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Didn't travel or just being lazy? An empirical study of soft-refusal in mobility diaries

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Abstract
In mobility panels, respondents may use a strategy of soft-refusal to lower their response burden, e.g. by claiming they did not leave their house even though they actually did. Soft-refusal leads to poor data quality and may complicate research, e.g. focused on people with actual low mobility. In this study we develop three methods to detect the presence of soft-refusal in mobility panels, based on respectively (observed and predicted) out-of-home activity, straightlining and speeding. For each indicator, we explore the relation with reported immobility and panel attrition. The results show that speeding and straightlining in a questionnaire is strongly related to reported immobility in a (self-reported) travel diary. Using a binary logit model, respondents who are predicted to leave their home but report no trips are identified as possible soft refusers. To reveal different patterns of soft-refusal and assess how these patterns influence the probability to drop out of the panel, a latent transition model is estimated. The results show four behavioral patterns with respect to soft-refusal ranging from a large class of reliable respondents who score positive on all three soft-refusal indicators, to a small 'high-risk' class of respondents who score poorly on all indicators. This 'high-risk' group also reports the highest immobility and has the highest attrition rate. The model also shows that respondents who do not drop out of the panel, tend to stay in the same behavioral pattern over time. The amount of soft-refusal expressed by a respondent therefore seems to be a stable behavioral trait.

Keywords Travel behavior · Soft-refusal · Response behavior · Mobility panels · Speeding · Straightlining · Attrition · Latent transition analysis

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Introduction

In travel behavior research, multi-year panels have been set up to understand (changes in) the drivers of travel behavior over time. Participants in these panels typically complete—on a regular basis (e.g., every year)—a (self-reported) multiple-day travel diary along with a questionnaire containing personal and psychographic information. The resulting data are ideally suited to model and understand the (causal) mechanisms behind travel behavior, and the changes therein over time at the individual level (see e.g. Scheiner et al. (2016) and de Haas et al. (2022)).

To use the data effectively for this purpose, it is crucial that the data quality is guaranteed. One cause of poor data quality, which has received considerable attention in research, relates to (selective) attrition, either within-wave or between-waves. In the context of travel behavior research, it has been shown that panel attrition is related to household income, household size, educational level and reported number of trips (Golob et al. 1986; Kitamura & Bovy 1987).

However, next to attrition, there are other processes that may result in low data quality, which have received less attention in research. One such mechanism relates to the notion of soft-refusal, which describes the tendency of some respondents to refuse participation in a 'soft' way, e.g. Madre et al. (2007) showed that there are respondents who claim they did not leave their house even though they actually did. Identifying these "soft refusers" is important as they may have strong impacts on study results. For instance, if there are indeed respondents who report to stay at home while they actually made trips, the data will not reflect actual mobility levels. This may become specifically problematic in the context of research that is focused on identifying vulnerable groups with actual low mobility. Obviously, having these vulnerable groups mixed with soft refusers complicates research efforts focused on questions related to this subject such as transport poverty.

Next to reporting to stay at home while the respondents in fact did not stay at home, two other sources of bias may be identified, namely straightlining and speeding, which have been extensively studied in general survey research (but not in a travel behavior context). Straightlining can be defined as the tendency to provide the same answer to every item in a grid (Struminskaya et al. 2015) and speeding as the tendency to complete the questionnaire in a (much) shorter time than average. These tendencies are often described as satisficing (Barge and Gehlbach 2012; Krosnick et al. 1996) and can actually also be seen as instances of "soft-refusal"; respondents still participate but refuse in a soft way by minimizing effort and not providing accurate answers.

Against this background several relevant research questions can be formulated, namely to what extent do these instances of soft-refusal actually occur and to what extent are they correlated with reported immobility (i.e. no trips are reported for a single day)? Next to the relation with reported immobility, the present study will focus on the link between soft-refusal and attrition. Formulated specifically, to what extent are these soft-refusal indicators associated with attrition?

Being able to identify respondents who do not fill out surveys or travel diaries correctly provides the option to increase data quality by removing these people from the sample. Given the multi-year context of a mobility panel, it is important to decide whether to remove only a single wave of data of these respondents, or to remove the respondent from the panel entirely (i.e., no longer inviting the respondent for following waves). Given the costs and efforts involved in recruiting new panel members, the first option is more desirable, but should only be chosen if it is likely that the respondent will behave better in future waves. To this end, this study also addresses the question whether being a soft refuser is a 'fixed state' over time, or whether respondents can shift to being a reliable respondent in a future wave.

The present study uses data from the Netherlands Mobility Panel (MPN) to study this research question. The MPN is a longitudinal household panel in which respondents yearly fill out an extensive questionnaire and report three days of travel behavior in an online travel diary (Hoogendoorn-Lanser et al. 2015). The methods presented in this study to identify soft-refusal make use of both the questionnaire and the travel diary. Based on the questionnaire, speeding and straightlining will be studied as indicators of soft-refusal, while the travel diary is used to directly identify respondents who report no trips while they were expected to leave their home on that given day based on their sociodemographic profile. As such, the present study aims to contribute by presenting and testing new methods (to identify soft-refusal) and by empirically investigating to what extent soft-refusal may be present in multi-year mobility panels and how it relates to attrition. We wish to note that, while we focus on soft-refusal in multi-year mobility panels, many of our results have direct relevance for one-shot mobility diaries and travel surveys as well.

In the next section, previous studies on the link between response behavior and data quality are discussed. Results of these previous studies are used to specify the methods to identify soft-refusal in the present study. The methods to identify soft-refusal are in detail discussed in the method section, as well as the conceptual model to study soft-refusal over time. Next, the data is discussed followed by the results of the analyses. Finally, the results of the methods to identify soft-refusal are discussed followed by the results of our longitudinal analysis to study soft-refusal over time.

Previous research on response behavior in surveys

To achieve high data quality from (web) surveys, respondents should participate in a thoughtful way. In reality, respondents may try to lower their respondent burden by strategic behavior. Krosnick et al. (1996) applied the concept of satisficing[1] (the idea that people often expend the effort necessary to make a satisfactory or acceptable decision) on surveys to describe different strategies respondents may use to lower their response burden. They argued that, while some respondents may have an intrinsic motivation to provide high-quality data, many respondents may not be inclined to put a lot of effort into answering questions carefully. These types of respondents may take different strategies, for instance picking the first acceptable answer option or only superficially interpreting questions, resulting in sub-optimal answers. Two types of these strategies have been studied quite extensively, namely straightlining and speeding, which we will discuss in the next section. In the following section we discuss underreporting of trips and the link with attrition. Next, we discuss the research contributions of the present study.

