, gender, urbanity, residential accessibility, and parking situation at home (see also section 4).

Within the RI-CLPM framework, it is possible to examine both the causal relation between several variables and the magnitude of change in behaviour under various conditions, distinguishing between- and within-person effects. The autoregressive effects and cross-lagged relationships represent processes at the intrapersonal level over time. The correlation between the random-intercept factor for mode preference and mode use shows how young adults differ from each other, i.e. the interpersonal level.

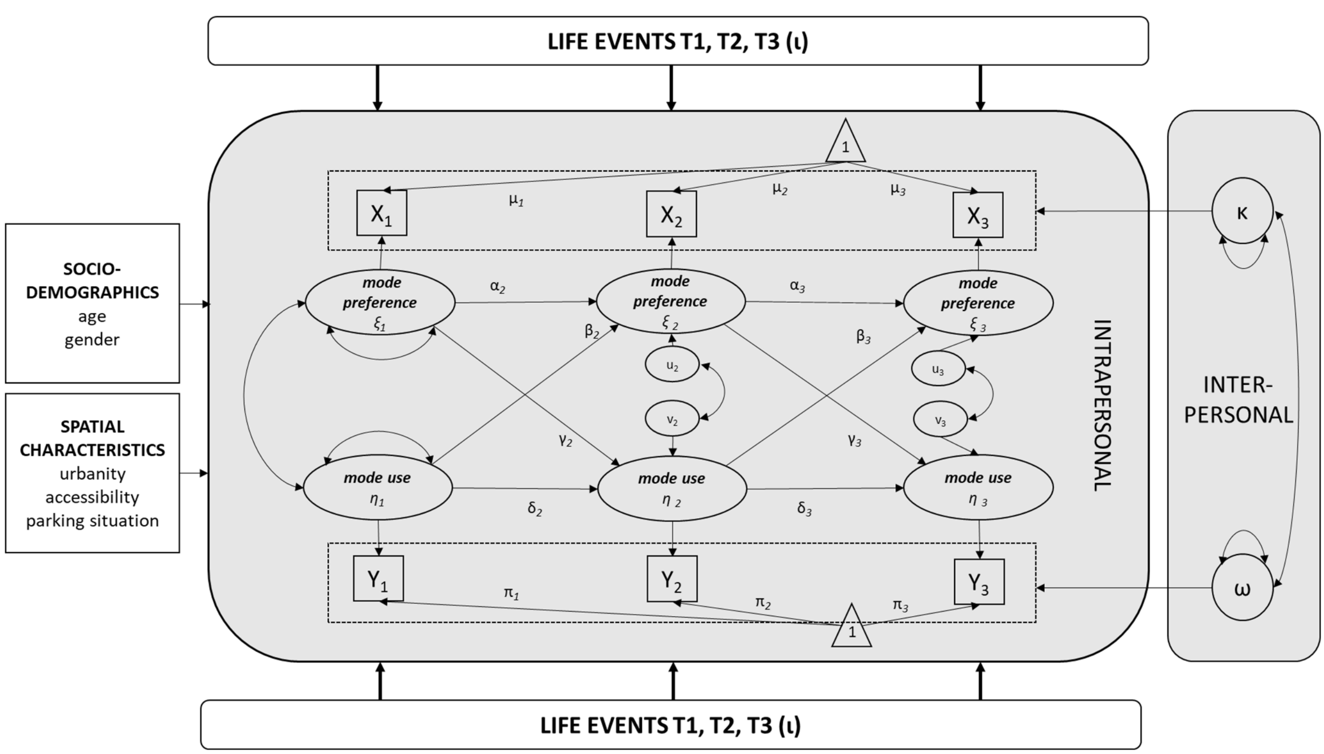

Fig. 1. Random-intercept cross-lagged panel model. Triangles represent constants (which define the mean structure), rectangles represent observed variables, and circles represent latent constructs.

4. Data

4.1. Netherlands Mobility Panel

To answer our research questions, we used data from the 2014, 2015 and 2016 waves of the Netherlands Mobility Panel (in Dutch: Mobiliteitspanel Nederland, MPN). The MPN is an annual online household panel, in which all household members aged 12 and over are asked to participate. The MPN consists of approximately 2,000 complete households and 6,000 individuals every year. For an elaborate description of the set-up of the MPN, see Hoogendoorn-Lanser et al. (2015). Respondents were randomly selected and recruited from an online access panel. The attrition rate between the waves lies between the 18 and 28% (La Paix Puello et al., 2017). Each wave, the sample is refreshed to retain a representative sample of the Dutch population.

The main objective of the MPN is to examine the short- and long-term dynamics in the travel behaviour of households and individuals. Another goal of the MPN is to gain more insight into the relationship between sociodemographic characteristics and individual changes in travel behaviour (Hoogendoorn-Lanser et al., 2015). Mobility-related and background information is collected through household and individual questionnaires. In addition, respondents are asked about changes in their work situation (e.g., changing job, changes in working hours, change of work location) and changes in their household situation (e.g., the birth of a child, start living together, moving home). This unique combination of information on life-changing moments and (changes in) travel behaviour enabled us to study the relationship between life events and mode choice behaviour.

4.2. Sample selection

In our analysis, we examined whether young adults were more likely to change their mode preference and frequency of mode use when faced with a life event such as becoming a parent, moving home or changing jobs. According to existing research, these are the life events that appear to have the greatest impact on travel behaviour (see, for example, Rau and Manton, 2016; Clark et al., 2014). The total MPN sample for 2014, 2015 and 2016 consists of 12,348 individuals, of which 3,900 participated in all three waves. From this group, we selected respondents aged between 18 and 39 in 2014 (i.e. young adults), because this age-group experiences the highest frequency of life events and it has been suggested that young adults are easier to influence than older people (Beige and Axhausen, 2012). Our final sample consisted of 1,180 respondents, who participated in 2014, 2015 as well as in 2016. To measure the variation in mode preference and mode use over time, while controlling for individual characteristics that do not change over time, only respondents who participated in 2014, 2015 and 2016 were included in the sample. Including only participants who responded to all three waves, might lead to attrition biases. However, for our main variables of interest, mode preference and frequency of mode use, we did not find any significant differences between participants who dropped out and those who participated in 2014, 2015 and 2016. This suggests there are no major attrition biases in our sample regarding mode preference and mode use. In La Paix Puello et al. (2017) more information can be found about the impact of non-random attrition in the MPN data on travel behavior,

4.3. Variable specification

4.3.1. Mode preference and mode use

Every year participants of the MPN are asked about their preferred transport mode for eight different purposes (i.e. work, business, education, daily groceries, shopping, visiting family or friends, going out, recreational trips and sports activities). First, we calculated the number of times each mode was mentioned as the preferred mode. Mode preference for the car, public transport (PT), and the bicycle was derived as the ratio between this frequency and the total number of purposes that were scored, resulting in scores from 0 to 1 for each transport mode. Respondents could choose more than one preferred mode for each purpose. Young adults were more likely to select multiple modes compared to respondents aged 40 years and older. This might suggest that young adults are more flexible in terms of mode choice.

