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Inter- and Intrapersonal variation in destination choice

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This paper examines spatial-temporal inter- and intrapersonal variation in destination choice, based on longitudinal smartphone data for the Netherlands. Mixed logit destination choice models were estimated using two years of data (2014 and 2015) from the Dutch Mobile Mobility Panel, in which over 68,000 trips for 442 respondents were recorded with a smartphone app during an annual four-week measurement period. A distinction was made between trips to compulsory activities (such as work) and trips for discretionary purposes (such as recreation) as they are associated with different trip characteristics. Discrete destination alternatives were defined based on individuals' behaviour in terms of repeatedly visited destinations and the statistical distribution of a spatial repetition index. The model results show that intrapersonal variation in destination choice, departure time and mode choice was relatively high for less frequently visited locations, which indicates novelty-seeking behaviour in destination choice. Furthermore, we found a strong connection between activity, departure time, and destination choice. And, mode choice and departure time choice were highly repetitive for destinations visited repetitively (e.g. work), but not for discretionary activities.

Keywords: *destination choice, inter- and intrapersonal variation, mixed logit, panel data, compulsory and discretionary activities.*

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1. Introduction

So far, the dynamics of travel behaviour have been explored broadly with a focus on interpersonal variability – variation *between* individuals' travel patterns. Less attention has been given to intrapersonal variability – variation *within* an individual's travel behaviour. This variation can be day-to-day (e.g. Pas and Sundar (1995), Deutsch-Burgner (2015)), week-to-week (e.g. Tarigan et al. (2012)), between workday and weekend, or even month-to-month and year-to-year (Tarigan et al., 2012). The level of repetition in explanatory variables (e.g. trip characteristics, spatial components, or socio-economic characteristics) is a measure of this intrapersonal variation.

To measure intra- and inter-personal variation in travel patterns, long-duration panel data is needed but this data is not commonly available. Travel surveys typically still consist of one-day to one-week travel diaries (Hoogendoorn-Lanser et al., 2015, Deutsch-Burgner, 2015, Buliung et al., 2008, Stopher and Zhang, 2010, Montini et al., 2016), which does not allow a proper analysis of intrapersonal variation in travel behaviour. The growing usage of GPS devices and, more recently, smartphones make longer-duration travel surveys possible. This has resulted in a growing number of studies on intrapersonal variation (see for overviews Schönfelder and Axhausen, 2010; Thomas et al., 2019). For example, several studies showed the importance of intrapersonal variation in mode choice decisions (Heinen and Chatterjee, 2015, Thomas and Geurs, 2016, Thomas et al., 2019). Others have examined leisure activity-travel patterns (see for example Tarigan et al. (2012) and La Paix Puello et al. (2019)). Some studies that analysed the spatial variation in behaviour with the aid of long-duration mobile phone data (see for example (Järv et al., 2014) found that individuals show high variability in spatial aspects, but modest variability in the frequency of activities.

Studies using multiple-week trip diaries clearly show that travel behaviour measured is neither repetitious nor variable (see for an overview Schönfelder and Axhausen, 2010). An analysis of inertia effect in the long-term panel shows that effects of habit (intra-personal correlation) are stronger over subsequent weeks than inside every single week, and activity variables are more significant when computed at a weekly level (Cherchi and Cirillo, 2014, Cherchi et al., 2017). Other studies used GPS data to analyse activity patterns in a multi-person single-day (Shou and Di, 2018), or multiple-day (Järv et al., 2014) mobile trace of anonymous users, or estimated choice models to estimate mode choice (Calastri et al., 2019).

This paper presents an investigation of the factors that influence inter- and intrapersonal variation in destination choice, using multiple-week travel survey data collected with smartphones. We explored two years of panel data from the Dutch Mobile Mobility Panel (Geurs et al., 2014), comprising trip data for over 440 individuals (over 65,000 trips). Further, we determined a *Spatial Repetition Index (SRI)* and *Temporal Repetition Index (TRI)* based on the trip frequency for the same activities by week and by trip purpose. We calculated them as the ratio of activities carried out at repeated destination postcodes or visited during the same time range, respectively, to the total number of activity destinations visited by a respondent during a specific week.

The paper has a twofold contribution to the literature. Our multi-week GPS-based panel data firstly allows us to contribute to the knowledge in the field by examining intra- and inter-personal variation in destination choice, considering socio-economic, temporal and spatial factors over multi-week repeated samples. Secondly, we disentangle temporal and spatial factors in destination choice using a choice model and construct a choice set over the known alternatives, which has not been done in other panel studies. Previous studies have for example examined spatio-temporal dimensions of destination choice (Schüssler and Axhausen, 2009) or activity-space modelling using GPS data (Schönfeld and Axhausen, 2010) but have not used a choice modelling framework. The advantage of using a choice modelling framework is that it allows the analysis of the impact of intrapersonal variation on the estimation of travel demand. We can also identify the mobility constraints of the currently visited destinations at an individual level. Including repetition in destination choices can also relevant from a policy perspective. Policies targeting mode shifts are less effective if people or specific population segments show strong a habitual behavior.

This paper is organised as follows. Section 2 presents a literature review. Section 3 introduces the dataset, including data preparation and descriptive statistics (intrapersonal variation as well as socio-economic, trip and spatial variables). Section 4 contains the analytical framework of the conceptual model. Sections 5 and 6 discuss the model estimation results including forecasting and elasticity. Section 7 sums up the conclusions of this paper.

2. Factors that influence destination choice and variability

In travel behaviour, hence in travel behaviour research, destination choice is a crucial step, which displays interpersonal population heterogeneity (Mishra et al., 2013, Ye et al., 2012). There is still a gap in travel demand modelling with regards to the temporal and spatial correlations within activity and travel decision making (e.g., activity location, geography of trip chains) (Schönfelder and Axhausen, 2010, Schlich et al., 2004, Cirillo et al., 2003). Travel demand arises from the needs and desires to participate in various activities at different times and locations (Hägerstraand, 1970). Thus it is likely that both types of temporal and spatial variability exist in everyday human travel patterns (Tarigan et al., 2012).

Several variables influence activity choice and the spatiotemporal relationship, such as departure time as a measurement of temporal variation (Schönfelder and Axhausen, 2010, Schlich et al., 2004, Cirillo et al., 2003) and accessibility, but mostly for non-work trips (Huang, 2014, Hooper, 2015, Limanond and Niemeier, 2003). Destination choice depends on the characteristics of the alternatives and of the travellers (Simma et al., 2002) and usually results in mode choice and destination choice being executed simultaneously. As a result, people have habitual combinations of mode choice and destination choice for daily activities (Hannes et al., 2009, Buliung et al., 2008). Individuals change this combination from a predefined set of alternatives only if the habitual alternative is unavailable (Hannes et al., 2009); this effect is stronger for public transport users than for car drivers (Buliung et al., 2008).

Hannes et al. (2009) stated that, for leisure and recreational trips, mode choice takes place before destination choice. In some cases, people may engage in more travel than is strictly required, which does not depend on mode or route; this novelty-seeking is considered part of the attractiveness of the destination, which was decided on first (Schlich et al., 2004, Arentze and Timmermans, 2005, Schönfelder and Axhausen, 2010, La Paix Puello et al., 2018, Mokhtarian and Salomon, 2001)).