[1] In a travel behavior context, satisficing may also refer to an individual's decision strategy to choose an alternative (e.g., travel mode or trip route) that satisfies a minimum threshold as opposed to a maximizing strategy in which an individual strives to choose the alternative with the highest utility. To avoid confusion, satisficing strategies to the lower response burden in a survey will be referred to as soft-refusal in the remainder of this paper.

Straightlining and speeding

Couper et al. (2013) argue that grid questions can be distinguished between grids where straightlining is plausible and where straightlining is implausible. Plausible straightlining refers to a situation where straightlining may be a reasonable answer. They suggest that implausible straightlining occurs with behavioral questions, for which more natural variation exists, while attitudinal items are associated with plausible straightlining, as these are typically aligned with one another. Schonlau and Toepoel (2015) studied straightlining in three annual waves of a web survey. In line with the reasoning by Couper et al. (2013), they found a considerably higher amount of straightlining among grids for which straightlining is plausible compared to grids where this is implausible. Furthermore, they found that implausible straightlining is associated with younger age and that the amount of straightlining increases among respondents who participate in the panel for multiple waves.

Considering a shift towards web-only surveys in the past years, studying straightlining seems to have become more important. A study to compare data quality of telephone surveys to web surveys found that straightlining occurs more often in web surveys than in telephone surveys (Fricker et al. 2005). While most studies define straightlining as providing the same answer to each question in the grid, Kim et al. (2019) compare five methods of measuring straightlining. The methods range from a simple nondifferentiation method (i.e. measuring the proportion of respondents using a single response category) to a scale point variation method (i.e. inferring the probability that a respondent differentiates answers). They concluded that while each of the methods measures a slightly different aspect of straightlining behavior, they are all highly correlated. It can be expected that straightlining may also be an issue in a travel behavior context, as travel behavior surveys often include attitudinal statements in the form of grid questions.

Another strategy respondents may use to lower their response burden is to speed through the survey. As argued by Tourangeau et al. (2000) respondents must go through four mental steps when answering survey questions. Respondents must comprehend the question, must retrieve relevant information from their memory, form a judgement based on the available information and finally they have to formulate an answer or select an answer category. Given the mental efforts involved in these processes, answering each question in a survey should take a certain amount of time for a respondent to be able to provide a meaningful answer. It is therefore assumed that respondents with very short response latencies provide low quality data compared to other respondents.

Several studies have presented evidence that speeding is indeed associated with poor data quality. For instance, Malhotra (2008) found strong primacy effects (choosing the first option) among low-educated respondents who speeded through the survey. Greszki et al. (2015) on the other hand, found that providing no answer or choosing the ‘don’t know’ option was associated with response times below the time it should theoretically take to comprehend the question. In a travel behavior context, Chen et al. (2016) found that answering fast in a choice experiment leads to more random choice behavior (i.e. a larger variance of the random error term of the utility function). Furthermore, Zhang and Conrad (2014) showed that speeding is also related to straightlining as persistent speeders show a higher share of straightlining.

Response behavior and attrition

As travel behavior studies often include a (multiple-day) travel diary, some effects of soft-refusal may also be present in the recorded travel behavior. However, as the ground truth (the person's actual travel behavior) is usually unknown, it is very difficult to assess whether the reported travel behavior is (in) correct. Several studies did show that soft-refusal (respondents who underreport trips or incorrectly report to stay at home during the survey period) may be an issue in self-reported travel diaries (e.g., Bricka and Bhat (2006); Madre et al. (2007); Wolf et al. (2003)). Madre et al. (2007) suggested using a binary logit model to identify respondents who have a very high probability of leaving their home (based on sociodemographic characteristics), but who nonetheless reported to stay at home. Soft-refusal in a travel diary is a likely candidate strategy to ease response burden. No additional studies were found in a travel behavior context that assess the presence of soft-refusal and its effects on reported mobility. It can be hypothesized that respondents who show soft-refusal in a questionnaire (e.g. straightlining and speeding), may also show soft-refusal behavior in the accompanying travel diary (e.g. by incorrectly reporting no trips).

An issue specific to longitudinal surveys that influences data quality in multi-year mobility panels is attrition. Contrary to soft-refusal, we can consider attrition a 'hard' way of refusal as respondents no longer participate in the panel. As longitudinal surveys aim to monitor a sample for a longer period of time, attrition becomes a problem when it changes the composition of the sample or is related to the study outcome (i.e. it is non-random). Earlier studies have indeed shown that attrition is usually non-random and related to sociodemographic characteristics, such as educational level, income and household composition (e.g. Golob et al. 1986; Gustavson et al. 2012; Tambs et al. 2009). Specifically in a travel behavior context, it was found that attrition rates are higher among respondents who reported very few trips compared to respondents who reported more trips (e.g., Kitamura and Bovy (1987); La Paix Puello et al. (2017); Van Wissen and Meurs (1989)). This may be an indication that attrition itself can be used as an indicator of soft-refusal in the wave before dropping out.

Research contributions

While there is ample evidence that soft-refusal may have an effect on data quality, no study is available that assesses different indicators of soft-refusal in a travel behavior context and its relationship with reported travel behavior. Therefore, the main contribution of the present study is that it assesses the presence of soft-refusal in a longitudinal mobility panel and shows how soft-refusal is related to reported immobility. More specifically, we will assess three different methods to identify possible soft-refusal. First, similar to Madre et al. (2007), we will directly identify possible soft refusers in the travel diary by predicting out-of-home activity. People with a high model-implied probability of an out-of-home activity, but no observed out-of-home activity are identified as soft-refusers. The following two methods focus on response behavior in the questionnaire. We will identify the extent to which straightlining and speeding is present in the questionnaire and we will show how these behaviors are related with reported immobility in the travel diary. Next to these three methods, we will assess to what extent these indicators on soft-refusal are associated with attrition. Furthermore, as we focus on a longitudinal mobility panel, we will assess how soft-refusal develops over time among individuals. To do so, we will classify respondents into different response behavior classes based on the indicators of soft-refusal and study transitions between these classes over time using a Latent Transition Analysis (LTA).

Methods

In this section, we discuss different methods to identify possible soft refusers in a longitudinal travel survey and to assess soft-refusal over time. First, we discuss the three methods to identify soft-refusal, based on (1) predicting out-of-home activity (2) straightlining, and (3) speeding, followed by the conceptual model to assess soft-refusal over time.

