Travel pattern transitions: Applying latent transition analysis within the mobility biographies framework
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Transities tussen reispatronen: Latente transitie analyse toegepast binnen het mobility biographies framework

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Samenvatting

In dit paper worden latente klasse analyse en transitie analyse toegepast binnen het mobilities biographies framework om het effect van bepaalde levensgebeurtenissen op veranderingen in reisgedrag vast te stellen. Mobility biographies studies zijn gebaseerd op de assumptie dat er bepaalde belangrijke gebeurtenissen zijn in het leven van een individu die invloed hebben op het reisgedrag. Met behulp van latente transitie analyse wordt bekeken of, en hoe, mensen overgaan op een ander reispatroon over het verloop van tijd. Data van de eerste drie waves van het Mobiliteitspanel Nederland (MPN) zijn gebruikt om verschillende reispatronen te definiëren en transities tussen deze patronen te analyseren. Met behulp van latente klasse analyse zijn zes verschillende reispatronen gedefinieerd. In de helft van deze reispatronen speelt de auto een belangrijke rol. Vier exogene variabelen en zes levensgebeurtenissen binnen de zogenaamde huishoudelijke-, werk- en residentiële biografie zijn opgenomen in de analyses om hun effect op de overgangen tussen verschillende reispatronen van mensen te evalueren. Voor alle levensgebeurtenissen zijn significante resultaten gevonden. Dit is een indicatie dat er wellicht inderdaad een ‘window of oppurtunity’ bestaat om het reisgedrag van mensen te veranderen bij bepaalde levensgebeurtenissen. De resultaten laten zien dat, gemiddelde gezien, mensen met een mono-modaal reispatroon minder geneigd zijn om van reispatroon te veranderen, vergeleken met mensen met een multimodaal reispatroon. Dit effect is echter sterker voor strikte autogebruikers dan voor mono-modale fietsgebruikers. De algemene tendens is dat het aandeel van de reispatronen waarin de auto een belangrijk aandeel heeft, toeneemt na levensgebeurtenissen. Na de geboorte van een kind is deze verschuiving het sterkst. Na de geboorte van een kind stijgt het aandeel van deze reispatronen tot bijna 82%. Verder laat de transitie analyse zien dat het effect van levensgebeurtenissen en andere exogene variabelen afhangt van het initiële reispatroon. Zo worden strikte autogebruikers bijvoorbeeld over het algemeen minder beïnvloed door levensgebeurtenissen vergeleken met mensen met een ander reispatroon. Dit geeft aan dat het belangrijk is om reisgedrag in het verleden mee te nemen binnen mobility biographies studies.

1. Introduction

Travel behaviour can generally be described as inert or habitual behaviour; it does not change very often (Gärling & Axhausen, 2003; Chorus & Dellaert, 2012). It is therefore interesting to gain more insight into when travel behaviour does change. Because a lot of travel behaviour studies are based on cross-sectional data, any events leading up to changes cannot be modelled. A relatively new approach to study developments within travel behaviour is the mobility biographies approach. Mobility biographies studies take a life-course approach and assume there are certain key events (life events) in an individual's life course that trigger change in travel behaviour (Lanzendorf, 2003). Mobility biographies studies are often based on longitudinal data to analyse individual changes over time.

These life events have been described as 'windows of opportunity' to change everyday routines (Schäfer, Jaeger-Erben, & Bamberg, 2012). Multiple studies have shown that people are indeed more susceptible to interventions after life events such as a residential move or changing jobs (Thøgersen, 2012; Anable, 2013; Verplanken & Roy, 2016). Recent overviews of mobility biographies studies are provided by Müggenburg et al. (2015) and Schoenduwe et al. (2015). Knowledge about these windows of opportunity could benefit transport policy that is aimed at changing travel behaviour or realizing a modal shift.

This paper aims to apply the relatively new latent class clustering technique within the mobility biographies framework to reveal different travel patterns and assessing the influence of life events on changes in travel behaviour by extending the latent class model to a latent transition model. While traditional clustering techniques deterministically assigns people to clusters, latent class analysis takes measurement error into account by probabilistically assigning people to clusters. Latent class- and transition analysis has already successfully been used to identify different types of multimodal travellers (Molin, Mokhtarian, & Kroesen, 2016) and to assess the influence of several exogenous variables on changes in travel behaviour (Kroesen, 2014).