Various types of spatial mobility constraints also influence the modal variability (Heinen and Chatterjee, 2015). Furthermore, mode repetition is associated with the urbanity levels at both origin and destination (Thomas et al., 2019). Similarly, sunny weather stimulates people to cycle (Hannes et al., 2009). Travel time (e.g. Wu et al. (2011), Auld and Mohammadian (2011)) and travel distance (e.g. Simma et al. (2002), Pozsgay and Bhat (2001)) are major trip characteristics for mode choice. Therefore, mode choice and its associated components (e.g. urbanity and weather) likely play an important role in destination choice.

Huff and Hanson (1986) concluded that individuals' travel activity patterns are characterised by both repetition and variability. Intrapersonal variability can be estimated for different dimensions of travel behaviour, such as trip purpose, mode choice, route choice, destination choice, activity duration, the starting time of the activities (Heinen and Chatterjee, 2015, Schönfelder and Axhausen, 2010), trip frequency, travelled distance or the spatial distribution of destinations (Deutsch-Burgner, 2015). Schlich and Axhausen (2003) found a high degree of repetition in several combinations of mode, trip purpose, arrival time and destination. Location-based repetition varies across activity types and over time (Buliung et al., 2008). For example, grocery-shopping and sports activity trips might have a different level of repetition in terms of departure time, duration, location, etc.

To measure repetition, several indicators have been developed. For instance, Schüssler and Axhausen (2009) suggested that evaluation and weighting of different types of aspects of destination choice alternatives and looking at how they interact can help clarify the similarities among them. Schüssler and Axhausen (2009) analysed destination choice based on similarities derived from travel mode, similarities caused by spatial proximity, similarities emerging from spatial learning and spatial repetition, and similarities originating from the impression the travellers have of destinations (attitude). We considered the third approach (i.e., similarities emerging from spatial learning and spatial repetition) best for our purpose since the dataset for this pair from the Dutch Mobile Mobility Panel consists of multiple-day observations and evidence of location-based repetition in the travel pattern (Buliung et al., 2008). Also, Regarding the choice set generation, early studies on destination choice used a subset of choice alternatives (random selection), see for example Schlich et al. (2002), and La Paix Puello et al. (2019), Chowdhury (2017) for an overview. Those studies used longitudinal data, but used a random selection of alternatives to generate the choice set. We, by contrast, use a known set which characteristics vary per person.

3. Data description

3.1 Data description and preparations

We used data from the Dutch Mobile Mobility Panel (DMMP), for which respondents were recruited from the Longitudinal Internet Studies for the Social Science (LISS) panel (see Scherpenzeel and Das (2010), a representative sample of the Dutch population. Trip characteristics including the origin and destination location, arrival and departure time, mode, and trip purpose are automatically detected by a smartphone app (*Movesmarter*). Figure 1 shows the data collection overview of the *Movesmarter* app (left side of the figure), server and web portal. The detected trip characteristics are uploaded to a database on a back-end server (center-figure) where a series of algorithms is used to process, clean, and enrich the trip data. Respondents access to a web portal (right side of the figure) and, revise and edit, if necessary, the trips in a web-based prompted recall survey.

To avoid overrepresentation of young people, respondents in the panel without a smartphone or with a smartphone that was not supported by iOS or Android were provided with a loan smartphone (Samsung Galaxy Gio). In the panel, about 59% used the loan smartphone, 24% owned a smartphone supported by Android, and 17% owned a smartphone supported by iOS. Thomas et al. (2018) described the collection methodology of a multiple-week registration sample of the last wave (2015) of the Dutch Mobile Mobility Panel, resulting in over 600 respondents. They found that the overall success rate in mode choice detection is 82 percent, being substantially higher for longer trips. The difference of underreporting trips from the app versus a survey was 15%. And, they concluded that smartphone-based data collection helps to reduce underreporting trips. Thomas et al., 2018 for more details about the data inference and quality of the data.

Figure 1. Movesmarter app - data collection overview (Geurs et al., 2018)

We selected respondents who participated in the 2014 and 2015 waves, in which two batches of data were collected during four weeks in the March-July period. For these 442 respondents, 68,626 valid trips were recorded. This dataset, therefore, allows in-depth analysis of inter- and intrapersonal variation in travel behaviour. Thomas et al. (2019) developed a mode choice model based on the smartphone-based collected data of four weeks.

3.2 Spatial unit of analysis

In theory, positioning data from smartphones allow analysis at a very high spatial resolution. However, we chose to use the 5-digit postcodes (PC5 level) as the spatial unit of analysis instead of 6-digit postcodes. Firstly, the captured GPS coordinates can vary significantly for repeated trips to the same location (Schönfelder and Axhausen, 2010), for example concerning the availability of car parking spaces. Secondly, the smartphone app needs some time to detect when and where a trip has started and ended.

3.3 Specification of variables

The calculation of *Spatial Repetition Index (SRI)* and *Temporal Repetition Index (TRI)* is based on the trip frequency for the same activities(Eqs. 1 and 2) by week and by trip purpose. We calculated them as the ratio of activities carried out at repeated destination postcodes or visited during the same time range, respectively, to the total number of activity destinations visited by a respondent during a specific week. The indexed estimates provide a weekly measure of spatial and temporal repetition in activity-travel patterns.

The TRI reflects the number of times a location was visited; the SRI reflects the number of times the location was visited at the same time of the day. An index value close to 1 indicates highly repetitive spatial or temporal behaviour, with most activities occurring at repeat locations or also during the same time range. An index value close to 0 indicates that there is little repetition in visits of destinations or of activity during the same (time) period during the day. In other words, a repetition index close to 0 means high intrapersonal variability. The following equations (Eq. 1 and 2) show the calculation of these indices.

$$SRI_{nt} = \frac{RL_{nt}}{TA_{nt}} \quad (1)$$

$$TRI_{nt} = \frac{RT_{nt}}{TA_{nt}} \quad (2)$$

TA_{nt} is the total number of activities carried out by respondent n, during period t (week). RL_{nt} is the number of times the locations were visited for the same purpose (in a week t) and RT_{nt} is the number of repeated (departure) time ranges during which a respondent *n* over the period t (week) for the same activity. For example, one person can have multiple values of repetition index since there are multiple weeks of data per person.

As socio-economic characteristics, we used the respondents' gender, age, occupational status, educational status, marital status, urbanity level of residential area, number of children in the household and net individual income. Travel time, mode choice and departure time were considered trip characteristics. The following time ranges were used; Early morning (7-9), late morning (9-12), early afternoon (12-14), late afternoon (14-17), evening (17-20), night (20-24) and midnight to dawn (24-4).