Methods to identify soft-refusal

To assess the presence of soft-refusal in longitudinal travel surveys, we study three different methods in which we make use of indicators that are available from the survey itself.

Method 1: predicting out-of-home activity

The first method which we use to identify respondents who possibly used a soft-refusal strategy, relies on a prediction of out-of-home activity. Using a binary logistic regression model, we calculate the probability that a respondent will leave their home on a given day. While there is obviously a random component in whether people leave their home on a given day, there are several indicators, especially on working days, that can be used to effectively predict whether people will leave their home or not. Indicators such as sociodemographic variables (e.g. age, work status and household composition), stated frequencies of the use of travel modes and number of working days per week are used in the model. This method is similar to the approach of Madre et al. (2007). If such a model predicts that there is a very high probability that an individual leaves their home on a given day, and if that individual nonetheless reports no trips, this could indicate soft-refusal.

Since (reported) immobility levels are different on weekdays, Saturdays and Sundays, three separate models for these different types of days are estimated. The models are limited in the sense that all reporting days are treated as independent observations while each respondent reports three days per wave in the MPN. This violation of the assumption of independent observations is not considered a major issue in the present study, as the goal of these models is not to show to what extent certain factors influence out-of-home activity, but to identify respondents who do not report any trips while a high chance of out-of-home activity is predicted.

Method 2: straightlining

The next two methods to identify respondents who possibly used a soft-refusal strategy, makes use of indicators on how respondents behave when filling out a survey. Travel behavior surveys usually do not only consist of a travel diary, but also include one or more questionnaires to collect background information of the respondent. We assess whether straightlining is present in the survey. If a respondent straightlines one or more grid questions, this could indicate laziness or low commitment to the study. To determine whether respondents straightline, we use a simple nondifferentiation method as this is the most extreme form of straightlining and it is easy to apply. Furthermore, as discussed earlier, Kim et al. (2019) concluded that this simple method is highly correlated with more sophisticated measures of straightlining.

Method 3: speeding

As a third method we assess to what extent speeding in the questionnaire is present and how this is related to reported immobility. A difficulty when assessing whether a respondent is speeding, is determining a threshold value that is considered to result in a valid versus an invalid response. Zhang and Conrad (2014) calculated a threshold value by assuming that respondents should take at least 300 ms per word to read a question. This method, however, does not account for differences in reading speed between respondents and neither for differences in difficulty of each question. Therefore, in the present study we compare response times of respondents to determine whether a respondent is speeding. A characteristic of many (travel behavior) surveys is that the length of the survey depends on several factors. These could either be characteristics of the respondents (e.g. age or device that is used to fill out the survey) or answers that people give on certain question (e.g. certain questions are only presented if respondents answered earlier questions in a specific way). To account for such differences in the length of the questionnaires for different respondents, we estimate a regression model that predicts survey time based on several indicators. The included indicators are all known to have an influence on fill out time of the survey (e.g., work status or device that is used to fill out the survey). To determine if a respondent is speeding, we use the ratio between predicted survey time from the regression model and actual survey time.

Both straightlining and speeding can be considered strategies to lower the response burden. Incorrectly reporting to stay at home a full day in the travel diary is also a way to lower the response burden. We therefore hypothesize that poor response behavior in the questionnaire (i.e. straightlining or speeding) is an indicator of poor response behavior in the travel diary. To test this hypothesis, we will assess to what extent straightlining and speeding in the questionnaire are related to reported immobility in the travel diary.

If respondents used a strategy to lower their response burden, this may indicate that they lost interest and might be more likely to drop out of the panel before the next wave. We will assess to what extent the indicators on soft-refusal are associated with attrition. This is done by comparing reported immobility of three different types of respondents; those who are identified as a possible soft refuser by the three methods, those who are not identified as a possible soft refuser but remain in the panel and those who are not identified with any of the three methods, but who did drop out of the panel. If it is possible to predict attrition based on indicators of soft-refusal, this would improve the refreshment of the panel since it would be known beforehand which (socio-demographic) type of respondents should be recruited to fill in the gaps left by those participants who are likely to leave.

Method to study soft-refusal over time

To study soft-refusal behavior over time, we use a latent transition analysis. Within this model, it is assumed that at each time point the same set of latent classes can be defined that explain associations between the included indicators (Collins andLanza 2009). In the present study, we define the latent classes using the three indicators on soft-refusal we described in the previous section. As a result, the latent classes represent different behavioral patterns with respect to soft-refusal. For example, it may be expected that certain

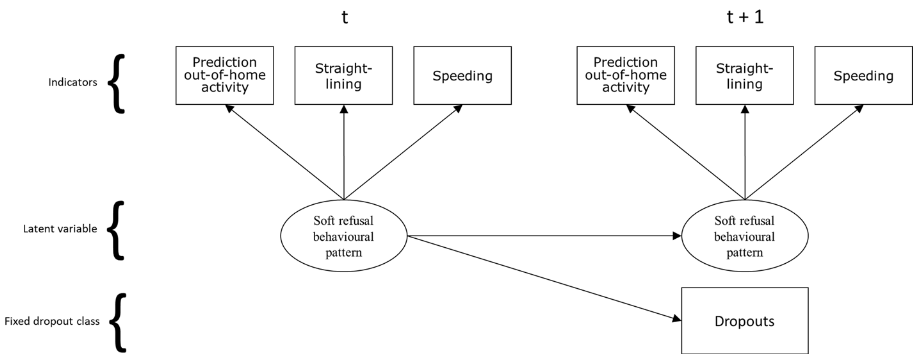

Fig. 1 Conceptual model of the latent transition analysis

respondents perform well or poor on all indicators, but there may also be different behavioral patterns in which respondents score poor on certain indicators but well on others. Figure 1 shows the conceptualization of this model. At each time point, individuals are probabilistically assigned to the latent classes and the parameter estimates can be used to compute transition probability matrices.

To decide on the appropriate number of clusters, we estimate a 1- through 10-class model and use the Bayesian Information Criterion (BIC) and the relative reduction in L^2 to determine which model fits best as described by Magidson and Vermunt (2004). The BIC takes both model fit and parsimony into account. A model with a lower BIC is preferred. To determine the reduction in L^2, the L^2 of the 1-class model is used as a baseline measure of the total amount of association in the data. The reduction in L^2 of higher class models represents the association that is explained by the model. It is no longer justifiable to add an extra class to the model, if this results in a small relative reduction of L^2.