The first contribution of this study is that it applies a latent clustering- and transition analysis within the mobility biographies framework. This paper considers travel patterns, defined by self-reported trip rates, instead of the use or ownership of a single modality. This offers a holistic view of travel behaviour and the effects of life events. This also offers the possibility to assess how the use of different travel modes influences the probabilities that one will change its travel pattern. It can, for instance, be expected that people who use different modes, are more prone to change their behaviour since they are already familiar with multiple modes. Diana (2010) showed that multimodal travellers show a stronger propensity to use other modes, something that was also concluded by Kroesen (2014).

The second contribution is the fact that the influence of both life events and other exogenous variables on changes in travel patterns are assessed. Besides six life events (change in the number of adults in the household, changing jobs, stop working, moving house, birth of a child and start or changing education), nine exogenous variables are included in the analyses (gender, age, educational level, household composition, income, working hours per week, level of urbanization, distance to a train station and number of reported weekend days). It can be expected that these exogenous variables have an influence on one's initial travel pattern, as well as on the transition probabilities.

The third contribution of this paper is that it considers the initial travel pattern of people when analysing changes in travel patterns. It has been argued that past behaviour is an important predictor of future behaviour (Ouellette, 1998). The initial travel behaviour (past behaviour) of people is, however, not often included in other mobility biographies studies. This could be the reason that sometimes no effects are found in mobility biographies studies. It is expected that unimodal travellers are less influenced by life events compared to multimodal travellers.

2. Model Conceptualization

Latent class- and transition analysis will be used to reveal different travel patterns and assess how transitions between these classes are influenced by the occurrence of different life events. Figure 1 shows the conceptual model for the latent transition analysis.

Latent class analysis is used to cluster respondents together based on their similarities with respect to the included indicators. Latent class analysis is built on the assumption that all of the associations between the indicators are explained by an underlying latent variable. The latent variable is an unobserved variable, which is inferred from observed indicators. In this study, trip rates of different modalities (car, bike, public transport and walking) are used as indicators. The latent variable represents an individual's travel pattern.

After defining the different travel patterns, transitions between these patterns are assessed by extending the latent class model to a latent transition model. A latent transition model can be described as repeated latent cluster analyses over-time where the same travel patterns are defined at each time point to assess transitions between the patterns (Collins & Lanza, 2010). The parameter estimates from the latent transition analysis can be used to compute transition probability matrices.

Latent class- and transition analysis allow for the use of covariates. Covariates are used to predict initial cluster membership and interact with transitions between clusters. The effects of the covariates are able to vary for every latent class (as indicated by the interaction effect in figure 1). By interacting life events and other exogenous variables with transitions, their effect on transition probabilities can be assessed by computing different transition matrices. Latent transition analysis thereby allows to assess whether people with different travel patterns are differently affected by life events.