Next, spatial variables were distributed over the destination postcodes. We retrieved land use information from the Open Street Map data (allotments; cemetery; commercial & industrial; park, forest & scrub; farm, grass & orchard; meadow & vineyard; military; heath & nature reserve; recreation ground; residential; retail, etc.), and connected them with a 6-digit postcode area. This way, each 6-digit postcode became linked to a set of land use percentages. As a measure of accessibility, we looked at how many jobs (data retrieved from the LISA dataset (Pritchard et al., 2019) were accessible by public transport (walk and ride - WnR), bicycle (bike and ride - BnR) and car from a particular departure postcode. Built-environment variables were retrieved from a Statistics Netherlands (CBS) database (e.g. distance to doctor, daycare, train station, highway onramp, supermarket, restaurant, leisure, ice skating, swimming pool). Furthermore, we classified the weather conditions during the trip as clear sky, cloudy or rainy. The days of the week were categorised as either weekend days (Saturday and Sunday) or workdays.

3.4 *Segmentation of the data*
We segmented the data into two classes based on trip purpose: (a) destinations for compulsory activities – where a respondent is bound to visit – consisting of home, work, and business trips, trips for personal care, education and to take one or more people somewhere or pick them up (accounting for 63% of trips in our dataset), (b) destinations for discretionary activities such as shopping, groceries, visits, sports or hobby, hiking, sight-seeing, or walking, going out, spare-time or leisure trips and other trips (37% of trips in our dataset).

3.5 *Setup of alternatives*
Having a large number of alternatives in the choice set is considered a major challenge in destination choice modelling (Auld and Mohammadian, 2011, Thill, 1992). Modelling destination choice at postcode or municipal level produces a large number of alternatives. However, drawing a subset of the alternatives from the universal choice set for each trip makes it possible to deal with this situation (Simma et al., 2002). For example, Pozsgay and Bhat (2001), Wu et al. (2011), Scarpa and Thiene (2005), Mishra et al. (2013), and Auld and Mohammadian (2011) defined aggregated zone/groups as alternatives, where each zone/group may contain several possible alternatives.

We defined aggregated destination alternatives based on similarities emerging from *spatial* learning and spatial repetition (Schüssler and Axhausen, 2009). Also, awareness is a necessary precondition for choice (Decrop, 2010). Previous studies analyzed the 'horizontal' variety seeking in discretionary activities, where consumers select an assortment of alternatives to diminish the marginal returns from each one (Bhat, 2005). The choice set generation considers the following three components of behavioural models: awareness - *we estimated a model based on the known* *(visited) destinations.*, mutually exclusiveness - *since one person only choose one type of destination at the time*; and variety seeking.

As the distribution of repetition indexes is different between compulsory and discretionary destination, we segmented the behaviour of the respondents based on the percentile distribution of the SRI, as follows:

- Low (0-25%);
- Medium (26-50%);
- High (51-75%);
- Very high (75-100%).

As this is the first study that uses an SRI to construct alternatives in a destination choice model, no threshold values were available in the literature and percentile distributions were used. For trips to compulsory destinations, we defined the SRI distribution as follows:

- Low 0-0.111; up to 25 percentile
- Medium 0.112-0.308; up to 50 percentile
- High 0.309-0.421; up to 75 percentile
- Very high >0.421; over 75 percentile

We classified trips to discretionary destinations according to the following SRI values:

- Low 0-0.040; up to 25 percentile
- Medium 0.041-0.056; up to 50 percentile
- High 0.057-0.091; up to 75 percentile
- Very high > 0.091; over 75 percentile

3.6 Descriptive analysis

In total, 456 respondents participated in both the 2014 and the 2015 wave, but a few did not complete the follow-up survey and their data were therefore discarded. As a result, a total of 442 respondents with 31,441 trips in 2014 and 435 respondents with 37,185 trips in 2015 remained. Trip rates per day per person were higher in 2015 (3.05) than in 2014 (2.56).

Intrapersonal variation

The cumulative distribution of the SRI and TRI (Figure 2) shows that almost 60% of the trips have an SRI below the median (0.2258), and the much lower TRI means that the variation in departure time is greater than the variation in destination choice. Figure 2 validates the assumption that compulsory destinations have a higher repetition index than discretionary destinations, both spatially and temporally.

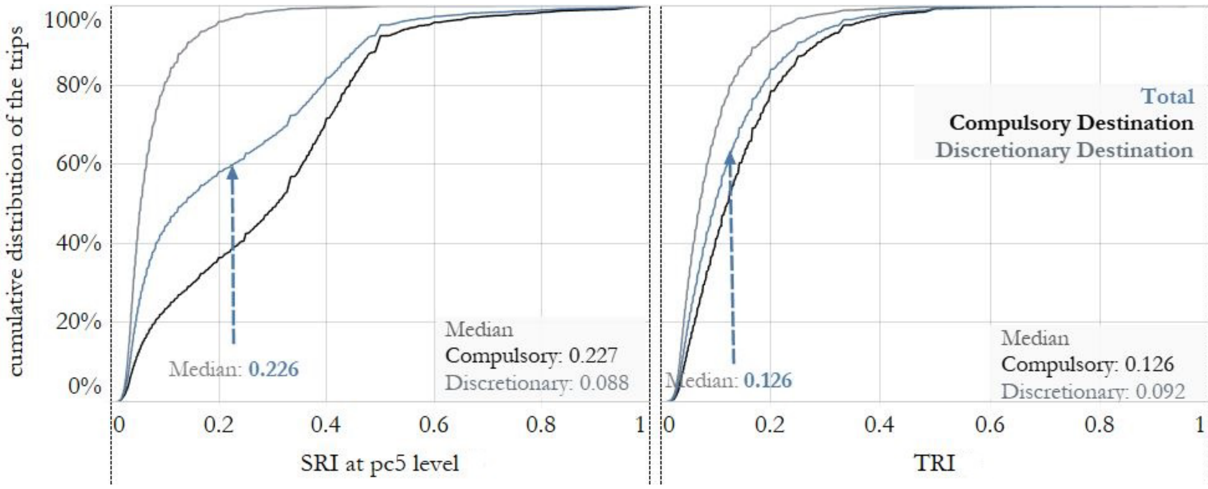

Figure 2. Distribution of SRI and TRI

While more than 90% of the trips to a discretionary destination have an SRI below 0.2, trips to compulsory destinations have an SRI of over 0.5, and something similar applies for the TRI. This high intrapersonal variability in discretionary destinations reveals the variety-seeking behaviour of the respondents in their free time.

Socio-economic and trip characteristics

Along with the descriptive statistics of significant socio-economic variables, Table 1 lists the SRI and TRI medians for trips to compulsory and discretionary destinations.