The transition matrices show to what extent people stay within the same class or shift to another behavioral pattern over time. Note that from the moment respondents drop out of the panel, information on soft-refusal is no longer available. This could bias the transition matrices, as attrition rates may be different between the different classes. Therefore, a separate class is added to the model to present respondents who dropped out. With this class included, the transition matrices will not only show transitions between behavioral patterns, but also the relation of a behavioral pattern with attrition.

Case study data

To test the different methods to identify soft-refusal and assess whether being a soft refuser is stable behavior over time or not, we make use of panel data from the Netherlands Mobility Panel (MPN). The MPN is an annual household panel that started in 2013 and consists of approximately 2,000 complete households. The MPN was set up to study the short-run and long-run dynamics in travel behavior of Dutch individuals and households and to assess how changes in personal- and household characteristics correlate with changes in travel behavior. To this end, household members of at least 12 years old are asked to complete a three-day travel diary each year and fill in an extensive questionnaire that includes questions on topics such as occupational status, use of

Table 1 Number of yearly respondents and reported immobility in the Netherlands Mobility Panel (MPN 2013–2020)

Year	# Respondents	Reported immobility (%)		Year	# Respondents	Reported immobility (%)	
		Weekdays	Weekend			Weekdays	Weekend
2013	3.996	13.0	24.8	2017	5.413	12.9	25.3
2014	5.466	13.3	26.3	2018	6.100	16.1	27.0
2015	3.915	13.5	27.1	2019	5.349	16.7	28.7
2016	4.208	13.8	27.1	2020	4.881	27.4	37.3

different modes of transport and life events in the past year. Respondents are equally distributed over weekdays and have the same starting weekday each year. Furthermore, every household is asked to fill in a questionnaire about household related characteristics, such as information about household composition and ownership of means of transport. The different questionnaires and the travel diary are not sent to respondents at the same time. The household questionnaire is sent first, while the personal questionnaire is distributed one week later. Two weeks later, respondents are invited to report their trips in the travel diary. A more extensive description of the MPN can be found in Hoogendoorn-Lanser et al. (2015).

Data from the first seven waves of the MPN (2013–2019) are used. The reported immobility is derived from the three-day travel diary. If a respondent does not report any trips he or she is considered to be immobile on that specific day. It is important to highlight that a certain amount of reported immobility may be expected, as also argued by Madre et al. (2007). While we do not have information on what the level of immobility should be (the ground truth), it can be argued that reported immobility consists partly of true immobility and partly of soft refusal.

Although data from the eighth wave in 2020 is available, this wave is not included in the present study. In 2020, the COVID-19 pandemic has significantly impacted travel behavior. Because of governmental measures to reduce the spread of COVID-19 in the Netherlands, many people started working from home and many people were limited in their daily activities such as shopping and doing sports (de Haas et al. 2020). As a result, the reported level of immobility increased sharply as is shown in Table 1. As this study is focused on identifying people who wrongfully report to be immobile, using this wave of the MPN with a very different level of reported immobility compared to all other waves would unnecessarily complicate the study. Note that there also between 2013 and 2019 some fluctuations in the levels of reported immobility can be observed. Especially the reported levels of immobility on weekdays in 2018 and 2019 are higher compared to the other years. We don't have an explanation for this increase.

Results

In this section, we present the results of the three methods to identify soft-refusal and show the link with reported immobility. Next, we show how the three methods are correlated and study soft-refusal over time with the latent transition analysis.

Predicting out-of-home activity

The first method to identify possible soft refusers is based on a binary logit model that predicts the likelihood that an individual leaves their home on a given day. Table 2 shows the parameter estimates for the three separate models. The models include several sociodemographic variables (age, gender, education level, number of working days per week, number of days working from home per week, migration background and household composition) as well as information about travel behavior from the questionnaire (ownership of a car and bicycle and stated frequency of use of the car, bicycle, and walking). Finally, the wave number is included to account for differences in immobility between years as well as an indicator on whether the respondent reported trips on the same day in another wave. Although respondents can indicate whether they are ill on the reporting day in their trip diaries, this information is not included in the models. While being ill is a strong indicator of staying home, we hypothesize that some respondents may incorrectly indicate that they are ill to justify that they are not reporting any trips. A downside of not including this information in the models is that respondents who are truly ill on the reporting day may be incorrectly identified as a soft refuser.

All included indicators are significant predictors of out-of-home activity in the model for weekdays. Discussing all parameters in detail is out of the scope of this study, but parameter estimates are in the expected direction. For instance, respondents who work more days per week have a higher chance of leaving their home on weekdays, while an increasing number of days working from home reduces that chance. Furthermore, respondents who indicate in the questionnaire to use the car, bicycle or walking more than four times per week have a higher chance of leaving their home on any day compared to people who state to use these modes with a lower frequency.

For each reporting day, the models can be used to calculate the probability that a respondent leaves his home. For weekdays this probability ranges from 22 to 98%, with a mean of 86%, while for Saturdays and Sundays this ranges from 17 to 96%, with means of respectively 79 and 67%. To identify respondents who might show soft-refusal, an arbitrary choice must be made on the cut-off value. In other words, how high should the predicted probability be to consider a respondent who does not report any trips as a potential soft refuser. A higher cut-off value will lower the number of false-positives, while increasing the number of false-negatives. Figure 2 shows how the cut-off value affects the share of respondents who are identified as possible soft refusers. In the present study, we chose a relatively high cut-off value of 90%, as we consider lowering false-positives more important than false-negatives. It should be noted that even with a high cut-off, the results will include false-positives. There may be several reasons why an individual does not leave their home while this is expected based on the information included in the model. For instance, it may be that the individual (or a child) is ill or the individual works more days from home during the reporting period than he or she does on average.