In the MPN survey, the frequency of mode use is measured in two ways. Firstly, respondents were asked to report their mode use on a seven-point ordinal scale ranging from “never” to “four or more days a week”. Secondly, respondents reported the modes of trips made in a three-day trip diary. In this paper, the self-reported frequency of mode was used in the analysis as less frequently used travel modes were underreported in the trip diary, for example, the use of public transport.

4.3.2. Explanatory variables

To control for time-invariant confounders, explanatory variables with meaningful differences in mode choice behaviour were included in the model. We will briefly discuss which explanatory variables we included in our analysis. Socio-economic characteristics at both individual and household level affect mode choice behaviour (e.g., Commins and Nolan, 2011; Feng et al., 2014; Vij et al., 2013). In our analysis, we included gender and age, based on the evidence that women are less likely to use the car and that increasing age is associated with increased car use and less public transport use (see, for example, Paulssen et al., 2014). Built environment variables describing the characteristics of the spatial and transport infrastructure have a significant effect on mode choice decisions (e.g., Rubin et al., 2014; Dieleman et al., 2002; Limtanakool et al., 2006; Van Acker and Witlox, 2010). We enriched the MPN dataset with spatial characteristics of the residential location. Based on the zip code we included for every respondent the distance from home to public transport services, and the nearest highway exit. Following Hilbers et al. (2005), we derived a dichotomous variable describing whether an individual’s residential neighbourhood is easily accessible by high-frequent public transport (1) or not (0) (i.e. A-location). An A-location means that the distance to a large (intercity) railway station is <3 km. In the Netherlands, intercity stations are located in central urban areas where land use is dominated by offices and shops. This explains the relatively low share of people that live here. Also, we controlled for urban density (reference = urban, i.e. >1500 inhabitants/km^2) and paid parking or not (reference = no costs or permit necessary).

4.3.3. Life events

For each life event, we created a binary variable according to whether the life event occurred in 2014, 2015, 2016 (1) or not (0). It is possible that life events coincide, for instance moving home often coincides with a change in household structure. Although the sample size is very small for these inter-relationships, there are some significant associations between life events for young adults (Table 1). Young adults are more likely to move home either before or after starting a new job. However, the effect sizes, which measures how strongly two life events are associated, are very small (Cramer’s V $<$ 0,10[1]), implying that there is a low association (Cohen, 1988). Therefore, we only included the impact of a single life event on mode choice behaviour[2].

4.4. Sample description

Table 2 presents descriptive statistics for mode preference and mode use regarding the included variables for young adults at the baseline

[1] Cramers V is an effect size measurement for the chi-square test of independence.

[2] Other life-events, such as marriage / start living together might be important life changing moments for young adults. The main reason for not including marriage is that it is not measured directly with the MPN and cannot be derived from other variables.

Table 1
Significance tests for coinciding life events, Pearson Chi Square values (χ^2) and Cramer's V.

life event	time	t1		t2		t3	
		χ^2	V	χ^2	V	χ^2	V
		Birth of a child					
New job	t1	0,525	0,021	0,393	0,018	0,459	0,020
New job	t2	0,540	00,21	2,516	0,046	0,042	0,006
New job	t3	0,252	0,015	2,584	0,047	2,794	0,053
		Moving home					
Birth of a child	t1	3,043	0,051	1,035	0,030	1,316	0,033
Birth of a child	t2	0,000	0,000	3,488	0,054	0,076	0,008
Birth of a child	t3	0,184	0,013	1,906	0,040	0,158	0,012
		New job					
Moving home	t1	2,897	0,050	6,518*	0,074	1,408	0,035
Moving home	t2	1,925	0,040	12,847*	0,098	2,934	0,050
Moving home	t3	4,881*	0,064	10,099*	0,093	3,106	0,051

Note: * association is significant at the 0.05 level.

Table 2
Sample characteristics of young adults in 2014 (N = 1,180).

		Sample	Pop.	Mode preference (mean score)			Mode use (% weekly users)		
		2014	2014	car	PT	bicycle	car	PT	bicycle
Gender	Male	42%	47%	0.56	0.13	0.37	79	32	67
	Female	58%	53%	0.49	0.17	0.43	72	35	75
Age group	18–29 yrs.	59%	57%	0.45	0.18	0.45	69	46	78
	30–39 yrs.	41%	43%	0.62	0.10	0.34	83	16	63
Urban density home location (inhabitants/km^2)	Urban (>1,500)	51%	57%	0.41	0.19	0.46	64	40	77
	Rural (≤1,500)	49%	43%	0.63	0.11	0.34	86	28	67
Paid parking or not at home location	Costs or permit	86%	87%	0.56	0.15	0.39	79	31	71
	No costs or permit	14%	13%	0.28	0.17	0.51	50	50	78
Accessibility home location	No A-location	95%	95%	0.53	0.15	0.39	76	33	71
	A-location	5%	5%	0.26	0.18	0.50	57	46	79

situation in 2014. Young adults who had a high car preference and who were frequent car users were more likely to be male, live in rural areas, and to be 30 to 39 years old (in comparison to the 18 to 29 age group). Young adults who were frequent public transport users had a greater tendency to be 18 to 29 years old, live in single families, urban areas and at A-locations (i.e. nearby public transport). Young adults who preferred cycling and were frequent bicycle users appeared more likely to be women with a high level of education and to live in urban areas. Compared to the Dutch population of young adults in 2014[3], female and people living in rural areas are somewhat underrepresented. Overall, our sample is a good representation of the Dutch young adult population.

Table 3 shows the frequency of life events in our sample and Fig. 2. The frequency of the three selected life-events by age. Each year, about 12 to 13% of the young adults moved home and 7 to 9% became parents. In 2014, 14% of the respondents found a new job, in 2015 and 2016 this was 19%. Previous research showed that changes in travel behaviour are more likely when people move from urban to non-urban areas or vice versa (e.g., Scheiner and Holz-Rau, 2013). However, in our sample only a small number (i.e. 15–17 in the years 2014 to 2016) moved home to a neighbourhood with a very different urban density. Therefore, we did not make this distinction in our analysis.