Table 1. Descriptive statistics of socio-economic variables (SRI, TRI, median)

		% in sample	Compulsory Trips (% by column)	Discretionary Trips (% by column)	Compulsory SRI	Compulsory TRI	Discretionary SRI	Discretionary TRI
Gender	Female	49.21	50	53	0.316	0.118	0.056	0.071
	Male	50.79	50	47	0.303	0.125	0.056	0.071
Age (years)	15-24	11.06	9	9	0.300	0.125	0.059	0.067
	25-34	14.00	14	12	0.286	0.125	0.050	0.063
	35-44	21.22	22	18	0.300	0.114	0.050	0.065
	45-54	24.38	22	23	0.278	0.125	0.056	0.074
	55-64	25.73	21	24	0.333	0.125	0.059	0.077
	≥65	15.35	10	15	0.385	0.121	0.067	0.083
Education	Basic education	6.090	4	5	0.375	0.125	0.063	0.083
	VMBO	15.80	14	13	0.351	0.130	0.063	0.079
	HAVO/HBO	16.03	15	15	0.296	0.120	0.059	0.071
	MBO	25.06	27	27	0.310	0.118	0.056	0.071
	HBO	27.54	27	26	0.286	0.119	0.056	0.071
	WO	12.19	13	13	0.286	0.120	0.053	0.067
Occupational status	Employed	61.44	66	54	0.280	0.125	0.050	0.065
	Retired	13.14	11	17	0.360	0.111	0.063	0.083
	Other	25.42	23	29	0.346	0.118	0.063	0.077
Marital status	Married	53.19	53	53	0.316	0.118	0.056	0.071
	Unmarried	28.92	30	27	0.277	0.130	0.044	0.056
	Other	17.90	17	19	0.308	0.118	0.059	0.074
Household composition	Single	23.25	21	24	0.310	0.118	0.059	0.071
	Married w/o children	35.21	31	34	0.333	0.126	0.059	0.077
	Married with child(ren)	39.28	40	35	0.306	0.118	0.053	0.069
	Single parent	5.87	7	6	0.250	0.111	0.046	0.063
	Other	1.81	2	2	0.257	0.141	0.048	0.065

Table 2. cont.,-Descriptive statistics of socio-economic variables (SRI, TRI, median)

		% in sample	Compulsory	Discretionary	Compulsory		Discretionary	
			Trips (% by column)		SRI	TRI	SRI	TRI
Urbanity level of residential area	Urban	65.7	63	66	0.304	0.125	0.056	0.074
	Semi-urban	20.9	20	19	0.333	0.121	0.059	0.071
	Not urban	15.8	16	15	0.286	0.111	0.056	0.067
Mode choice	Bicycle	24.1	23.81	24.60	0.333	0.120	0.059	0.073
	Bus-Tram-Metro (BTM)	2.07	2.31	1.64	0.130	0.167	0.056	0.087
	Car	57.9	60.46	53.46	0.310	0.118	0.056	0.069
	Ferry/Boat	0.07	0.05	0.11	0.050	0.172	0.050	0.118
	Moped	1.57	1.5	1.69	0.333	0.125	0.067	0.083
	Other	0.62	0.53	0.77	0.379	0.200	0.059	0.077
	Taxi	0.05	0.05	0.04	0.405	0.080	0.077	0.069
	Train	1.93	2.44	1.04	0.091	0.184	0.044	0.097
	Walk	11.71	8.85	16.64	0.294	0.122	0.056	0.077
Travel time class (minutes)	0-7	28.91	29.04	28.71	0.333	0.111	0.061	0.071
	8-15	28.13	28.07	28.25	0.318	0.118	0.056	0.071
	16-30	24.37	24.97	23.30	0.292	0.130	0.056	0.071
	31-60	13.3	13.36	13.18	0.263	0.133	0.053	0.071
	61-120	4.41	3.83	5.39	0.267	0.118	0.056	0.071
	>120	0.89	0.72	1.17	0.257	0.103	0.056	0.071
Departure time	Early morning (7-9)	12.54	16.56	5.55	0.152	0.152	0.063	0.059
	Late morning (9-12)	18.53	15.65	23.53	0.263	0.095	0.059	0.083
	Early afternoon (12-14)	14.92	12.87	18.43	0.323	0.087	0.056	0.071
	Late afternoon (14-17)	24.47	23.18	26.72	0.345	0.139	0.056	0.083
	Evening (17-20)	18.65	18.39	19.07	0.353	0.143	0.053	0.065
	Night (20-24)	9.27	11.16	6.02	0.375	0.111	0.053	0.056
	Midnight to dawn (24-4)	1.63	2.18	0.68	0.333	0.083	0.05	0.053
Type of day	Workday	76	68	49	0.290	0.125	0.059	0.077
	Weekend	24	32	51	0.357	0.105	0.053	0.067
Weather conditions (during the trip)	Clear sky	36.6	37	36	0.304	0.119	0.056	0.071
	Cloudy	54.58	55	55	0.313	0.125	0.056	0.071
	Rainy	3.83	4	5	0.293	0.111	0.056	0.071
	Undefined	4.59	5	4	0.333	0.133	0.067	0.077

Table 1 reveals that the female respondents in our dataset undertook more trips to discretionary destinations than the males. They also repeatedly visited the same location (SRI) more often than males in trips to compulsory destinations, although the departure time (TRI) varied more for males. Trip repetition to discretionary destinations increased with the respondent's age.. For both types of destination, the SRI and TRI increase with age of the traveller. Retired people tended to visit the same place for the same purpose within the same week, while employed respondents' behaviour appeared to be more explorative (lower SRI). Both the trip share and repetition indices are low for university graduates (WO-level education), which reflects that they travel less, but when they do, they travel to a greater variety of places. The variation in departure time is lower for married people than for unmarried people for trips to discretionary destinations and the reverse is true for compulsory destinations. Respondents living in urban areas completed 60% of their trips at almost the same departure time.

Table 1 shows that the car was the dominant mode for daily travel, followed by the bicycle and walking. This table also shows that the taxi has a high spatial repetition index, with trips to compulsory destinations being most often for personal care (0.24% versus 0.06% to home, 0.01% to work and 0.03% to take people to or pick them up from the trip destination). This is because mostly older adults use taxis in the Netherlands, namely to go to a hospital, treatment or care centre and in those weeks, there are fewer trips to other activities. Use of bicycle, moped or car had a high SRI, as did walking and other modes. Although all modes have similar repetition indices, the lower SRI for train use reflects high intrapersonal variability in the destination choice of train users, which can be related to students trips (with free transport cards or discounts)

The distribution of trips across travel time classes reveals that 95% of the trips took less than 1 hour, and the distribution is the same for both types of destinations. The shortest travel time (0-7 minutes) has the highest SRI median, both for trips to compulsory and discretionary destinations. The SRI decreases with increasing travel time, which is as expected, and consistent with a previous study on mode choice variation (Thomas et al. 2019). Long-distance trips (>60 minutes) were taken more often to discretionary destinations. Unlike the SRI, the TRI for trips to discretionary destinations is the same for all trip durations.

The late morning and early afternoon have a higher share of trips for shopping, sports and leisure purposes (discretionary) than of trips to work, education and healthcare (compulsory) (see Table 1). For trips to compulsory destinations, the SRI increases with the time of the day (lowest for the early morning, with the highest TRI, however). For trips to discretionary destinations, the SRI is highest in the early morning, which means that people tended to leave early for repeatedly visited discretionary destinations. However, the TRI indicates that the degree of repetition of the departure time for the same activity is higher in the late morning and late afternoon.

Table 1 also shows that most of the trips were recorded during workdays (76%) and that trips to compulsory destinations were more frequent on workdays (68%), while discretionary destinations were visited more often during the weekend (51%). A higher SRI for trips taken on the weekend represents low intrapersonal variation in compulsory location choice. The higher TRI for trips to both compulsory and discretionary destinations on workdays means that people repeated a particular activity within the same (time) period. More than half of the trips were made in cloudy weather, which reflects the climate of the Netherlands. Since the data were collected in spring and summer, relatively little precipitation occurred during the trips. Although we expected there to be fewer trips to discretionary destinations when it rained, we found the opposite. A possible explanation can be that these trips were planned in advance so that even though it rained, the respondents still travelled to a specific destination to carry out a particular activity.