In total, just over 5 percent of respondents are identified as a possible soft refuser in any of the three models, as shown in Table 3. The reported immobility in this table refers to the average immobility for the three reporting days (i.e., if a respondent reports no trips on one of their reporting days their level of immobility would be 33.3%). A result of the relatively high cut-off value of 90% is that only few respondents are identified as possible soft refusers on Saturdays and Sundays. The reported immobility of respondents who are identified as a possible soft refuser is considerably higher than

Table 2 Parameter estimates binary logit models to predict out-of-home activity (MPN 2013–2019)

		Weekday		Saturday		Sunday	
		B	S.E	B	S.E	B	S.E
Intercept		0.64**	0.09	0.84**	0.18	−0.09	0.15
Gender	Male	Ref		Ref		Ref	
	Female	0.04	0.02	0.05	0.05	0.03	0.04
Age	12–17 years	1.06**	0.07	0.20	0.12	−0.03	0.10
	18–24 years	0.28**	0.05	0.24*	0.10	0.37**	0.09
	25–34 years	−0.20**	0.04	−0.07	0.08	0.00	0.07
	35–44 years	Ref		Ref		Ref	
	45–54 years	0.16**	0.04	0.18*	0.08	0.03	0.07
	55–64 years	0.25**	0.05	0.22*	0.09	0.19*	0.08
	65–74 years	0.42**	0.05	0.59**	0.10	0.35**	0.09
	75 + years	0.33**	0.06	0.39**	0.12	0.29**	0.11
Education level	Low	Ref		Ref		Ref	
	Mid	0.10**	0.03	0.03	0.06	0.08	0.05
	High	0.31**	0.03	0.21**	0.07	0.22**	0.06
Origin	Native	Ref		Ref		Ref	
	Foreign	−0.19**	0.04	−0.21**	0.08	−0.18*	0.07
Number of 12 + in household	1	0.00**	0.00	0.00*	0.00	0.00**	0.00
	2	−0.14**	0.03	−0.13*	0.07	−0.04	0.06
	3 or more	−0.27**	0.04	−0.22**	0.08	−0.28**	0.06
Number of 12- in household	0	0.00**	0.00	0.00	0.00	0.00	0.00
	1	0.14**	0.05	0.13	0.08	0.06	0.07
	2 or more	0.23**	0.05	0.02	0.08	0.06	0.07

Table 2 (continued)

		Weekday		Saturday		Sunday	
		B	S.E	B	S.E	B	S.E
Level of urbanization	Urban (1500 + inhabitants/km^2)	Ref		Ref		Ref	
	Sub-urban (1000–1500 inhabitants/km^2)	0.07*	0.03	−0.02	0.06	−0.01	0.05
	Rural (less than 1000 inhabitants/km^2)	−0.03	0.03	−0.06	0.05	−0.04	0.05
Working days/week	1	Ref		Ref		Ref	
	2	0.09	0.06	0.03	0.12	0.03	0.10
	3	0.24**	0.06	−0.03	0.12	0.13	0.11
	4	0.42**	0.06	0.24*	0.12	0.23*	0.10
	5 or more	0.56**	0.05	0.09	0.10	0.24**	0.08
	No job	−0.32**	0.04	−0.42**	0.09	−0.19*	0.08
Working from home days/week	0	Ref		Ref		Ref	
	1	0.12**	0.04	0.17*	0.08	0.16*	0.06
	2	−0.17**	0.05	−0.09	0.10	−0.10	0.08
	3	−0.52**	0.08	0.03	0.17	−0.07	0.14
	4	−0.83**	0.10	−0.56*	0.22	0.19	0.21
	5 or more	−1.21**	0.09	−0.82**	0.21	−0.30	0.19
Owns a bicycle	No	Ref		Ref		Ref	
	Yes	0.22**	0.03	0.18**	0.05	0.19**	0.05
Car in the household	No	Ref.**	0.00	Ref.**	0.00	Ref.**	0.00
	1 or more cars	0.20**	0.04	0.08	0.08	0.17*	0.07
Frequency of car use	More than 4 times/week	Ref		Ref		Ref	
	1–3 times/week	−0.16**	0.03	−0.21**	0.06	−0.01	0.05
	Less than 1 times/week	−0.28**	0.04	−0.40**	0.07	−0.20**	0.06

Table 2 (continued)

		Weekday		Saturday		Sunday	
		B	S.E	B	S.E	B	S.E
Frequency of bicycle use	More than 4 times/week	Ref		Ref		Ref	
	1–3 times/week	−0.30**	0.03	−0.28**	0.06	−0.28**	0.05
	Less than 1 times/week	−0.48**	0.03	−0.52**	0.06	−0.41**	0.05
Walking frequency	More than 4 times/week	Ref		Ref		Ref	
	1–3 times/week	−0.06*	0.03	−0.03	0.05	−0.19**	0.05
	Less than 1 times/week	−0.18**	0.03	−0.25**	0.06	−0.26**	0.05
Reported trips same day in previous or following wave	No	Ref		Ref		Ref	
	Yes	1.50**	0.03	1.46**	0.06	1.21**	0.04
	Did not participate in other years	0.88**	0.04	0.75**	0.07	0.65**	0.06
Wave number	1	Ref		Ref		Ref	
	2	−0.20**	0.05	−0.30**	0.09	−0.08	0.08
	3	−0.32**	0.05	−0.45**	0.10	−0.26**	0.08
	4	−0.28**	0.05	−0.40**	0.10	−0.20*	0.08
	5	−0.10*	0.05	−0.31**	0.09	−0.02	0.08
	6	−0.38**	0.05	−0.41**	0.09	−0.09	0.08
	7	−0.31**	0.05	−0.30**	0.09	−0.15*	0.08

*$P \leq 0.05$, **$P \leq 0.01$, Nagelkerke R Square: Weekday: 0.132, Saturday: 0.138, Sunday: 0.130

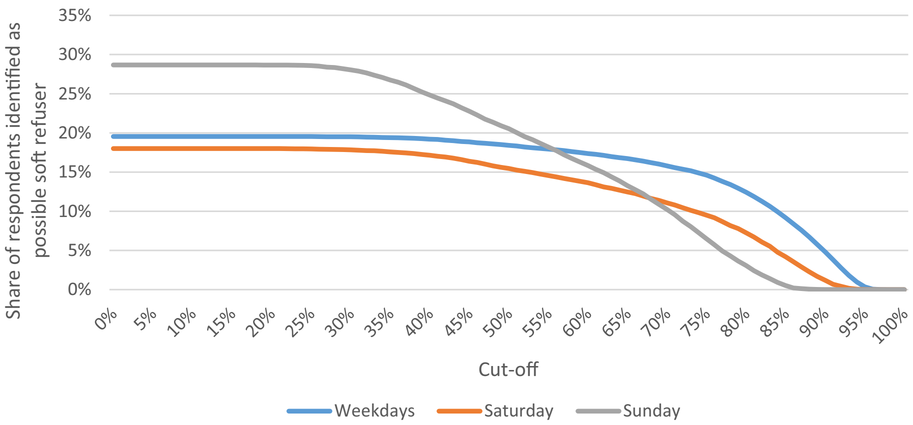

Fig. 2 Share of respondents who are identified as a possible soft refuser based on the binary logit out-of-home activity model by cut-off value (MPN 2013–2019)

Table 3 Reported immobility for possible soft refusers based on the binary logit out-of-home activity model versus other respondents (MPN 2013–2019)

	Potential soft refuser (%)	Reported immobility possible soft refusers (%)	Reported immobility other respondents (%)
Weekdays	4.8	52.2	17.7
Saturdays	1.2	47.3	21.0
Sundays	0.0	33.3	23.2
Total	5.3	51.2	17.6

that of respondents who are not identified as a possible soft refuser. However, since this method only identifies respondents who reported to stay at home on at least one of their three reporting days, the theoretical minimum level of reported immobility among the possible soft refuser group is 33.3%.