New jobs were most prevalent at the age of 25–29 years, after finishing school. Childbirth peaks in the early 30s, while moving home seems to have a double peak. The first one at 25–29 years, also after finishing school, and the second one at 40–44 years, possibly linked to increasing family size and needing a bigger home some years later.

Table 4 shows the level of change of frequency of mode use and mode preference for all purposes between the waves. The share of respondents that did not change frequency of mode use varies between 50 and 70%. Car users were the most stable group in terms of the frequency of mode use. Furthermore, almost half of the respondents did not change their preference for public transport, while car and bicycle preference show more dynamics. There are no significant differences in the level of change of frequency of mode use and mode preference between the waves.

Table 3
Frequency of life events of young adults (N = 1,180).

	2014	2015	2016
Moving home	13%	12%	12%
birth of child	9%	9%	7%
New job	14%	19%	19%

5. Results

A separate SEM is estimated to explain frequency of mode use and mode preference for each of the three modes considered: car, public transport and bicycle. Final models were constructed by model trimming: we removed non-significant structural paths to find the most parsimonious model. For evaluation of model fit, we used the following three model fit indices (see Table 5), mostly used in structural equation modelling: Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and (Standarazied) Root Mean squared Residual ((S)RMR). For each goodness of fit indicator, we applied the cutoff criteria from Hu and Bentler (1999), which is shown in Table 5. To perform the analyses, we used the software program R and the package LAVAAN (Rosseel, 2012). As we can observe, the three models satisfy the minimum fit to be considered a valid model.

In this section, we firstly present and discuss the model results of the interpersonal correlations (κ*ω) and intrapersonal correlations (ξ*η) (section 5.1), the autoregressive (α and δ) and cross-lagged effects (β and γ) between mode preference and mode use (section 5.2). Secondly, we describe the impact of life events on mode use and mode preference (ι) for each transport mode (section 5.3). The coefficients ι provide evidence of the relationship between life events and mode preference and mode use (research question 1), while the interpersonal correlations,

[3] Data from Statistics Netherlands for 2014 (CBS, 2014).

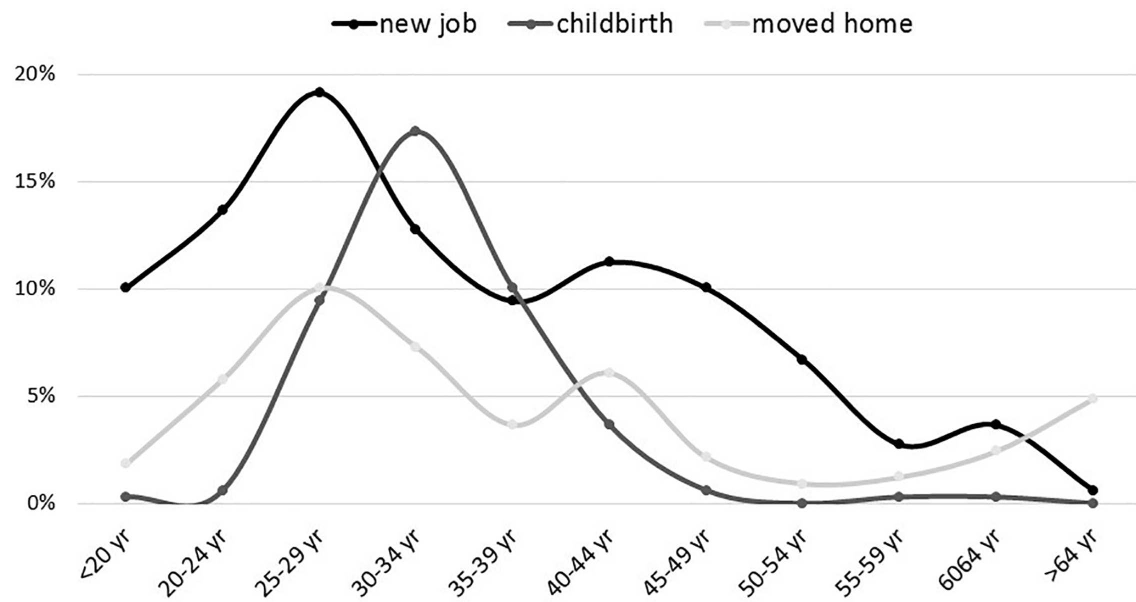

Fig. 2. Frequency of life events by age (Source: MPN).

Table 4
Level of change in frequency of mode use and mode preference between waves of young adults (N = 1,180).

Frequency of mode use	car use 2014–2015	2015–2016	PT use 2014–2015	2015–2016	bicycle use 2014–2015	2015–2016
Decrease	14%	14%	22%	19%	24%	22%
No change	69%	70%	51%	53%	60%	59%
Increase	17%	16%	27%	28%	16%	19%
Mode preference	car preference 2014–2015	2015–2016	PT preference 2014–2015	2015–2016	bicycle preference 2014–2015	2015–2016
<50% decrease	2%	2%	1%	2%	4%	2%
1 to 50% decrease	27%	28%	26%	24%	36%	36%
no change	33%	35%	50%	53%	28%	28%
1 to 50% increase	36%	33%	22%	21%	31%	32%
>50% increase	3%	3%	1%	0%	1%	2%

Table 5
Summary of fit indices.

	CFI1	RMSEA	(S)RMR
RI-CLPM – CAR	0.958	0.054	0.035
RI-CLPM – PT	0.971	0.046	0.044
RI-CLPM – BICYCLE	0.978	0.037	0.034
Criteria for good model fit	>0.95	<0.06	<0.08

autoregressive and cross-lagged effects provide evidence of the mediating effects of mode preference and mode use (research question 2). To examine the difference between the inter- and intrapersonal dynamics and the impact of life events on the frequency of mode use and mode preference, the results were split across the Tables 6 and 7. This prevents different effects are mixed up. Tables 6 and 7 presents the standardized effects (ß), which are indicators of effect size. In a RI-CLPM parameters reflect how intrapersonal variations relative to their own scores are correlated or can be predicted. The significance of the estimated parameters is based on the t-statistic.

5.1. Inter- and intrapersonal correlations

The interpersonal correlation between the random-intercept factors shows how stable between-person differences in mode preference are associated with between-person differences in frequency of mode use (Table 6). The interpersonal correlation between car preference and car use was very high (ß=0.731, $p < 0.001$). This indicates that young adults who reported a higher preference for the car over time are more likely to use the car more frequently over time than other young adults. Also, young adults who have a higher preference for the bicycle across the three waves tend to be more frequent bicycle users over time (ß=0.727, $p < 0.001$). No significant interpersonal correlation between mode use and mode preference was found for public transport. This means that more frequent public transport users do not necessarily have a higher preference for public transport than other young adults across the three waves, or vice versa. The positive intrapersonal correlations for all transport modes reflect that at the personal level, an above-average score of the frequency of mode use at time t goes hand-in-hand with an above-average score of mode preference at time t, in addition to the interpersonal correlation.