The spatial variables we used are land-use functions (dominant land use at PC5 level) and job accessibility by car and public transport, as a proxy for accessibility to all activities. The data was taken from earlier work that used TomTom speed profiles as well as general transit feed specifications (GTFS) and produced estimates at PC5 level (Pritchard et al., 2019). The first GTFS model is a typical transit model with pedestrian access and egress, referred to as a *walk-and-ride* model. The second is the *bike-and-ride* model, which incorporates cycling as a feeder mode, resulting in significantly higher public transport accessibility levels. Discretionary activities are more often available at destinations with land use related to retail, health and nature reserve, park, forest, and scrub area. Compulsory activities are more often conducted in residential, recreation, commercial, and industrial land areas. Furthermore, built-environment variables (i.e. distance to different facilities from the destination) are divided into four levels (in km), based on the percentile distribution for each variable: Low (25%), medium (50%), high (75%) and very high (100%)[6].

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[6] The analysis of the accessibility variables is not detailed in this paper, but is available upon request.

4. Choice modelling framework

Destination choice is a choice between discrete alternatives. We developed mixed logit (ML) models for (a) compulsory destinations and (b) discretionary destinations since ML allows measuring the intrapersonal dynamics via error components, which create correlations among the utilities for different alternatives. The main advantage of using a mixed ordinal structure lies in having an alternative-specific setup for both respondent heterogeneity and estimated parameters. We developed and compared two models since trips to compulsory destinations have very different characteristics than trips to discretionary destinations (Figure 3). The variables were systematically tested in the model specification.

The theoretical framework of the discrete choice model was developed based on random utility theory (McFadden, 1973) as this approach offers a dominant paradigm for trip distribution modelling (Mishra et al., 2013), in which the structural equation links the deterministic model to a statistical model of human behaviour. The model we built is based on the random utility maximisation theory, which has been widely used to estimate discrete choice behaviour (Wu et al., 2011, Scarpa and Thiene, 2005). Figure 3 shows the conceptual framework. On the left are the explanatory variables. On the right are the alternatives (dependent variables), which are the repetition levels of the activities, which we divided into two types of activity (compulsory and discretionary), as explained before. Solid lines represent the observable relationship, while dotted lines represent the unobserved.

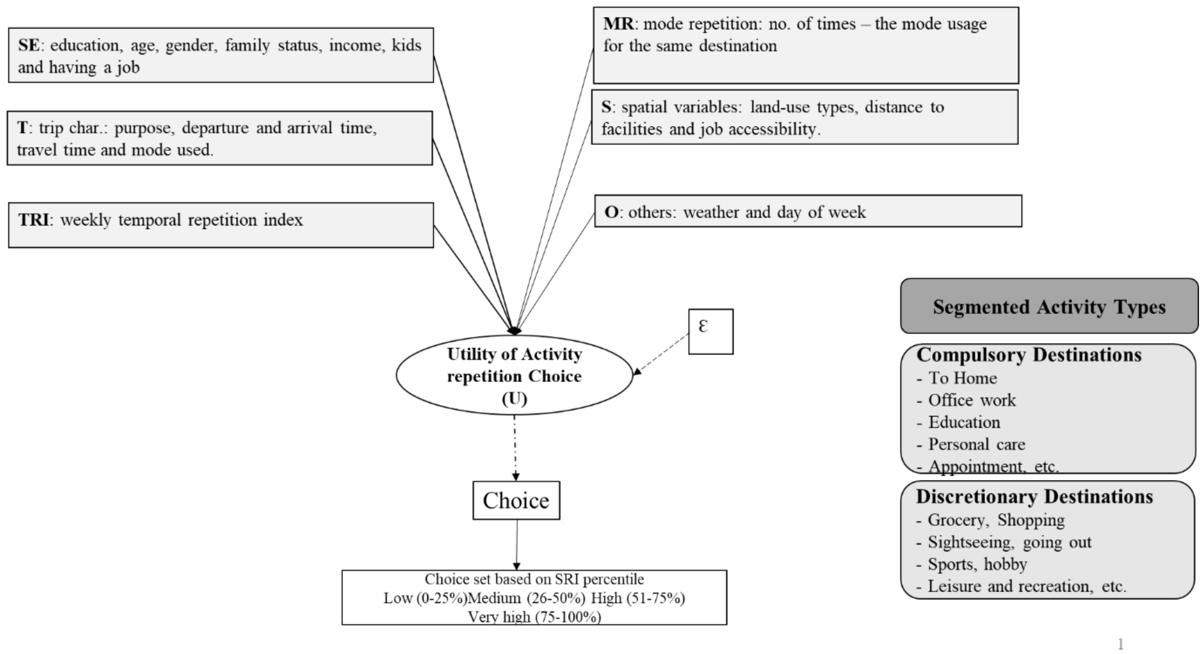

Figure 3. Conceptual model framework

A panel database includes repeated observations, thus use of mixed multinomial logit is appropriate for such data because it accounts for the correlation among observations belonging to the same individual (Yáñez et al., 2011). A mixed logit (ML) model is any model in which the probability of a choice can be expressed as an integral of standard logit probabilities, evaluated at parameters ω, over a density of parameters (Train, 2009). The vector ω can assume any desired distribution, and can take correlation among individuals into account. The utility for the model structure can be written as:

$$U_{nitd} = \beta^{SE} SE_n + \beta^T T_{nd} + \beta^{TRI} TRI_{nt} + \beta^{MR} MR_n + \beta^s S_{ni} + \beta^r O_{nd} + \omega_{ni} + \varepsilon_{nit} \quad (3)$$

Here, n persons have a set of alternatives i over choice situations t. U_{nitd} is the utility of a destination alternative i. ε_{nit} is the error term, which is a random variable following an extreme value (Gumbel) distribution with location parameter *0* and scale parameter *1*. Where SE is the socio-economic characteristics of the respondent n. T stands for the characteristics of the trip d to reach the destination. TRI represents the weekly temporal repetition index per person n during week t. MR is the mode repetition, as the number of times the same mode is used by person n to visit the (same) destination *(e.g.* postcode*)*. S represents the spatial variables at the destination i visited by the person n. O represents variables stands by 'other trip characteristics' (e.g. weather and day of the week) during the day that the trip (d) to the visited destination was carried out. If φ is the vector of fixed parameters, the unconditional probability is the integral of this product overall values of ω:

$$P_{ni} = \int \overbrace{\left(\frac{e^{U_{nitd}}}{\sum_j e^{U_{njtd}}}\right)}^{\text{Logit probability}} \overbrace{f(\omega_{ni}|\varphi)}^{\text{Density function}} d\omega_{ni} \tag{4}$$