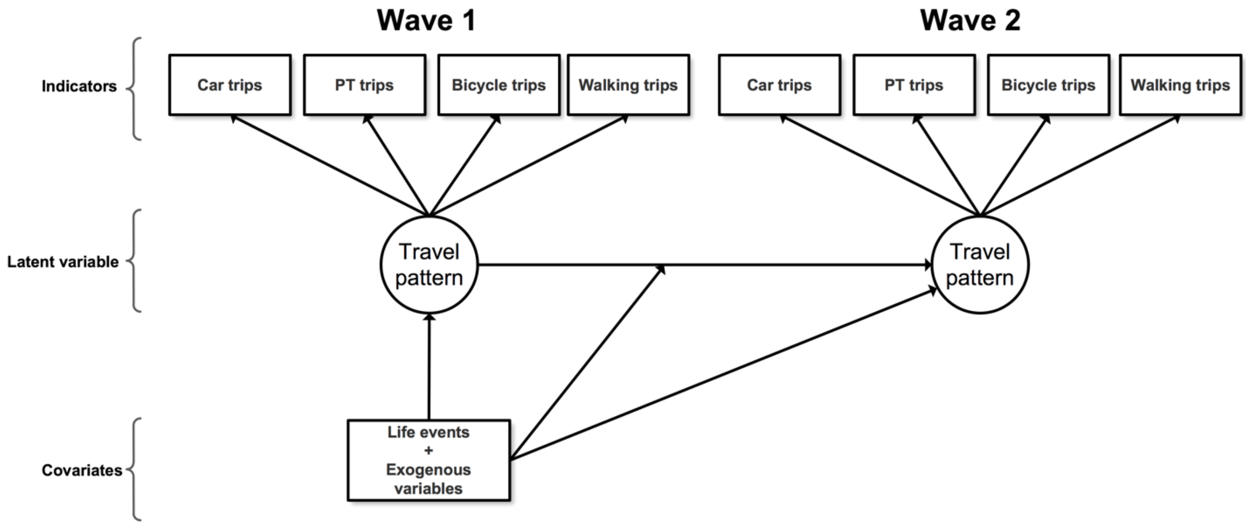

FIGURE 1 Conceptual model of the latent class- and transition analysis

In total, nine active covariates are included as predictors for initial cluster membership; gender, age, educational level, household composition, income, working hours per week, level of urbanization, distance to a train station and a variable to control for the number of reported weekend days. The life events are not used as predictors for initial cluster membership, but are assumed to influence the transitions between clusters.
Within the mobility biographies framework, three domains of life events are typically considered; events in the household biography, the employment biography and the residential biography (Schoenduwe, Mueller, Peters, & Lanzendorf, 2015). Within these three domains, six life events are included to assess their effects on changes between travel patterns. With respect to the household biography a change in the number of adults and the birth of a child are included. A change in the number of adults could occur due to multiple life events such as partners who start living together or divorce. With respect to the employment biography changing jobs, stop working and starting or changing an educational programme are included. Finally, with respect to the residential biography a residential move is included.

3. Method

3.1 Data

To assess over-time changes of individuals, longitudinal data is required. In this study, panel data from the Netherlands Mobility Panel (MPN) are used. The MPN is an annual household panel that started in 2013 and consists of approximately 2,000 households. Each year, household members of at least 12 years old are asked to complete a three-day travel diary and fill in a questionnaire that includes questions about different events in the past year. Every household is also asked to fill in a questionnaire about household related characteristics, such as information about household composition and ownership of means of transport. More information about the MPN can be found in Hoogendoorn-Lanser et al. (2015). Currently, data from the first three waves are available and used for the present analysis.

Travel patterns can be defined in different ways. Different types of indicators can be used to distinguish the different patterns. In this study, trip rates of four modalities are used. In the MPN travel diary all trips are reported including the mode, distance and duration of the trip. Due to the self-reported nature of the travel diary, distance and duration might be biased due to rounding errors (Rietveld, 2001). The trip rate is assumed to be the most accurate reported indicator. The trip rates are count variables. Their distributions can therefore be approximated by the Poisson distribution and Poisson regression models can be used to model the relationships between the latent class variable and the indicators (Vermunt & Magidson, Latent class cluster analysis, 2002).
Although household members older than 12 years are asked to participate in the MPN, information about life events is not requested until respondents are at least 16 years old. Children younger than 16 years are therefore removed from the sample. To uncover transitions between travel patterns, respondents should have completed at least two consecutive waves. In total there are 3,807 respondents who completed at least two consecutive waves, of which 1,711 completed all three waves. The data is organized as a pooled wave-pair sample, similar to the approach described by Golob (1990). An advantage of pooling wave-pairs over using a pure-stayer sample is the fact that no data is lost. Especially since life events do not occur regularly and their frequency is therefore rather low, removing data is not desired. The pooled wave-pairs sample consists of 5,518 wave pairs from 3,807 respondents (2,519 unique households).
A clear disadvantage of pooling wave-pairs is the fact that redundant information is present in the data for consecutive wave-pairs from the same respondent (Golob, 1990). Observations are therefore no longer independent. Besides dependencies due to pooling wave-pairs, there are also dependencies due to the fact that there are multiple respondents from the same household in the panel. The standard errors will be corrected for the fact that respondents belong to the same household. This is done by treating the household as the independent observational units, instead of respondents (Vermunt & Magidson, 2016). The statistical software package Latent Gold is used to estimate both the latent class- and the latent transition models (Vermunt & Magidson, 2005). The latent class model is estimated using data from both waves simultaneously. Measurement invariance over time is therefore assumed. Unfortunately, Latent Gold does not support an analysis to test measurement invariance over time. Estimating two different latent class models for both waves separately showed, however, that the same clusters are present in both waves with only minimal differences.
Although nine active covariates are used as predictors for initial cluster membership, not all are used to interact with transitions between waves. This would result in a high number of parameters which leads to estimation problems. Therefore, besides the six life events, four covariates (gender, age, educational level and level of urbanization) are interacted with transitions. These covariates were chosen because they are also often taken into account in previous studies, see e.g. (Clark, Chatterjee, Melia, Knies, & Laurie, 2014; Kroesen, 2014).