5.2. Autoregressive and cross-lagged effects

The estimated parameters for the autoregressive and cross-lagged effects represent intrapersonal dynamics. The autoregressive effects (α and δ) for mode preference and frequency of mode use were all significant and positive ($p < 0.05$). For example, the estimated parameter for the effect of car preference in 2014 on car preference in 2015 was 0.528 and for bicycle use in 2015 on bicycle use in 2016 0.369 (see Table 6). Positive estimates reflect that at the individual level above average scores at time t imply above-average scores at time $t + 1$. Generally, the

Table 6
Autoregressive and cross-lagged effects between frequency of mode use and mode preference (T1 = 2014, T2 = 2015, T3 = 2016), N = 1,180.

	CAR		PT		BICYCLE	
	ß	SE	ß	SE	ß	SE
autoregressive effects						
mode preference T1 -> mode preference T2 (α_2)	0.528***	0.064	0.248***	0.078	0.169***	0.064
mode preference T2 -> mode preference T3 (α_3)	0.569***	0.069	0.153**	0.082	0.287***	0.056
frequency mode use T1 -> frequency mode use T2 (δ_2)	0.251***	0.069	0.811***	0.036	0.360***	0.064
frequency mode use T2 -> frequency mode use T3 (δ_3)	0.230***	0.061	0.768***	0.057	0.369***	0.050
cross-lagged effects						
mode preference T1 -> frequency mode use T2 (β_2)	0.211***	0.253	0.057**	0.330	0.112***	0.296
mode preference T2 -> frequency mode use T3 (γ_2)	0.279***	0.230	0.068*	0.343	0.131***	0.259
frequency mode use T1 -> mode preference T2 (β_2)	0.129***	0.012	0.412***	0.005	0.199***	0.011
frequency mode use T2 -> mode preference T3 (γ_2)	0.136***	0.012	0.463***	0.005	0.033	0.009
interpersonal correlation						
mode preference * frequency mode use (κ*ω)	0.731***	0.025	0.039	0.056	0.727***	0.017
intrapersonal correlation						
mode preference * frequency mode use T1 (ξ_1*η_1)	0.271***	0.024	0.616***	0.058	0.199***	0.014
mode preference * frequency mode use T2 (ξ_2*η_2)	0.316***	0.009	0.346***	0.006	0.302***	0.010
mode preference * frequency mode use T3 (ξ_3*η_3)	0.333***	0.008	0.333***	0.007	0.306***	0.008
sociodemographics -> mode preference						
gender (male = ref)	−0.105***	0.017	0.061*	0.011	0.072***	0.014
urbanity (urban = ref)	0.245***	0.025	−0.203***	0.012	−0.101***	0.015
parking home location (free parking = ref)	−0.134***	0.038	−0.041	0.016	−0.017	0.023
age group (18–29 yr = ref)	0.223***	0.020	−0.171***	0.012	−0.122***	0.015
accessibility home location by PT (no A-location = ref)	−0.078***	0.038	0.002	0.025	0.029	0.036
sociodemographics -> frequency mode use						
gender (male = ref)	−0.063**	0.064	0.028	0.114	0.051	0.079
urbanity (urban = ref)	0.135***	0.077	−0.182***	0.123	−0.062	0.083
parking home location (free parking = ref)	−0.114***	0.125	0.113***	0.159	−0.001	0.126
age group (18–29 yr = ref)	0.187***	0.072	−0.261***	0.119	−0.158***	0.084
accessibility home location by PT (no A-location = ref)	−0.001	0.145	0.009	0.229	−0.006	0.197

Notes: ***p < 0.00, **p < 0.05, *p < 0.10.

Table 7
Impact of life events on mode preference and frequency of mode use (ι), N = 1,180.

	2014		2015		2016		2014		2015		2016	
	CAR PREFERENCE						FREQUENCY OF CAR USE					
	ß	SE	ß	SE	ß	SE	ß	SE	ß	SE	ß	SE
new job 2014	0.06*	0.03	0.06	0.10	0.01	0.02	0.06	0.10	−0.00	0.09	0.09***	0.07
birth of a child 2014	0.11***	0.03	0.07***	0.01	0.04	0.02	0.07***	0.10	−0.01	0.10	0.02	0.09
moving home 2014	−0.08***	0.03	−0.05*	0.11	0.02	0.02	−0.05	0.11	−0.04	0.10	−0.01	0.08
new job 2015	−0.06	0.02	−0.07	0.10	0.02	0.02	−0.07*	0.10	0.05	0.08	0.06***	0.07
birth of a child 2015	0.10***	0.03	0.05	0.12	0.02	0.03	0.05	0.12	0.09***	0.07	0.07	0.07
moving home 2015	−0.10***	0.03	0.02	0.10	−0.08***	0.02	0.02	0.10	−0.04	0.12	−0.06	0.10
new job 2016	0.01	0.02	−0.00	0.09	0.05***	0.02	−0.00	0.09	−0.01	0.08	0.06***	0.07
birth of a child 2016	0.10***	0.03	0.08***	0.12	0.06***	0.03	0.08***	0.12	0.03	0.08	0.05***	0.07
moving home 2016	−0.02	0.03	−0.01	0.11	−0.02	0.02	−0.01	0.11	0.05	0.09	0.01	0.08
	PT PREFERENCE						FREQUENCY OF PT USE					
	ß	SE	ß	SE	ß	SE	ß	SE	ß	SE	ß	SE
new job 2014	−0.08***	0.01	−0.06***	0.01	−0.05***	0.01	0.06	0.10	0.00	0.11	−0.01	0.10
birth of a child 2014	−0.07***	0.02	0.01	0.01	−0.03	0.01	0.07***	0.10	−0.00	0.11	−0.02	0.14
moving home 2014	0.01	0.02	0.01	0.02	−0.03	0.02	−0.05	0.11	0.01	0.10	0.04	0.12
new job 2015	0.05	0.02	0.05	0.01	0.00	0.01	−0.07	0.10	0.02	0.10	−0.01	0.09
birth of a child 2015	−0.02	0.02	−0.01	0.01	0.01	0.01	0.05	0.12	−0.02	0.13	0.01	0.14
moving home 2015	0.03	0.02	−0.01	0.01	0.02	0.02	0.02	0.10	0.01	0.10	0.01	0.12
new job 2016	0.03	0.02	0.02	0.01	−0.02	0.01	−0.00	0.09	−0.01	0.09	−0.04**	0.10
birth of a child 2016	−0.109***	0.02	−0.03	0.01	−0.06***	0.02	0.08***	0.12	0.00	0.15	−0.03*	0.14
moving home 2016	−0.02	0.02	0.02	0.01	0.02	0.02	−0.01	0.11	0.02	0.10	0.02	0.11
	BICYLCE PREFERENCE						FREQUENCY OF BICYLCE USE					
	ß	SE	ß	SE	ß	SE	ß	SE	ß	SE	ß	
new job 2014	−0.06	0.03	−0.04	0.02	−0.07*	0.02	−0.10***	0.13	−0.02	0.10	−0.07**	0.02
birth of a child 2014	−0.13***	0.03	−0.06**	0.03	−0.06*	0.03	−0.09***	0.16	−0.06**	0.13	−0.06**	0.03
moving home 2014	0.10***	0.03	0.09***	0.02	0.07**	0.02	0.03	0.14	0.04	0.11	0.07***	0.02
new job 2015	0.06	0.02	0.08***	0.02	−0.01	0.03	0.02	0.12	0.01	0.09	−0.01	0.02
birth of a child 2015	−0.10***	0.03	−0.08***	0.03	−0.05	0.03	−0.07	0.16	−0.05	0.13	−0.05	0.03
moving home 2015	0.13***	0.03	0.11***	0.02	0.08	0.02	0.06	0.14	0.05	0.12	0.08***	0.02
new job 2016	−0.01	0.02	−0.05	0.02	−0.01	0.02	0.03	0.12	−0.05**	0.09	−0.01	0.02
birth of a child 2016	−0.02	0.04	−0.09***	0.03	−0.07*	0.03	0.01	0.18	−0.02	0.14	−0.07**	0.03
moving home 2016	0.03	0.03	0.05*	0.02	0.09	0.02	−0.00	0.14	0.06***	0.11	0.09***	0.02