To estimate the mixed logit models, simulation methods are typically used. Thus, in Eq. 4, for any given value of φ, it is possible to generate ω_{ni}^r, r=1,…,R drawn from $f(\omega|\varphi)$, which can be used later on to compute the simulated probability. The simulated log-likelihood (SLL) function maximises the estimated parameters:

$$SLL(\beta_n) = \sum_n \ln(\check{P}_{ni}) \tag{5}$$

For the model applications, we calculated the elasticities, which have policy implications. The elasticities mean the effect of a change in a variable over the estimated probabilities. It means that we can measure the effect of changing visits time-frame (e.g. temporal repetition index) on the repetition of the visited location (SRI, alternatives of the choice set). Then, the elasticity of a dependent variable ($\check{P}_{ni}$) concerning another variable (TRI_{nt}) in a function can be expressed as follows:

$$E(\check{P}_{ni}, TRI_i) = \frac{d\check{P}_{ni}}{dTRI_i}\frac{TRI_{nt}}{\check{P}_{ni}} \tag{6}$$

For the models, we determined the alternative specific constant (ASC_i), using the alternative with a Very High SRI (for compulsory activities, SRI>0.42; for discretionary activities, SRI >0.091) as reference. Different model specifications were systematically tested. We chose the final models based on the t-test (90% confidence level) and overall goodness-of-fit measure. We used PythonBiogeme (Bierlaire, 2016) to estimate the models with 250 draws and using maximum likelihood estimation. To capture the correlation across observations for the same respondent, alternative-specific error components were estimated in the mixed logit structure.

5. Model results

Table 2 shows the model results. The ASC values indicate that if the other parameters remain the same, the alternative with a low SRI (=<0.040) is the most preferred one for discretionary destinations, followed by alternatives with a medium SRI (0.041-0.056) and, next, a high SRI (0.057-0.091). This result reflects the variety-seeking behaviour of the respondents in their free time, for example to explore new locations for leisure activities; this is consistent with what others have found (Schlich et al., 2004, Arentze and Timmermans, 2005, Schönfelder and Axhausen, 2010, La Paix Puello et al., 2018). On the other hand, alternatives with a medium SRI (0.112-0.308) are highly preferred for compulsory destinations, followed by the alternatives with a low (=<0.111) and, next, a high SRI (0.309-0.421). This result was expected since most trips to the office, education, appointments and home are repeated for the same locations, but here too, we may still see a degree of variety-seeking as the alternative with the highest SRI is the least preferred.

Table 3. Model results

		Compulsory		Discretionary	
	Category	**value**	**t-test[7]**	**value**	**t-test**
	ASC (Very High SRI - V4)	Ref.			
	ASC (High SRI - V3)	5.63	***41.53***	5.63	***49.38***
	ASC (Medium SRI - V2)	7.81	***65.67***	5.97	***46.03***
	ASC (Low SRI - V1)	10.1	***61.71***	6.82	***55.17***
Mode choice	Train (Low SRI - V1))	0.486	***4.67***	0.445	***2.65***
	Moped (High SRI - V3)	0.55	***4.03***		
	Walk (Medium SRI -V2)	-0.663	***-8.77***		
Departure time	Late morning (High SRI - V3)			-0.0695	***-1.83***
	Early afternoon (Medium SRI -V2)			0.0806	***1.98***
	Late afternoon (Medium SRI -V2)	0.154	***3.87***	0.163	***3.04***
Travel time (minutes)	Car (Medium SRI -V2)	-8.98E-06	***-1.9***		
	Car (Low SRI-V1)	-4.04E-05	***-6.69***		
	Bicycle (High SRI-V3)			2.09E-05	***3.99***
	Bicycle (Medium SRI - V2)			1.89E-05	***3.34***
	Bicycle (Low SRI -V1)	3.08E-05	***7.49***	3.43E-05	***5.82***
	Public transport (High SRI-V3)	-2.33E-05	***-6.53***	-2.20E-05	***-4.76***
	Public transport (Medium SRI -V2)	-4.68E-05	***-11.68***	-2.30E-05	***-4.63***
	Public transport (Low SRI -V1)	-7.10E-05	***-14.05***	-3.40E-05	***-6.45***
	Walk (High SRI-V3)	3.03E-05	***4.3***		
	Walk (Low SRI-V1)	9.63E-05	***11.52***		
Repetition index	TRI (High SRI-V3)	-5.44	***-29.33***	-8.75	***-25.57***
	TRI (Medium SRI-V2)	-8.84	***-42.76***	-14.8	***-33.89***
	TRI (Low SRI -V1)	-15.4	***-52.53***	-23.5	***-43***
	Mode repetition (MR) (High SRI-V3)	-0.00598	***-4.06***	-0.239	***-26.74***
	Mode repetition (MR) (Medium SRI -V2)	-0.0622	***-39.41***	-0.462	***-33.28***
	Mode repetition (MR) (Low SRI -V1)	-0.365	***-76.23***	-0.646	***-40.51***
Land use (percentages)	Recreation ground (High SRI-V3)			0.484	1.48
	Park, forest, scrub (High SRI-V3)			-0.361	***-3.54***
	Park, forest, scrub (Medium SRI -V2)			-0.367	***-4.86***
	Park, forest, scrub (V1)			-0.246	***-3.57***
	Retail (V3)			0.6	***2.92***
	Retail (Medium SRI -V2)			0.659	***3.33***
	Retail (Low SRI -V1)			0.74	***3.59***
	Commercial, industrial (High SRI-V3)	2.12	***13.63***		
	Commercial, industrial (Medium SRI -V2)	3.88	***24.6***	0.207	***2.68***
	Commercial, industrial (Low SRI-V1)	3.88	***24.4***		
	Residential (Medium SRI-V2)	-0.911	***-16.53***		
	Residential (Low SRI -V1)	-1.15	***-18.2***		
Accessibility	Job accessibility by public transport - Walk and Ride (Medium SRI-V2)	7.37E-06	***17.43***		
	Job accessibility by public transport - Walk and Ride (Low SRI -V1)	1.03E-05	***19.95***		
	Job accessibility by public transport - Bike and Ride (High SRI-V3)	1.47E-06	***5.8***		
	Job accessibility by car (Medium SRI-V2)			3.11E-07	***3.1***
	Job accessibility by car (Low SRI-V1)	-5.71E-07	***-3.91***		
	Distance to restaurants (Medium SRI-V2)			0.289	***4.8***

[7] For the 90% confidence interval, p-value should be smaller than 0.1 and t-test larger than 1.64. For the 95% confidence interval, p-value should be smaller than 0.05 and t-test larger than 1.96. For the 95% confidence interval, p-value should be smaller than 0.01 and t-test larger than 2.57.