3.2 Descriptive Statistics

Table 1 shows the measurement and distribution of variables in the sample. Age is included both as a standardized linear variable and the quadratic term of this variable to account for the non-linear effect of age. For simplicity reasons, the table only shows the mean and standard deviation of age. As can be seen, the frequency of the included life events is rather low. A decrease in the number of adults in the household shows the lowest occurrence rate with only 2.6%. Changing jobs is the most frequently observed life event with 8.9%.

TABLE 1 Sample Composition (N = 5,518 Wave Pairs)

Variable		
Indicators		
Car trip rate	Mean (SD)	4.6 (4.3)
PT trip rate	Mean (SD)	0.5 (1.3)
Bike trip rate	Mean (SD)	2.5 (3.6)
Walking trip rate	Mean (SD)	1.5 (2.6)
Active covariates		
Gender	Male	46%
	Female	54%
Age	Mean (SD)	46.7 (17.0)
Educational level	Low	26%
	Mid	40%
	High	34%
Working hours	Less than 12 h/week	25%
	12-35 h/week	31%
	35+ h/week	44%
Net income per year	No income	10%
	Less than €12,000	19%
	€12,000 - €24,000	36%
	€24,000 - €36,000	20%
	More than €36,000	5%
	Missing	10%
Level of urbanization	Urban (1500+ inhabitants/km²)	48%
	Sub-urban (1000-1500 inhabitants/km²)	24%
	Rural (less than 1000 inhabitants/km²)	29%
No. HH-members 12-	Mean (SD)	0.3 (0.7)
No. HH-members 12+	Mean (SD)	2.3 (1.1)
Distance to train station (km)	Mean (SD)	3.4 (3.6)
No. of weekend days reported	Mean (SD)	0.9 (0.8)
Change in number of adults in HH (%)	Decrease	2.6%
	Increase	5.9%
Birth of a child (%)		3.3%
Changing jobs (%)		8.9%
Stop working (%)		4.9%
Start/change education (%)		4.0%
Residential move (%)		4.0%
Inactive covariates		
Car ownership		74%
PT card ownership		31%
Occupational status	Paid job	57%
	Student	8%
	Retired	19%
	Other	16%

4. Results

4.1 Travel Patterns

A 1-class to 10-class model is estimated without any covariates to assess only the variance between the indicators. The BIC value suggest that a model with a least 10 classes would be appropriate. After the 6-class solution, however, the reduction of L^2 becomes rather small (less than 3%). This suggests that using a model with 6 classes would be appropriate to model the data. Since a model with a high number of classes would be hard to interpret, the 6-class model is used.

Table 2 presents the profiles of the 6-class model, including all covariates. Based on the Wald-statistics it can be concluded that the indicators and all active covariates, except gender, are significant. All indicators significantly differ between the classes and all active covariates, except gender, significantly affect class membership. Apparently, whether a respondent is male or female is no significant predictor of travel pattern membership. It can, however, be seen that the distribution of gender does differs among the classes.

The first and largest class (30% of the sample) represents strict car users. Besides making on average 8 trips by car in three days, they barely use other modalities to travel. The strict car class is the only class with a higher share of men. Strict car users show the highest employment rate of 71%, with 44% of the class members working fulltime. A relatively high share of strict car users lives in rural areas. This could be explained because rural areas usually are not well-connected by public transport and distances are too large to travel by bike.

The second class (19% of the sample) are respondents who also show high car usage, but complement this with the bike. On average, they show a car trip rate of 1.6 trips lower compared to the strict car users, but besides car trips, they make over 4 trips by bike. Their overall trip rate is therefore higher than the strict car users. In terms of household composition, level of urbanization and education level, the second class is comparable with the first class. The second class, however, represents more women with a lower employment rate. The bike is primarily used for non-work related trips.

The third class (16% of the sample) consists of people who mostly use the bike. The bike class shows the highest share of females and a high share of people without a job. The class has a relatively high share (17%) of students. As expected, most respondents in this class live in urban areas. Over a third of respondents within this class are part of a 1-person household. Besides almost making 8 trips by bike in three days, they also occasionally use the car. The 0.8 car trips per three days translates to just under 2 trips per week (1 two-way trip).