Notes: ***p < 0.01, **p < 0.05, *p < 0.10.

autoregressive effects were also the largest in the model. This means that mode use at time t is the best predictor for mode use at time $t + 1$, and mode preference at time t is the best predictor for mode preference at time $t + 1$. Regarding mode preference, the strongest autoregressive effects were found for public transport (ß=0.811 and ß=0.768, both $p < 0.00$). For the car, the stability effects were stronger for mode preference (ß= 0.528 and ß=0.569, both $p < 0.00$) compared to the frequency of mode use (ß=0.251 and ß=0.230, both $p < 0.00$). For public transport and the bicycle, the opposite effect was found: the stability effects were stronger for frequency of mode use compared to mode preference. This suggests that for both public transport and the bicycle, frequency of mode use is more likely to stay more stable than mode preference.

Also, the results show that cross-lagged effects (ß and γ) between frequency of mode use and mode preference in a prior period (and vice versa) were weaker compared to stability effects, and not significant for all relationships. For instance, the effect of car preference in 2015 on car preference in 2016 (ß=0.569) was 4.2 times higher than the effect of car use in 2015 on car preference in 2016 (ß=0.136). This means that habit and inertia effects have a stronger influence on mode preference than changes in mode use or vice versa. Frequency of mode use shows a significant and positive regression on all later measures of mode preference, except for the prediction of the preference for cycling in 2016 (ß=0.033, $p > 0.10$). The frequency of public transport use had the largest positive effect on mode preference for that mode in the next year (ß=0.412 in 2014 and ß=0.463 in 2015, both $p < 0.00$). This indicates that when the frequency of public transport use of young adults was higher than expected at time t (based on his or her average score over time), these young adults also have a higher preference for public transport at time t + 1. However, there were no significant cross-lagged effects between mode preference and mode use for public transport across the waves. This means that, after an increase in mode use, young adults develop a stronger preference for public transport over time, whereas an increase in mode preference does not necessarily lead to an increase in the frequency of public transport use. The baseline sociodemographics and spatial characteristics significantly affected the frequency of car use and preference for the car. Young adults aged 30–39 years and those living in rural areas were more likely to use the car more frequently, whereas female respondents and those having no free parking space at home or good access to public transport services were more likely to use the car infrequently. For public transport and the bicycle, a negative association was found between increasing age and those living in rural areas and mode preference.

5.3. Impact of life events on mode preference and frequency of mode use

We now discuss the impact of life events, both within and between waves, on mode use and mode preference for each transport mode (ι). We found a positive and significant association between childbirth and car preference and the frequency of car use (Table 7). Parents became more car-minded, both after the birth of a child and in anticipation of this life-changing moment. Between moving home and car preference we found a negative association, although there was no significant relationship between moving home and the frequency of car use. Young adults with a new job showed less preference for public transport across all waves, although this did not result in a significant change in the frequency of mode use. Young adults with a new job show a lower frequency of bicycle use in all three waves, although not all coefficients were significant at the 0.05-level. Movers developed a more positive attitude towards cycling over time and were more likely to use the bicycle more often. In general, the birth of a child seemed to have the greatest effect on mode preference and the frequency of mode use. Young parents use the car more frequently and develop a less positive attitude towards public transport and cycling. Furthermore, movers intend to cycle more often, while young adults with a new job were less likely to prefer public transport.

6. Discussion and implications

6.1. Discussion

Based on the literature, we expected past behaviour to be a good predictor of current behaviour. For example, Thøgersen (2006) addressed the question of stability in travel behaviour and found that past behaviour is the main predictor of ongoing behaviour. The results of the present study confirm these findings. Young adults showed very stable behaviour regarding mode preference and frequency of mode use. For the car, stability in car preference is more than two times higher than stability in the frequency of mode use. This corresponds with the finding of Olde Kalter et al. (2020), who found that traveller's profiles based on attitudes towards the car were remarkably stable over time. However, based on existing research, it can be argued that this is not solely a stable attitude towards the car, but might also be the case for multimodal preferences (Haas et al., 2016; Kroesen and Cranenburgh, 2016). The stability effects of frequency of mode use found in this study are two (for bicycle) or three (for public transport) times higher compared to stability effects of mode preference. This suggests that young adults are more likely to change their preference towards public transport and cycling then their frequency of public transport or bicycle use. Besides stability effects, previous research on mode choice behaviour showed that there is a strong relationship between mode preference and mode use (e.g., Buehler, 2011; Bjerkan and Nordtømme, 2014; Olde Kalter et al., 2015). In our three-wave panel study, we found that after an increase in mode use over time, young adults develop a stronger preference for that mode. In contrast, an increase in mode preference does not necessarily lead to an increase in the frequency of mode use. This implies changes in travel behaviour are more likely to precede changes in preferences rather than the other way around, e.g. young adults who start using the car more frequently are more likely to show stronger car preferences later on. This process can be explained by the cognitive dissonance reduction theory, as discussed by Kroesen et al. (2017) who found similar effects in a two-wave panel study for the Netherlands and indicates that a dynamic Theory of Planned Behaviour should include a feedback loop from behaviour to preference.