		Compulsory		Discretionary	
	Category	**value**	**t-test[7]**	**value**	**t-test**
	Distance to restaurants (Low SRI -V1)			0.336	***4.98***
	Distance to leisure activities - low (Low SRI-V1)			0.104	1.62
	Distance to leisure activities - high (V2)			-0.0822	***-1.89***
	Distance to sports ice skating - (High SRI-V3)			-0.132	***-2.79***
	Distance to doctor - high (High SRI-V3)	-0.242	***-3.83***		
	Distance to doctor - high (Medium SRI-V2)	-0.527	***-8.87***		
	Distance to doctor - high (Low SRI -V1)	-0.352	***-5.11***		
	Distance to day care - high (Medium SRI-V2)	-0.0982	***-2.44***		
	Distance to train station - medium (Medium SRI-V2)	0.221	***5.92***		
	Distance to train station - high (Low SRI -V1)	-0.255	***-5.19***	-0.139	***-3.02***
	Distance to train station - low (High SRI-V3)			0.252	***4.35***
	Distance to train station - medium (High SRI-V3)			0.0566	1.34
	Distance to highway onramp - low (High SRI-V3)			0.099	***2.14***
	Distance to highway onramp - low (Medium SRI-V2)			0.142	***2.9***
	Distance to highway onramp - high (V2)	0.168	***4.59***		
Others	Weekend (Medium SRI-V2)	-0.668	***-17.55***	0.0599	***1.66***
	Weekend (Low SRI-V1)	-1.04	***-19.86***		
	Rain (V2& Low SRI -V1)	0.121	1.63		
Error comp.	Very High SRI -V4 - $\sigma_{\omega_{v4}}$	-4.85	***-55.03***	4.15	***44.39***
	High SRI -V3 - $\sigma_{\omega_{v3}}$	1.18	***38.68***	-0.844	***-20.96***
	Medium SRI - V2 - $\sigma_{\omega_{v2}}$	-0.512	***-19.69***	0.954	***14.31***
	Low SRI -V1 - $\sigma_{\omega_{v1}}$	0.906	***20.77***	2.04	***38.62***
Goodness of fit	Estimated parameters	44		43	
	Sample size	42480		24425	
	Initial log-likelihood	-6.80E+07		-3.90E+07	
	Final log-likelihood	-3.80E+07		-2.70E+07	
	Rho-square for initial model	0.448		0.324	

Mode use, departure time, and mode-specific trip duration were tested in the models as alternative-specific. The results show that mode choice was insignificant in most cases, which validates the claim of Schüssler and Axhausen (2009). For less repeatedly visited locations, the respondents preferred to walk. An alternative model specification (not included in this paper, but available upon request) confirmed these results by showing a positive effect of walking to discretionary destinations. The train was highly preferred for travelling to new destinations, (with a low SRI for both compulsory and discretionary activities). It means that when respondents tend to visit different destinations, they tend to travel by train.

When the variables mode repetition (MR) and TRI were added in both models, they were found statistically significant for all alternatives and for both compulsory and discretionary destinations, consistent with what Buliung et al. (2008) found. For high-SRI compulsory destinations, a moped was likely to be used and walking was not preferred for medium-SRI destinations. These results are in line with previous findings that indicate a significant correlation between activity schedules (duration) and mode choice (La Paix Puello et al., 2018).

Regarding the departure time, as expected, departures in the late morning were unlikely for trips to highly repetitive discretionary destinations (high SRI), while departures during the entire afternoon were likely for trips to medium-repetitive destinations (medium SRI). Furthermore, the results show that mode-specific travel time is an essential factor, which is consistent with what others have found; see for example Auld and Mohammadian (2011) and Wu et al. (2011). Regarding the temporal repetition index (TRI), the results confirmed that there is a strong association between temporal and spatial intrapersonal variation, the existence of temporal variation in the spatial dimension within any individual’s travel pattern, which was also found by (Schönfelder and Axhausen, 2010, Schlich et al., 2004, Cirillo et al., 2003).

Several land-use type variables, accessibility measures and built-environment variables were tested. The results indicate that the respondents were more likely to travel multiple times to a particular recreational ground and retail area as discretionary destinations, while discretionary destinations surrounded by park, forest and scrub areas were less likely to be visited repeatedly. Compulsory activities undertaken in commercial and industrial areas were likely to be repeated (in general), being the high-SRI (V3) alternative less affected by the availability of commercial retails. As can be expected, the percentage of land-use dedicated to residential areas was found significant for compulsory activities (home). Car accessibility was found to have an influence on the choice for a discretionary destination as it was positively associated with alternatives with a medium SRI. By contrast, BnR (high SRI) and WnR (medium and low SRI) were positively associated with compulsory destination alternatives.

The results also show that distance to restaurants, medical facilities and sports centres was a significant influence on the (repeated) choice for discretionary destinations. By contrast, compulsory destinations were more likely to be visited if these were located close to a train station or highway on-ramp. Regarding the weather, rain does not appear to have discouraged the respondents from reaching infrequently visited discretionary destinations and medium-to-low-SRI compulsory locations. The socio-economic characteristics we used are statistically insignificant. The error components in the t-test are significant, but this is as expected since error components represent the correlation within individuals and thus capture the effects of socio-economic characteristics (Mishra et al., 2013, Ye et al., 2012).

6. Model application

We also calculated the elasticities with the developed models. The elasticities explain the impact of a change in the TRI on the prediction of destination choice. Figure 4 shows the estimated elasticities and probabilities for both compulsory and discretionary destinations.

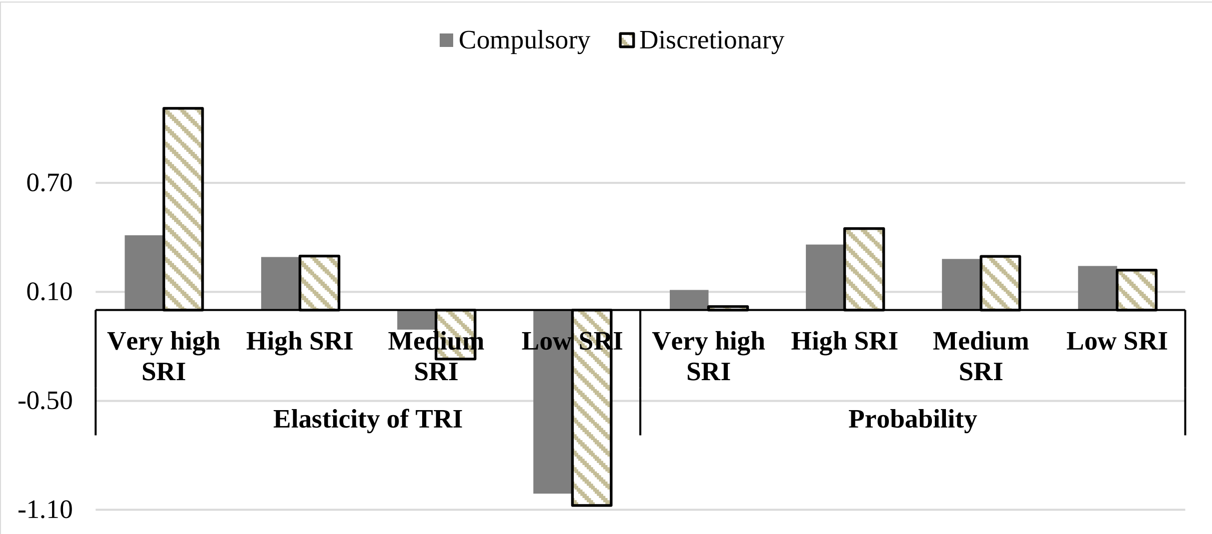

Figure 4. Elasticity of TRI and probability: Low (0-25%), medium (26-50%), high (51-75%) and very high (75-100%) SRI

The elasticities show that the demand for both compulsory and discretionary destinations is simultaneously affected by spatial and temporal repetitions. A high spatial repetition occurs with a high temporal repetition of alternatives, having the opposite effect for medium and low TRI values. This outcome means that TRI is significant for trips to work, home, education, and appointments (compulsory) as well as to leisure, sports, shopping, etc. (discretionary) and that the TRI is strongly linked with spatial repetition. This result is consistent with previous work with the same sample, in which intrapersonal variation was found relatively small for commutes, implying a high level of habituation (Thomas et al., 2019). Further, our results indicate that destination choices of long trips are more easily modifiable, which can be understood as a travel impedance, being distance an important part of transport costs.