The fourth class (13% of the sample) primarily make their trips by car or walking. They also make an occasional bike trip but rarely travel by public transport. The average age of this class is the highest of all classes. This is also reflected in the fact that this class shows the lowest employment rate and 29% of the people is retired. As a result, this class shows the highest leisure trip rate of all classes. People in this class walk on average 6.9 kilometres in three days. This is, compared to the walking distance of other classes, remarkably high.

The fifth class (11% of the sample) shows a very low overall trip rate. On average, people in this class only report a total of 1.3 trips in three days. The class shows a relatively high share of low-educated people (34%). Besides the low education level, there are no remarkable characteristics that could explain the low mobility. The average number of weekend days reported is the highest for this class.

The sixth and smallest class (10% of the sample) represents multimodal travellers who primarily use public transport. The average age of this class is the lowest and it has the highest share of students (31%). However, since there is only one public transport class, different types of public transport users are grouped in this cluster. From the students who belong to this class, 85% works less than 12 hours per week and 98% has a yearly income of less than €12.000. If students are not considered, 74% of public transport users have a job of at least 12 hours per week and 51% is highly educated. It can therefore be concluded that two types of people belong to the public transport class; students and highly educated working people.

TABLE 2 Profiles Of The 6-Class Latent Class Model

	Class	1	2	3	4	5	6
Indicators	Class size (%)	30	19	16	13	11	10
Trips by car (Wald = 1401, p < 0.00)	Mean	8.1	6.5	0.8	4.4	0.8	1.3
Trips by PT (Wald = 1456, p < 0.00)	Mean	0.1	0.1	0.3	0.2	0.0	3.4
Trips by bike (Wald = 1065, p < 0.00)	Mean	0.0	4.5	7.9	1.4	0.3	1.4
Trips by walking (Wald = 2997, p < 0.00)	Mean	0.5	0.6	1.2	6.3	0.2	1.5
Active covariates							
Gender (%) (Wald = 8 p = 0.14)	Male	53	45	38	42	48	45
	Female	47	55	62	58	52	55
Age (Wald = 183 p < 0.00)	Mean	46.8	49.4	44.3	53.3	47.1	36.5
Educational level (%)	Low	21	22	30	28	34	28
(Wald = 42 p < 0.00)	Mid	45	41	35	37	41	34
	High	34	37	35	35	25	38
Working contract (%)	Part-time (12-35 hours/week)	26	31	24	25	20	19
(Wald = 79 p < 0.00)	Fulltime (>35 hours/week)	44	29	19	20	28	32
	No job (<12 hours/week)	30	40	57	55	53	50
Net income per year (%)	No income	4	7	17	9	13	18
(Wald = 62 p < 0.00)	Less than €12,000	12	18	28	19	22	27
	€12,000 to €24,000	42	35	29	38	35	27
	€24,000 to €36,000	24	23	14	21	14	18
	more than €36,000	6	6	3	5	4	4
	Missing	12	11	9	9	12	7
Level of urbanization (%)	Urban	40	40	56	51	49	66
(Wald = 70 p < 0.00)	Sub-urban	23	28	23	22	21	18
	Rural	36	32	21	27	30	16
Household members 12 years or older (%)	1	20	20	34	29	23	34
(Wald = 23 p < 0.00)	2	54	50	35	53	46	30
	3+	27	30	31	18	30	36
Children 12- in household (Wald =39 p < 0.00)	%	23	21	14	16	16	6
Number of weekend days (Wald = 28 p < 0.00)	Mean	0.84	0.92	0.75	0.92	0.98	0.87
Distance to train station (Wald = 50 p < 0.00)	Mean (km)	3.9	3.5	2.8	3.3	3.5	2.5
Inactive covariates							
Car ownership (%)	One or more cars	94	88	47	79	67	37
PT card ownership (%)	One or more cards	16	23	45	31	22	78
Occupational status (%)	Paid job	71	62	46	46	49	50
	Student	2	4	17	2	6	32
	Retired	16	21	17	29	17	11
	Other	11	12	20	23	28	8
Car trip purpose	Working trips	2.3	1.2	0.1	0.7	0.2	0.3
	Shopping trips	1.5	1.3	0.1	1.0	0.2	0.2
	Leisure trips	2.2	2.3	0.4	1.6	0.3	0.6
	Other trips	2.0	1.6	0.2	1.1	0.1	0.2
PT trip purpose	Working trips	0.0	0.0	0.1	0.0	0.0	2.1
	Shopping trips	0.0	0.0	0.0	0.0	0.0	0.3
	Leisure trips	0.0	0.0	0.1	0.1	0.0	0.7
	Other trips	0.0	0.0	0.1	0.0	0.0	0.3
Bike trip purpose	Working trips	0.0	0.9	2.1	0.2	0.1	0.3
	Shopping trips	0.0	1.2	2.3	0.4	0.1	0.3
	Leisure trips	0.0	1.4	2.3	0.5	0.1	0.6
	Other trips	0.0	1.0	1.3	0.3	0.0	0.2
Walking trip purpose	Working trips	0.0	0.0	0.1	0.3	0.0	0.2
	Shopping trips	0.1	0.1	0.4	1.6	0.0	0.5
	Leisure trips	0.3	0.4	0.6	3.3	0.1	0.6
	Other trips	0.1	0.1	0.2	1.0	0.0	0.1
Distance (km)	Car	144.8	106.5	15.0	66.4	21.4	29.5
	PT	2.5	3.7	13.6	10.0	0.2	124.9
	Bike	0.1	12.5	23.4	4.3	1.2	4.4
	Walk	0.7	0.8	1.6	6.9	0.2	2.7