The results of this study highlight the importance of considering the impact of life events when examining changes in the travel behaviour of young adults. Young adults showed fixed habits regarding mode use and mode preference. However, life events act as a trigger for changes and affect both the travel behaviour and attitudes of young adults. This finding implies that a change in frequency of mode use is not only because of a change in attitude towards the car, public transport or bicycle or vice versa but also directly related to life events. The impact of life events on changes in the frequency of mode use and mode preference depends on the type of life event. In particular, car use among Dutch young adults increased significantly after the birth of a child. In addition, there is a significant positive relationship with a higher car preference. This means that young adults with above average scores for car preference at time t, are more likely to have an above average score for car preference a year later, after the birth of a child. At the same time, we found a negative association between the birth of a child and the use of public transport and the bicycle. This result is consistent with other studies about the inertia effects of car use that show car users as the most inert travellers (González et al., 2017). Moving home increased both the frequency of cycling and preference for the bicycle. This is in line with Janke and Handy (2019). Young adults with a new job showed less preference for public transport across all waves, although this did not result in a significant change in the frequency of the use of this transport mode.

6.2. Policy implications

Overall, this study provides more insight into the impact of life events on travel behaviour and indicates that policymakers can make use of life events as windows of opportunity. However, we know that developing interventions and implementation are not simple. Considering life events and lifestyle changes might help to establish more accurate policy scenarios. A contextual change in someone's life is an essential pre-condition for increasing the effectiveness of policy measures. Policy interventions can be more effective when centred around the three life events we studied in this paper (i.e. a new job, moving home and the birth of a child). Policymakers who want to utilise these life events to influence behaviour should primarily focus on three points: the target group, timing, and the parties that, in addition to the government, can make relevant contributions.

As a result, this paper identifies three main policy recommendations. Firstly, policymakers need a clear understanding of the target group. An intervention should be designed in such a way that the highest possible effect will be achieved in the selected target group. This means that interventions should match people's motives and specific interests. For example, young parents are probably more interested in safety and comfort whilst travelling. In contrast, the accessibility of residential and work locations may be more critical mobility-related issues for those who are looking for a new home. In this respect, it is worth mentioning that life events are strongly associated with social and cultural aspects. In cultures in which companies offer new employees a lease car by default, public transport is not an equal alternative. When applying policy interventions, it is essential to keep such social and cultural preferences in mind (Schwanen et al., 2012). Secondly, policymakers should take note of and, if possible, involve relevant stakeholders, such as employers, land register and midwives or consultancy agencies. In-depth interviews with young adults in the Netherlands reveal that young adults hardly receive any information about transport-related issues when they are about to relocate, change jobs or become a parent (Berveling et al., 2017). These life-changing moments could offer an excellent opportunity for policymakers and other parties to create more awareness of alternative, more sustainable, modes of transport. Thirdly, the timing and duration of policy measures are crucial aspects of implementation in order to achieve structural changes in travel behaviour. Policymakers should focus on the actions that cope with the new deliberation process brought by the life-event changes. This deliberation process can be anticipated by the individual and household characteristics of the target groups, such as income level, the urbanity of the residential location, gender, composition of the household. or first job age. A common mobility strategy in the Netherlands is stimulating cycling among employees. National fiscal regulations are available which allow employees to purchase new bicycles at reduced costs, and pilots are conducted to give employees the opportunity to test e-bikes. These measures could be targeted towards new employees.

6.3. Research implications

There are several possible directions for further research. Some life events coincide, which results in compounded effects. For illustration, increased car ownership is more likely after a new job or when someone moves from an urban to a rural area. It would be interesting to examine in which way these interactions affect travel behaviour. Also, it would be interesting to disentangle the effects of moving between urban and rural areas and moving within the same area. Based on existing research, we might expect that, for example, car use or car preference would decrease after moving from rural areas to more urban areas. Moving to a more urban area could explain the increase in cycling after moving home we found. However, in our sample, only a relatively small portion (i.e. <3%) moved to a different area, and consequently, it was not possible to estimate these effects. Another potential avenue for further research concerns the relationship between life events at the level of the individual and travel behaviour on the household level, as well as the difference between short-term and long-term effects. Generally, the short-term effects of life events on travel behaviour are higher than long-term outcomes. In particular, gender differences and (short- and long-term) effects of childbirth are interesting to explore. Shortly after becoming parents, young adults spend more time at home and at activities in their neighbourhood, resulting in less trips and car use. After a certain period, for example, when parents return to work, preference for the car might increase. Also, the difference between first-time parents and other parents is an exciting direction of future research. As a result of limitations in our dataset, we were not able to make these distinctions. When more waves of the MPN become available, both first-order and second-order effects could be included. Part of the stability effects we found for mode preference, might be a result of the direct way of measuring mode preference. However, mode preference might be a function of different underlying attitudes. Including other attitudinal variables would be interesting to explore the variation in mode preferences over time more thoroughly. Finally, one of the limitations of this study is that we examined the causal relationship between mode preference and the frequency of mode use over time. We examined the impact of one variable at time t on the other variable at time $t + 1$. The reversed causality between mode preferences and mode choice behaviour (i.e. the impact of one variable at time t on the other variable at time $t-1$) should be further analysed.

7. Conclusions

In this study, we examined the relationship between life events, mode preference and frequency of mode use over time for young adults in the Netherlands. We found that young adults show very stable behaviour over time: those who use the car, public transport of bicycle at an above average level, are more likely to use these transport modes at an above average level across the waves. Frequent car users are the most stable in their behaviour, compared to public transport and bicycle users. Concerning the relationship between mode preference and mode use, one of the main conclusions of this paper is that young adults who increase the use of the car, public transport or the bicycle are more likely to develop a more positive attitude towards this mode. Changes in mode preference seem to have less influence on the frequency of mode use, in particular for public transport users. Furthermore, the results of this study show the impact of three different life events (the birth of a child, getting a new job and moving home) on changes in travel behaviour and mode preference. Young adults who become parents show an increase in car use and develop a higher preference for the car over time. Public transport and the bicycle are less popular after the birth of a child. Moving home and changing jobs mainly affects cycling, both the frequency of use and preference, although these effects are not significant at all temporal scopes (i.e. first year or second year of event). This can be associated with the substantial role played by the urban characteristics and accessibility of public transport.