The probabilities show that the most likely chosen destinations are destinations with high and medium spatial repetition, which means that destinations with a very high SRI are not necessarily the most frequently visited ones, as a general rule. This is consistent with the substantial variation in individual activity spaces found by Järv et al. (2014).

Further, more than 80% of trips in our study were short (up to 30 minutes). Since the intrapersonal variation is high for discretionary destinations, we estimated the elasticity and probability for short trips (1-15 minutes and 16-30 minutes) to discretionary destinations. Figure 5 (on the left) shows the elasticity, which is almost symmetric. The elasticity values for short trips are greater than the average values presented in Figure 5 for all trips. It means that there is more intrapersonal repetition for short-distance trips, which is consistent with the results of Thomas et al. (2019). An alternative model specification (not included in the paper, but available upon request) showed that using definitions of alternatives based on the individuals' behaviour amplified the differences relative to using a model based on the statistical distribution of the choices.

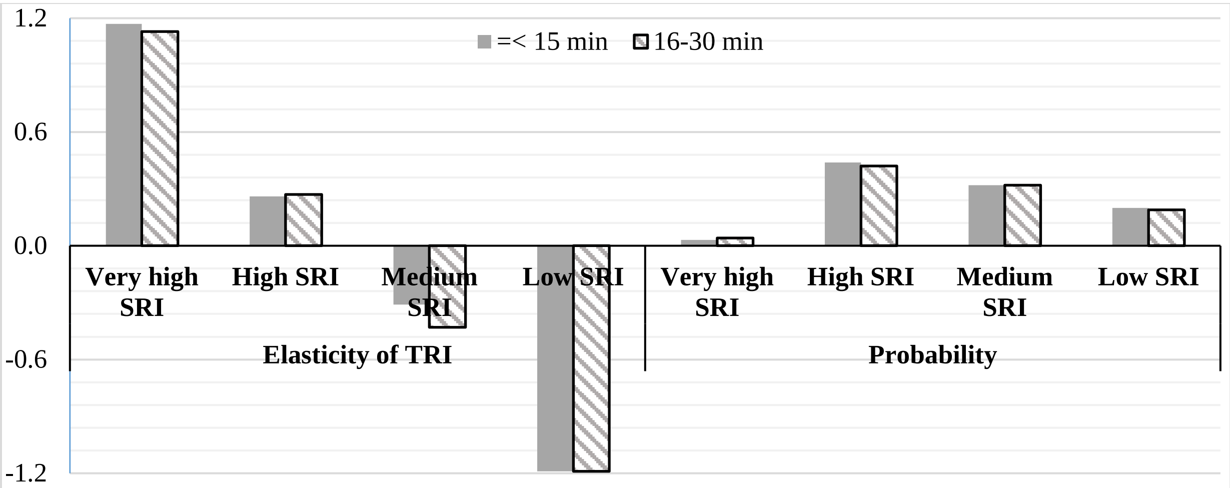

Figure 5. Elasticity and forecasting for short trips (16-30 minutes trips) towards discretionary destinations: Low (0-25%), medium (26-50%), high (51-75%) and very high (75-100%) SRI

7. Conclusions

This paper presents an investigation of the spatial-temporal interpersonal and intrapersonal variation in destination choice, based on longitudinal smartphone data for the Netherlands. Mixed logit destination choice models were estimated using two waves of data (2014 and 2015) from the Dutch Mobile Mobility Panel, in which over 68,000 valid trips for 442 respondents were recorded using a smartphone app during an annual four-week measurement period. Discrete destination alternatives were defined based on the statistical distribution of a spatial repetition index. The mixed logit structure represents the effect of intrapersonal variation, while the spatial repetition index and the temporal repetition index represent the effects of interpersonal variation. We found that both the SRI and TRI are statistically significant in destination choice in our study.

Several conclusions can be drawn from the research. Firstly, the results confirm that spatial variables (land use, accessibility, built environment) are associated with the type of activity carried out at the destination (compulsory or discretionary). Secondly, repetition in destination choice is affected by several factors, such as socio-economic characteristics and related alternatives (e.g.

travel time, travel mode and departure time), consistent with previous analysis (Schüssler and Axhausen, 2009, Mokhtarian and Salomon, 2001). Socio-demographic characteristics were found correlated with the level of intrapersonal variation, in line with the analysis of activity patterns by Shou and Di (2018). Thirdly, the model results and probability reflect variety-seeking behaviour among the respondents in their destination choices, in particular for discretionary activities. This also has been found in an earlier study of activity-space using multiple-week GPS data (Schönfeld and Axhausen, 2010). Fourth, in line with Schüssler and Axhausen (2009), this study confirmed the existence of links between activity type, destination and departure time. We also found that temporal (intrapersonal) variation in destination choice is lower for shorter distances in our study.

However, we identified temporal and modal variation in the decision-making for different destinations offering the same activity. For instance, the departure time varied greatly as did the chosen mode for travelling to less frequently visited locations. An unexpected find was that weather conditions had relatively little influence on travel behaviour that was linked to variety-seeking (infrequently visited discretionary destinations and medium-to-low-SRI compulsory locations), but this may also mainly reflect the climate in the Netherlands, where it often rains.

From a modeller perspective, this paper shows that an explicit estimation of destination choice considering spatial constraints and intrapersonal variation with discrete choice models, which is an added value to the discussion of choice set generation when alternatives are spatially. Also, the model shows the most relevant factors on different stages of the decision process: type of activity, transport mode, departure time. Finally, the present paper identifies different levels of habituation (correlation) and inertia effects on destination choices, due to both temporal correlations and proximity.

From a planner perspective, the paper estimates specific models for types of activities which show the different patterns of repetition, and therefore specific measures can be implemented to satisfy the needs of the travelers according to the type of activity. For example, public transport fares or plans by trip purpose or trip distance-purpose. And, the elasticities show the impact of temporal correlation on spatial repetition, showing that high spatial repetition is associated with high temporal repetition. From a transport planner perspective, it means that certain people exhibit strong habits determined by the spatial locations, and if planners want to change those habits, they should approach the spatial conditions. Our results indicate that trip distance is an important part of spatial correlation analysis.

In future research, this study can be extended to an analysis of TRI and SRI day-to-day and year-to-year as a measure of intrapersonal variability. Also, a combined destination choice-mode choice model could be developed based on the repetition indices; this may reveal more interesting factors that play a role in the travel behaviour of individuals.

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