4.2 Latent Transition Analysis

Table 3 shows the average transition probabilities of the sample. As expected, the unimodal classes (strict car and bike) show higher probabilities of staying in the same class compared to the more multimodal classes (car and bike, car and walk and public transport). All classes show a very low probability of going to the public transport class in the second wave. The bike and car and walk class show the highest transition rate to public transport, but still with a probability of only 4%. Higher probabilities are shown towards the bike cluster, or the car clusters that combines car with bike. All classes, except for the bike class, show a relatively high probability of becoming strict car users in wave 2 (ranging from 8% to 23%). This is in line with findings by Kroesen (2014).

TABLE 3. Average Transition Probabilities

	Wave 2					
Wave 1	**SC**	**CB**	**B**	**CW**	**LM**	**PT**
Strict car (SC)	0.70	0.13	0.00	0.05	0.09	0.02
Car and bike (CB)	0.23	0.53	0.13	0.05	0.05	0.01
Bike (B)	0.02	0.14	0.74	0.03	0.03	0.04
Car and walk (CW)	0.10	0.08	0.08	0.64	0.06	0.04
Low mobility (LM)	0.11	0.08	0.08	0.03	0.69	0.02
Public transport (PT)	0.08	0.04	0.02	0.07	0.12	0.67

In total, 71 significant parameters are found. Almost all constants have a significant negative parameter. This indicates that class membership has a positive effect on itself. In other words, initial class membership in wave 1 is a strong indicator for class membership in wave 2. As expected, dependent on the initial travel pattern, effects of life events and other exogenous variables are different.

Since the main focus of this paper is on assessing the effect of life events on transitions between travel patterns, the effect of the other exogenous variables will not be discussed in detail. The found significant effects are, however, in line with expectation. For instance, for the effect of age it is found that strict car users tend to shift towards the car and walk profile at older age, while for the car and bike users the probability of becoming public transport users decreases at older age.

For all life events significant effects are found, indicating that there might indeed be 'windows of opportunity' to change travel behaviour when a life event occurs. The effect on the average transition probabilities of the life events will be shortly discussed.

Table 4 presents the average transition probabilities in case of the different life events. If the event does not occur, the transition matrix is almost identical to the average transition matrix of the whole sample, as shown in table 3. This can be explained by the low frequency of the life events in the sample.

For the change of the number adults in the household, a matrix for both a decrease and increase in the number of adults is shown. When the number of adults in the household decreases, the public transport users are most affected. Their probability of becoming a strict car user increases from 8% to 35%. The low mobility class shows an increasing probability of transitioning to the bike class. A decrease in the number of adults could represent an event such as a divorce. The remaining household member(s) has to make trips which were previously done by the partner and therefore the travel pattern has to be adjusted. An increasing number of adults in the household, which could be because partners started living together, increases chances of remaining in the same travel pattern for the car and bike, low mobility and public transport class. For the remaining classes the probability of keeping the same travel pattern does not change much.

The overall effect of changing jobs is an increasing probability of becoming a member of one of the three car classes. Except the public transport class, all classes show an increase in the probability of becoming a strict car user. The probability of becoming a car and walk user decreases. A remarkable and unexpected effect is observed for the public transport class. The probability of transitioning to the low mobility class increases with 20%. A new job, or changing jobs, usually implies that work trips have to be made, while the low mobility class represents almost no trips. In-depth analysis (results not shown) revealed that most of the public transport users with a new job who transition toward the low mobility class increased their working hours due to the new job. The fact that they became a member low mobility might indicate that they have the ability to work from home at the new job, however more research is needed to confirm this.