CRediT authorship contribution statement

Marie-José Olde Kalter: Conceptualization, Methodology, Software, Formal analysis, Writing - original draft, Writing - review & editing. **Lissy La Paix Puello:** Writing - review & editing. **Karst T. Geurs:** Writing - review & editing.

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References

Andersen, S.M., Chen, S., 2002. The relational self: an interpersonal social-cognitive theory. Psychol. Rev. 109 (4), 619–645.

Axhausen, K., Frei, A., Ohnmacht, T., 2006. Networks, biographies and travel: first empirical and methodological results. In: Paper presented at the 11th Conference on Travel Behaviour Research, Kyoto, 16–20 August.

Bamberg, S., 2006. Is a residential relocation a good opportunity to change people's travel behavior? Results from a theory-driven intervention study. Environ. Behav. 38 (6), 820–840.

Bamberg, S., Schmidt, P., 2003. Incentives, morality, or habit? predicting students' car use for university routes with the models of Ajzen, Schwartz, and Triandis. Environ. Behav. 35 (2), 264–285.

Beige, S., Axhausen, K.W., 2012. Interdependencies between turning points in life and long-term mobility decisions. Transportation 39 (4), 857–872.

Berveling, J., Harms, L., Haas de, M., Scheepers, E., Wüst, H., 2017. Levensgebeurtenissen en mobiliteit. Kennisinstituut voor Mobiliteitsbeleid, Den Haag.

Bjerkan, K.Y., Nordtømme, M.E., 2014. Car use in the leisure lives of adolescents. Does household structure matter? Transp. Policy 33, 1–7.

Buehler, R., 2011. Determinants of transport mode choice: a comparison of Germany and the USA. J. Transp. Geogr. 19 (4), 644–657.

Burkholder, G.J., Harlow, L.L., 2003. An illustration of a longitudinal cross-lagged design for larger structural equation models. Struct. Equation Model. A Multidiscip. J. 10 (3), 465–486.

CBS, 2014. CBS Statline. Voorburg, The Netherlands.

Cherchi, E., Börjesson, M., Bierlaire, M., 2013. A hybrid mode choice model to account for the dynamic effect of inertia over time. International Choice Modelling Conference.

Chatterjee, K., Scheiner, J., 2015. Understanding changing travel behaviour over the life course: contribution from biographical research. Presented at the 14th International Conference on Travel Behaviour Research.

Clark, B., Chatterjee, K., Melia, S., 2014. Life events and travel behaviour: exploring the inter-relationship using the UK household longitudinal study. TRB, Washington.

Clark, B., Chatterjee, K., Melia, S., 2016. Changes to commute mode: the role of life events, spatial context and environmental attitude. Transp. Res. Part A 89, 89–105.

Cohen, J., 1988. In the Cohen's book: Statistical power analysis for the behavioral sciences, 2nd ed. Lawrence Erlbaum Associates, Hillsdale, New Jersey.

Commins, N., Nolan, A., 2011. The determinants of mode of transport to work in the Greater Dublin Area. Transp. Policy 18 (1), 259–268.

Delbosc, A., Currie, G., 2013. Causes of youth licensing decline: a synthesis of evidence. Transp. Rev. 33 (3), 271–290.

Dieleman, F.M., Dijst, M., Burghouwt, G., 2002. Urban form and trabel behaviour: micro-level household attributes and residential context. Urban Stud. 39 (3), 507–527.

Erikson, E., 1998. The Life Cycle Completed. W.W. Norton & company, New York, London.

Feng, J., Dijst, M., Wissink, B., Prillwitz, J., 2014. Understanding mode choice in the Chines context: the case of Nanjing metropolitan area. Tijdschrift voor Economische en Sociale Geografie 105 (3), 315–330.

Ghisletta, P., Spini, D., 2004. An introduction to generalized estimation equations and a application to assess selectivity effects in a longitudinal study on very old individuals. J. Educ. Behav. Stat. 29 (4), 421–437.

González, R.M., Marrero, Á.S., Cherchi, E., 2017. Testing for inertia effect when a new tram is implemented. Transp. Res. Part A: Policy Pract. 98, 150–159.

Haas, M.d., Scheepers, E., Harms, L., 2016. Transities tussen reispatronen: Latente transitie analyse toegepast binnen het mobility biographies framework. Colloquium Vervoersplanologisch Speurwerk, Zwolle.

Hamaker, E.L., 2012. Why Researchers Should Think" Within-Person": A Paradigmatic Rationale.

Hamaker, E.L., Kuiper, R.M., Grasman, R.P., 2015. A critique of the cross-lagged panel model. Psychol. Methods 20 (1), 102–116.

Harms, L., Jorritsma, P., Kalfs, N., 2007. Beleving en beeldvorming van de mobiliteit. Kennisinstituut voor Mobiliteitsbeleid, Den Haag.

Herde, A., 2007. Nachaltige Ernährung im Übergang zur Elternschaft. Technischen Universität Berlin.

Hilbers, H., Snellen, D., Hendriks, A., 2005. De invloed van de werklocatie. NAI Uitgevers / Ruimtelijk Planbureau, Rotterdam/The Hague, The Netherlands.

Hoogendoorn-Lanser, Sascha, Schaap, Nina T.W., OldeKalter, Marie-José, 2015. The Netherlands mobility panel: an innovative design approach for web-based longitudinal travel data collection. Transp. Res. Procedia 11, 311–329.

Hu, L.T., Bentler, P.M., 1999. Cutoff criteria for fit indices in covariance structure analysis: conventional criteria versus new alternatives. Struct. Equation Model.: A Multidiscip. J. 6 (1), 1–55.

Janke, J., Handy, S., 2019. How life course events trigger changes in bicycle attitudes and behavior: insights into causality. Travel Behav. Soc. 16, 31–41.

Klockner, C.A., 2005. Können wichtige Lebensereignisse die gewohnheitsmäBige Nutzung von Verkehrsmitteln verändern? Eine retrospektive Analyse. Umweltpsychologie 9, 28–45.

Kroesen, Maarten, 2014. Modeling the behavioral determinants of travel behavior: an application of latent transition analysis. Transp. Res. Part A: Policy Pract. 65, 56–67.

Kroesen, M., Cranenburgh, S.v., 2016. Revealing transition patterns between mono- and multimodal travel patterns over time: a mover-stayer model. Eur. J. Transp. Infrastruct. Res. 16, 754–771.