Straightlining

For the following two methods to identify possible soft refusers, we make use of indicators on how respondents filled out the survey. More specifically, we use indicators on straightlining and speeding. In the MPN, respondents are asked to fill out an extensive survey besides keeping a three-day travel diary. This questionnaire is sent out two weeks prior to the travel diary. In the even waves (2, 4 and 6), the questionnaire includes a relatively large number of grid questions. Depending on age and travel mode use (if respondents never use a certain mode they have the option to skip a grid question on attitudes regarding that mode), respondents fill out four to thirteen grid questions, with approximately 90% of respondents filling out at least eight grid questions. An indicator of measurement error is the amount of straightlined grid questions (Struminskaya et al. 2015). As discussed before, we consider a respondent to be straightlining when they provide the same answer to every item in the grid.

Table 4 Straightlining in the MPN and its relation with reported immobility (MPN 2014, 2016, 2018)

	Share of respondents (%)	Reported immobility (%)
0% straightlining	51.6	14.7
1–25% straightlining	35.0	18.2
25–50% straightlining	8.4	25.9
50–66% straightlining	2.4	32.3
> 66% straightlining	2.7	40.9

Table 5 Relation between straightlining in previous or subsequent wave and reported immobility (MPN 2013–2019)

	Share of respondents (%)	Reported immobility in subsequent wave (%)
0% straightlining	45.3	13.6
1–25% straightlining	43.3	17.3
25–50% straightlining	7.9	26.5
50–66% straightlining	1.8	30.6
> 66% straightlining	1.7	39.6

Just over half of respondents do not straightline any of their grid questions, while just over one third straightlines up to a quarter of their grid questions. It should be noted that straightlining part of the grid questions is not by definition an indicator of poor response behavior as certain grid questions focus on attitudes towards travel modes. Couper et al. (2013) argued that with these types of grid questions straightlining is plausible. For instance, people who are strongly oriented towards a certain travel mode may be very positive about all aspects of that mode, resulting in straightlining a grid question. We therefore assume that straightlining up to a quarter of the grid questions is plausible, while a higher share may indicate poor response behavior. Overall, 10.8% of grid questions are straightlined by respondents.

Table 4 shows the reported immobility in the travel diary related to the amount of straightlining in the questionnaire. Again, this level of immobility refers to the immobility of the three reporting days. Respondents are grouped together based on their share of grid questions they straightline to ease comparison. From the table it becomes clear that our hypothesis seems to be correct. Respondents who straightline more than a quarter of their grid questions report considerably more immobile days, with the level of reported immobility increasing with a further increase in the share of straightlining. Similarly to the prediction of out-of-home activity to identify soft refusers, it is likely that this method results in false-positives. In other words, while the reported level of immobility is considerably higher among respondents who straightline a large part of their grid questions, there will be respondents for whom this high level of straightlining and reported immobility is correct.

The questionnaires of the uneven waves (2013, 2015, etc.) of the MPN only include a few grid questions, making this method less reliable for these uneven waves. However, since most respondents participate at least two waves in the MPN, it is technically possible to explore whether this indicator on straightlining from even waves (2014, 2016, etc.) predicts soft-refusal in a previous or subsequent uneven wave. It turns out that the amount of straightlining in a previous or subsequent wave is strongly related to reported immobility

Table 6 Parameter estimates of regression model to predict response time (MPN 2013–2019)

		B	S.E			B	S.E
Intercept		1271.53**	14.92	Number of life events	0	Ref	
Age	12–14 years	−788.86**	19.08		1	79.48**	4.35
	15–17 years	−654.54**	18.60		2	116.72**	6.34
	18–19 years	−607.86**	19.17		3	141.80**	8.84
	20–24 years	−558.22**	16.18		4	170.56**	11.81
	25–29 years	−549.85**	15.41		5	243.74**	19.39
	30–34 years	−546.83**	15.22		6	300.97**	35.99
	35–39 years	−532.05**	15.08		7	352.69**	62.19
	40–44 years	−515.40**	15.09		8	686.89**	135.85
	45–49 years	−508.89**	14.90		10	−203.51	303.67
	50–54 years	−469.90**	14.77	Number of ICT events	0	Ref	
	55–59 years	−373.17**	14.70		1	93.78**	5.33
	60–64 years	−347.85**	14.21		2	157.36**	7.75
	65–69 years	−265.92**	13.05		3	163.61**	12.77
	70–74 years	−177.55**	13.28		4	222.32**	16.45
	75–79 years	−86.62**	14.40		5	176.78**	36.74
	80 + years	Ref			6	171.19**	57.49
Work status	Working	Ref			7	143.37**	47.54
	No job	−60.39**	5.16	Wave number	1	38.43**	6.66
	Retired	−78.68**	8.98		2	265.95**	6.11
	Student	−39.07**	9.71		3	210.30**	6.63
	Other	24.80	20.15		4	296.72**	6.46
Device	Tablet	Ref			5	528.77**	6.02
	PC	−55.60**	4.82		6	47.77**	5.90
	Mobile phone	48.75**	6.32		7	Ref	

$^*P \leq 0.05$. $^{**}P \leq 0.01$, Adjusted R-squared = 0.173

in uneven waves, as is shown in Table 5 (if respondents participated both the previous and subsequent wave, we took the average of straightlining in those waves).