A residential move also shows different effects for the different classes. For the unimodal classes (strict car and bike) the probabilities do not change much. The other classes are differently affected. The car and bike class shows an increase in the probability of becoming a strict car user, while the car and walk class shows a strong increase in becoming a member of the low mobility or public transport class. It is not expected that a change in the level of urbanization plays a significant role in these effects since only 6 people in the sample moved to a less urbanized area and 17 to a more urbanized area. These frequencies are too low to explicitly model the effect of a change in the level of urbanization.

After the birth of a child, all classes show an increasing probability of becoming a strict car user. All classes also show an increase in the probability of becoming a member of the car and walk class, except for the car and walk class itself. The car and bike class shows a high probability of becoming a car and walk user and vice versa. After the birth of a child the share of the strict car, car an bike and car and walk class together increases to 82%. The increase in car dependency could be explained because the car is a convenient mode of transport to travel with a baby.

The start or change of education increases the probability of becoming a public transport user for most classes. This is an expected result, since students are provided with a free public transport card in the Netherlands. The low mobility class shows the greatest changes. The probability of remaining in the low mobility class decreases from 69% to only 17%. This can be explained because students have to attend college and therefore have to travel.

Overall, it can be observed that the strict car users show very inert behaviour. For all events, except for stop working, the probability of remaining a strict car user after a life event stays similar to the probability when the event does not happen. The bike users, who are also more or less unimodal travellers, show less inert behaviour. This could be explained because a car is usually suitable for all kinds of trips, while a bike is limited due to its speed and lack of possibilities such as taking a baby with you.

TABLE 4 Transition Matrices For Different Life Events

Decrease of the number of adults in HH

	SC	CB	B	CW	LM	PT
SC	0.67	0.14	0.01	0.08	0.09	0.00
CB	0.15	0.62	0.15	0.00	0.01	0.07
B	0.00	0.02	0.88	0.00	0.04	0.05
CW	0.13	0.11	0.19	0.56	0.00	0.01
LM	0.01	0.05	0.36	0.02	0.54	0.02
PT	0.35	0.12	0.03	0.01	0.00	0.48

Birth of a child

	SC	CB	B	CW	LM	PT
SC	0.70	0.07	0.00	0.15	0.08	0.01
CB	0.27	0.32	0.00	0.38	0.02	0.00
B	0.03	0.16	0.12	0.64	0.05	0.00
CW	0.21	0.39	0.00	0.31	0.00	0.09
LM	0.36	0.08	0.04	0.04	0.45	0.03
PT	0.17	0.00	0.02	0.29	0.30	0.21

Increase of the number of adults in HH

	SC	CB	B	CW	LM	PT
SC	0.70	0.16	0.00	0.02	0.11	0.00
CB	0.27	0.58	0.13	0.00	0.02	0.00
B	0.01	0.11	0.71	0.03	0.10	0.05
CW	0.11	0.00	0.18	0.64	0.07	0.00
LM	0.02	0.02	0.14	0.04	0.74	0.04
PT	0.10	0.04	0.00	0.00	0.06	0.80

Start or change of education

	SC	CB	B	CW	LM	PT
SC	0.77	0.03	0.00	0.07	0.01	0.11
CB	0.29	0.27	0.18	0.06	0.16	0.04
B	0.02	0.17	0.46	0.22	0.00	0.14
CW	0.06	0.08	0.06	0.70	0.07	0.04
LM	0.21	0.23	0.01	0.00	0.17	0.38
PT	0.03	0.02	0.00	0.01	0.40	0.55

Changing jobs

	SC	CB	B	CW	LM	PT
SC	0.66	0.20	0.00	0.05	0.05	0.04
CB	0.29	0.45	0.15	0.04	0.05	0.01
B	0.15	0.14	0.60	0.01	0.04	0.05
CW	0.30	0.20	0.09	0.34	0.07	0.01
LM	0.12	0.04	0.14	0.02	0.62	0.06
PT	0.05	0.09	0.02	0.05	0.33	0.47