Kroesen, Maarten, Handy, Susan, Chorus, Caspar, 2017. Do attitudes cause behavior or vice versa? An alternative conceptualization of the attitude-behavior relationship in travel behavior modeling. Transp. Res. Part A: Policy Pract. 101, 190–202.

Kuhnimhof, Tobias, Armoogum, Jimmy, Buehler, Ralph, Dargay, Joyce, Denstadli, Jon Martin, Yamamoto, Toshiyuki, 2012. Men shape a downward trend in car use among young adults—evidence from six industrialized countries. Transp. Rev. 32 (6), 761–779.

Kuppens, Peter, Oravecz, Zita, Tuerlinckx, Francis, 2010. Feelings change: accounting for individual differences in the temporal dynamics of affect. J. Personality Social Pshycol. Advance online publication. 99 (6), 1042–1060.

La Paix Puello, L., Olde Kalter, M.J.T., Geurs, K.T., 2017. Measurement of non-random attrition effects on mobility rates using trip diary data. Transportation Research Part A: Policy and Practice 106, 51–64.

Lanzendorf, Martin, 2010. Key events and their effect on mobility biographies: the case of childbirth. Int. J. Sustain. Transp. 4 (5), 272–292.

Limtanakool, Narisra, Dijst, Martin, Schwanen, Tim, 2006. The influence of socioeconomic characteristics, land use and travel time considerations on mode choice for medium- and longer-distance trips. J. Transp. Geogr. 14 (5), 327–341.

Liu, X., 2016. Methods and Applications of Longitudinal Data Analysis. Academic Press, Oxford.

Müggenburg, Hannah, Busch-Geertsema, Annika, Lanzendorf, Martin, 2015. Mobility biographies: a review of achievements and challenges of the mobility biographies approach and a framework for further research. J. Transp. Geogr. 46, 151–163.

Oakil, Abu Toasin Md, Ettema, Dick, Arentze, Theo, Timmermans, Harry, 2014. Changing household car ownership level and life cycle events: an action in anticipation or an action on occurrence. Transportation 41 (4), 889–904.

Oakil, Abu Toasin Md, 2016. Securing or sacrificing access to a car: gender difference in the effects of life events. Travel Behav. Soc. 3, 1–7.

Olde Kalter, M.J.T., Geurs, K., Hoogendoorn-Lanser, S., 2015. Vervoerwijzekeuze in woon-werkverkeer. Eerste analyses met het nieuwe Mobiliteitspanel Nederland. Tijdschrift Vervoerwetenschap 51, 107–127.

Olde Kalter, M.J., La Paix Puello, L., Geurs, K.T., 2020. Do changes in travellers' attitudes towards car use and ownership over time affect travel mode choice? A latent transition approach in the Netherlands. Transp. Res. Part A: Policy Pract. 132, 1–17.

Paulssen, Marcel, Temme, Dirk, Vij, Akshay, Walker, Joan L., 2014. Values, attitudes and travel behavior: a hierarchical latent variable mixed logit model of travel mode choice. Transportation 41 (4), 873–888.

Rau, Henrike, Manton, Richard, 2016. Life Events and Mobility Milestones: advances in mobility biography theory and research. J. Transp. Geogr. 52, 51–60.

Rosseel, Y., 2012. lavaan: an R package for structural equation modeling. J. Stat. Softw. 48 (2), 1–36.

Rubin, Ori, Mulder, Clara H., Bertolini, Luca, 2014. The determinants of mode choice for family visits -evidence from Dutch panel data. J. Transp. Geogr. 38, 137–147.

Schäfer, Martina, Jaeger-Erben, Melanie, Bamberg, Sebastian, 2012. Life events as windows of opportunity for changing towards sustainable consumption patterns? J. Consum. Policy 35 (1), 65–84.

Scheiner, Joachim, Holz-Rau, Christian, 2013. Changes in travel mode use after residential relocation: a contribution to mobility biographies. Transportation 40 (2), 431–458.

Scheiner, J., 2016. Time use and the life course: a study of key events in the lives of men and women using panel data. Eur. J. Transp. Infrastruct. Res. 16(4, 638–660.

Schwanen, T., 2011. Car use and gender: the car of dual-earner families in Utrecht, The Netherlands. In: Auto Motives, pp. 151–171.

Schwanen, Tim, Banister, David, Anable, Jillian, 2012. Rethinking habits and their role in behaviour change: the case of low-carbon mobility. J. Transp. Geogr. 24, 522–532.

Selig, J.P., Little, T.D., 2012. Autoregressive and cross-lagged panel analysis for longitudinal data. In: B. Laursen, T.D. Little, N.A. Card, Handbook of Development Research Methods. pp. 265–278.

Steg, L., Kalfs, N., 2000. Altijd weer die auto. Sociaal en Cultureel Planbureau / Adviesdienst Verkeer en Vervoer, Den Haag, Nederland.

Susilo, Y., Liu, C., Börjesson, M., 2019. The changes of activity-travel participation across gender, life-cycle, and generations in Sweden over 30 years. Transportation 46 (3), 793–818.

Thøgersen, John, 2006. Understanding repetitive travel mode choices in a stable context: a panel study approach. Transp. Res. Part A: Policy Pract. 40 (8), 621–638.

Thompson, S., Michaelson, J., Abdallah, S., Johnson, V., Morris, D., Riley, K., Simms, A., 2011. Moments of change's as opportunities for influencing behaviour. Defra, London.

Van Acker, Veronique, Witlox, Frank, 2010. Car ownership as a mediating variable in car travel behaviour research using a structural equation modelling approach to identify its dual relationship. J. Transp. Geogr. 18 (1), 65–74.

Verplanken, Bas, Walker, Ian, Davis, Adrian, Jurasek, Michaela, 2008. Context change and travel mode choice: combining the habit discontinuity and self-activation hypotheses. J. Environ. Psychol. 28 (2), 121–127.

Vij, Akshay, Carrel, André, Walker, Joan L., 2013. Incorporating the influence of latent modal preferences on travel mode choice behavior. Transp. Res. Part A: Policy Pract. 54, 164–178.

Yáñez, M.F., Cherchi, E., Ortúzar, J.d.D., Heydecker, B.G., 2009. Inertia and schock effects on mode choice panel data: implications of the Transsantiago Implementation. In: International Conference on Travel Behaviour Research, Jaipur, India.

Zhang, J., Yu, B., Chikaraish, M., 2014. Interdependencies between household residential and car ownership behaviour: a life history analysis. J. Transp. Geogr. 34, 165–174.

Zeger, S.L., Liang, K.-Y., 1992. An overview of methods for the analysis of longitudinal data. Statist. Med. 11, 1825–1839.