Speeding

The second indicator of response behavior in the questionnaire we use to identify soft-refusal is the time respondents take to fill out the survey. When a respondent fills out a questionnaire very fast, it becomes likely that this respondent does not fill out the survey thoughtfully. We estimated a regression model to predict the response time for each respondent. The predictors in the model are known to either influence speed directly (age and device that people use to fill out the survey) or change the length of the survey (age, work status, number of experienced life events and wave number of the MPN). Table 6 shows the parameter estimates of the regression model. Discussing all parameter estimates is outside the scope of this study, but the parameter estimates are in the expected direction. For instance, younger respondents have a lower response time, while respondents who experienced more life events have a higher response time. Furthermore, respondents who used a tablet to fill out the survey are slower compared to respondents who used a PC, but

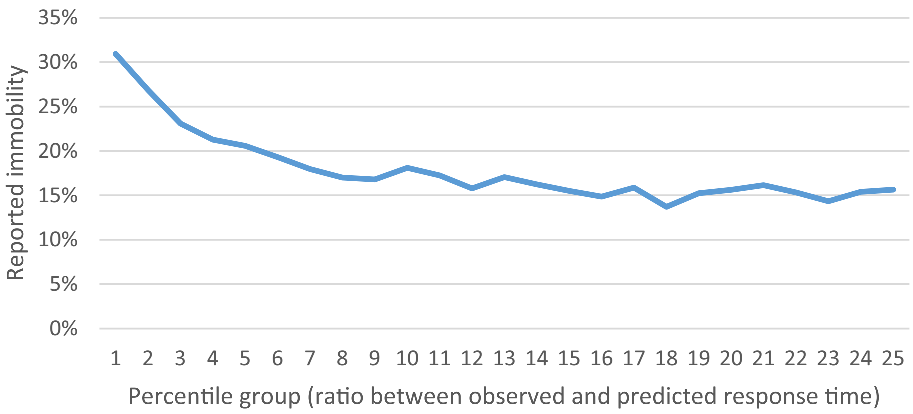

Fig. 3 Relation between speeding in the questionnaire and reported immobility in the travel diary (MPN 2013–2019)

faster than respondents who used a smartphone. Since the length of the questionnaire is not directly impacted by a respondents level of mobility and the questionnaire is filled out separately from the travel diary, the response time of the questionnaire should not be related to the reported level of immobility in the travel diary.

Using the parameter estimates, response times can be predicted for each respondent. By ranking respondents in groups based on their ratio between observed response time and predicted response time, a clear relation between speeding and reported immobility becomes visible. Respondents are ranked from the lowest ratio (faster than expected) to the highest ratio (slower than expected) in 25 percentile groups per wave. Figure 3 shows the average reported immobility per percentile group. The reported immobility is considerably higher among the first percentile groups compared to the other groups. The average ratio between observed response time and predicted response time in the first five percentile groups ranges from 0.35 to 0.60 (i.e., respondents in these groups are on average 1.67 to almost 3 times faster than expected). Starting from percentile group 17, respondents are slower than expected, but this does not seem to be related to reported immobility.

Attrition

When respondents drop out of the panel, it is possible that they already lost interest in their final wave of participation. Kitamura and Bovy (1987) found that reporting low mobility is related to attrition. Table 7 shows the level of immobility for respondents in the MPN based on their starting year and number of waves they participated. Although there are some exceptions, for instance respondents who started in 2013 and participated 5 waves, the level of immobility in the final wave of participation is considerably higher than the wave(s) before that.

As described in the previous sections, the indicators of soft-refusal can be used to identify groups of respondents with a relatively high level of reported immobility. It may be that we can use the indicators on soft-refusal to predict attrition. If this is possible, we could use this information in the recruitment of new respondents, as we would know beforehand which respondents will likely dropout. Table 8 shows the reported immobility of different groups of respondents based on attrition and identification as a possible soft

Table 7 Reported immobility in the MPN by year that respondents entered the MPN and the number of waves that respondents participated (MPN 2013–2019)

Year that respondents were recruited	# waves participated	Observed year						
		2013	2014	2015	2016	2017	2018	2019
2013	1	21.8%	–	–	–	–	–	–
	2	16.7%	20.6%	–	–	–	–	–
	3	17.7%	18.1%	24.7%	–	–	–	–
	4	13.3%	18.3%	16.7%	24.0%	–	–	–
	5	13.3%	16.2%	15.9%	21.1%	16.8%	–	–
	6	15.2%	15.6%	16.8%	20.8%	20.9%	20.3%	–
	7	12.1%	17.0%	15.2%	17.0%	16.2%	17.1%	23.8%
	8	12.7%	14.1%	14.8%	15.2%	14.0%	15.2%	16.6%
2014	1	–	20.9%	–	–	–	–	–
	2	–	15.7%	20.1%	–	–	–	–
	3	–	11.8%	11.7%	16.6%	–	–	–
	4	–	15.9%	14.3%	24.6%	26.8%	–	–
	5	–	14.7%	14.7%	17.6%	21.8%	19.0%	–
	6	–	18.5%	22.3%	21.2%	20.1%	23.6%	28.9%
	7	–	15.1%	15.2%	17.1%	15.2%	19.2%	19.0%
2015	*	–	–	–	–	–	–	–
2016	1	–	–	–	22.8%	–	–	–
	2	–	–	–	14.6%	13.7%	–	–
	3	–	–	–	15.0%	13.8%	18.8%	–
	4	–	–	–	16.8%	14.7%	19.2%	19.8%
	5	–	–	–	14.9%	15.8%	15.7%	18.8%
2017	1	–	–	–	–	21.1%	–	–
	2	–	–	–	–	14.0%	22.5%	–
	3	–	–	–	–	18.0%	17.1%	22.1%
	4	–	–	–	–	16.3%	17.9%	19.2%
2018	1	–	–	–	–	–	27.4%	–
	2	–	–	–	–	–	24.7%	30.1%
	3	–	–	–	–	–	23.1%	23.6%
2019	1	–	–	–	–	–	–	23.7%
	2	–	–	–	–	–	–	21.7%

*No new respondents were recruited in 2015

Table 8 Reported immobility of respondents based on attrition or identification as a possible soft refuser (MPN 2013–2019)

Dropped out after wave	Identified as possible soft refuser with either of the three methods	Reported immobility (%)	# Respondents
No	No	11.9	18,429
	Yes	27.1	8163
Yes	No	17.5	5371
	Yes	31.7	2484

Table 9 Parameter estimates of model to predict reported immobility based on indicators of soft-refusal and information on attrition (MPN 2013–2019)

	B	S.E
Constant	0.14**	0.00
Possible soft refuser based on straightlining	0.12**	0.00
Possible soft refuser based on speeding	0.06**	0.00
Possible soft refuser based on predicting out-of-home activity	0.12**	0.01
Respondent drops out after wave	0.03**	0.00

*$P \leq 0.05$. **$P \leq 0.01$, Adjusted R-squared = 0.067

refuser with the three methods we discussed before. For this table, we consider respondents as possible soft refusers if they either are identified in the binary logit out-of-home activity model, straightline more than 25% of their grid questions or are in the first five percentile groups regarding the ratio between observed and predicted response time.