Stop working

	SC	CB	B	CW	LM	PT
SC	0.54	0.22	0.02	0.02	0.17	0.04
CB	0.02	0.50	0.20	0.15	0.06	0.07
B	0.00	0.06	0.69	0.14	0.06	0.04
CW	0.01	0.03	0.08	0.79	0.05	0.05
LM	0.05	0.04	0.02	0.15	0.74	0.00
PT	0.06	0.01	0.01	0.17	0.28	0.47

Residential move

	SC	CB	B	CW	LM	PT
SC	0.67	0.16	0.00	0.05	0.10	0.02
CB	0.37	0.42	0.12	0.08	0.01	0.00
B	0.03	0.16	0.72	0.02	0.02	0.05
CW	0.05	0.12	0.07	0.30	0.27	0.19
LM	0.12	0.09	0.08	0.28	0.41	0.01
PT	0.00	0.10	0.11	0.26	0.00	0.52

SC = Strict CAR, **CB** = Car and bike, **B** = Bike, **CW** = Car and walk, **LM** = low mobility, **PT** = Public transport

5. Conclusions and Recommendations

In this paper, latent class- and transition analysis are applied on panel data within the mobility biographies framework to reveal different travel patterns and assess the effect of life events and other exogenous variables on transitions between these travel patterns. Six different meaningful and distinguishable travel patterns were identified. For all life events significant effects on transition probabilities were found. The transition analysis confirms that travel behaviour is inert. In addition, unimodal travellers show a higher probability of remaining in the same travel pattern, compared to multimodal travellers. All identified travel patterns show a very low probability of transitioning towards the public transport travel pattern.

Latent transitions analysis has been shown to provide meaningful insights in the effects of different life events and exogenous variables on changes between travel patterns. Latent

transition analysis can be a useful method within the mobility biographies studies as it offers the possibility to account for past travel behaviour when assessing the effect of different life events.
The results offer some interesting insights. After, for instance, the birth of a child a rise in the car dependency is observed, regardless of the initial travel pattern. Apparently, people see the car as one of the few suitable means of transport with a baby. This might indicate that people are not well informed about the possibilities of travelling by bike or public transport with a baby. Future research could assess whether a moment such as birth registration could be used to inform people about other safe possibilities to travel with their child besides car.
It is also observed that, for most classes, public transport use only increases after the start or change of education. A change of jobs, which also reflects students who start their first job after finishing their education, shows a shift towards car use again. Future research could focus on how students could be tempted to remain public transport users, even after they finished their education.
The question remains whether life events indeed create windows of opportunity for policy makers to change travel behaviour. The results show that after a life event, the probability that people change their travel pattern increases. However, the general tendency of this change shows a shift towards the more car dependent travel patterns. Future research should therefore assess if, and how, the direction of this shift can be changed.
An important drawback of latent transition analysis is the fact that it requires a large sample to reveal significant effects. In this study, the latent transition analysis is used to assess the effect of life events on changes in travel patterns. One of the characteristics of life events is the fact that they do not occur regularly. Since six different travel patterns were identified, the transition matrix consisted of 36 cells (6 initial clusters x 6 future clusters). Because travel behaviour is inert, most people will remain in the same class. The computation of the off-diagonal probabilities is therefore done with a limited number of observations. This is probably the main reason for finding 'only' 71 significant parameters. Fortunately, the MPN will be continued the next years. The observed frequency of life events will therefore grow, increasing the chances of finding significant effects. It is therefore recommended that another latent transition model will be estimated when data from more waves is available.
Another recommendation is aimed at the indicators that are used to define the travel patterns. A limitation of relying on the self-reported trip rates to define the travel patterns is the fact that respondents only reported three days of travel. Since it can be assumed that travel behaviour is different during weekdays compared to the weekend, the data might be biased because travel behaviour has only been reported for three days. Fortunately, respondents were assigned the same starting day every wave and therefore reported the same days every year. Starting from wave 2, respondents are also asked on their weekly frequency of mode use. It is recommended that this will be combined with the self-reported trip rates to get a more accurate overview of their travel behaviour in future research using the MPN data. Since the stated mode use is not available for the first wave, this study could only rely on the self-reported trip rates.
The last recommendation for further research is to include lagged effects to the analysis. It could, for instance, be that after a residential move people change their travel behaviour on the short term, but change this behaviour again on the long term (more than 1 year). Including lagged effects could reveal such behaviour. Modelling lagged effects would

require the sample to consist of respondent who participated at least three consecutive waves. Only when data from more waves is available this becomes a viable option.

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