From the table it is clear that reported immobility is highest amongst respondents who are identified by any of the three methods we discussed before. The lowest reported immobility can be found among respondents who do not drop out and are not identified as a potential soft refuser by any of the three methods. Compared to this group, the reported immobility of respondents who are not identified by any of the three methods as a soft refuser, but who did drop out is considerably higher. This may indicate that attrition in itself is also an indicator of possible soft-refusal in the final wave of participation. To test this hypothesis, a linear regression model is estimated to predict reported immobility using the indicators on soft-refusal and the information of attrition as predictors. Table 9 shows the parameter estimates of this model. As expected, all indicators on soft-refusal are significant predictors of reported immobility. In addition, the model confirms that attrition itself is also an indicator of possible soft-refusal, as it is a significant predictor of reported immobility in the previous wave. We should, however, take into account that earlier studies showed that attrition is related to low mobility (e.g., Kitamura and Bovy 1987; La Paix Puello et al. 2017; Van Wissen and Meurs 1989). While these earlier studies are also not sure whether the lower mobility is a reflection of reality, or a result of soft refusal, it may be possible that, at least to a certain extent, the level of immobility of respondents actually increased (e.g., due to retiring or a long-term illness) and they therefore considered themselves to be less relevant for a travel survey which results in dropping out of the panel.

Correlation between indicators of soft-refusal

Figure 4 shows how the different indicators on soft-refusal, including information on attrition, overlap each other in a Venn diagram. Respondents who are not identified by any of the methods and who do not drop out (53% of respondent-years) are not shown in this diagram. From the Venn diagram it becomes clear that three quarters of the respondents that may be a soft refuser are only identified by one of the four indicators. Approximately 21% is identified by two indicators as a possible soft refuser and just over 3% by three or four indicators. Hence, there is some overlap between the indicators, but correlations are not that strong. This in turn suggests that each indicator to some extent measures a separate aspect of soft-refusal.

While the Venn diagram visualizes the correlation between the different methods to identify potential soft refusers, it only shows this in a binary way (i.e. respondents are

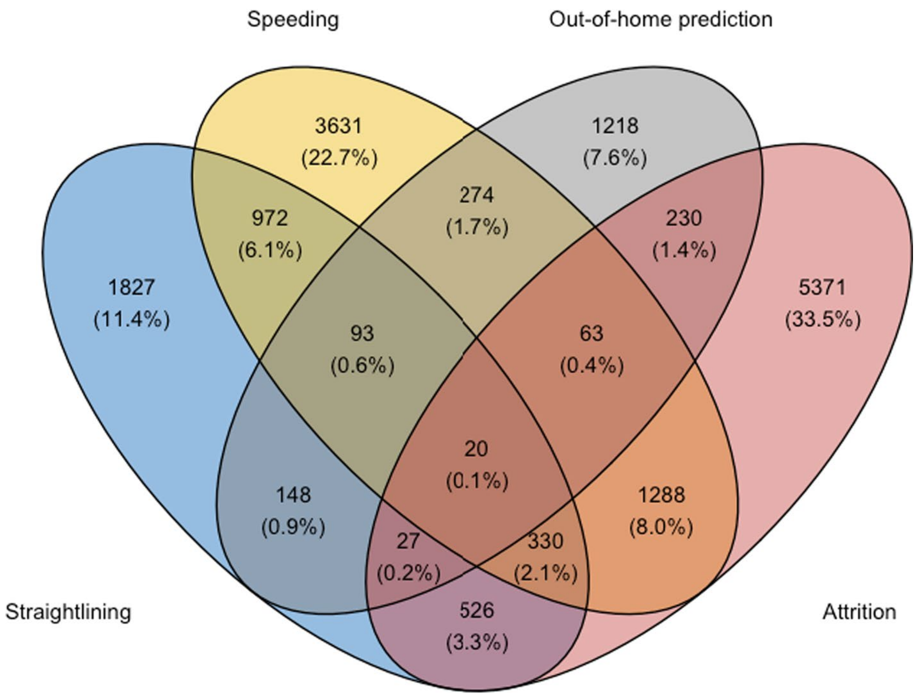

Fig. 4 Venn diagram of MPN respondents who are identified as a possible soft refuser (MPN 2013–2019, n = 16,018)

flagged by an indicator or not; it does not show exactly how they score on this indicator). There may be groups within the MPN with similar behavioral patterns in terms of these indicators. The Venn diagram does not show these underlying behavioral patterns and how people transition between these patterns over time. In the next section, these behavioral patterns and transitions between them over time are studied more in-depth using a Latent Transition model.

Behavioral classes with respect to soft-refusal

Table 10 shows the profiles of the five latent classes in the Latent Transition Analysis. It should be noted that only the even waves of the MPN (2014, 2016 and 2018) are used in the estimation. As discussed, only these waves include enough grid questions to reliably determine whether respondents are straightlining. As explained in the Method section, the BIC and reduction in L^2 were used to determine the number of classes. While the BIC suggests that a 6-class model fits the data best, the relative reduction in L^2 after the 5-class model is small (< 0.2%). Furthermore, the classification error of the 5-class model is considerably lower than that of the 6-class model (15.2% vs 22.4%). Therefore, the 5-class model was chosen. Overall, the five classes are well-interpretable.

The first class (‘Low risk’, 39% of the sample) includes respondents with the lowest risk of showing soft-refusal, as they are rarely identified by any of the indicators on soft-refusal. Almost all of them straightline a maximum of 25% of grid questions, they have the lowest share of flags from the binary logit out-of-home activity model and are mostly slower or as

Table 10 Profiles of the five latent classes in the Latent Transition Analysis (MPN 2014, 2016, 2018)

Class*		LR	SP	SL	HR	DO	Overall**
Size (%)		39	20	9	5	28	–
Size corrected for the dropout class (%)	54	27	12	6	–	–	
Indicators							
Straightlining	0% straightlining	66	52	9	2	0	51
	1–25% straightlining	31	42	42	21	0	35
	25–50% straightlining	2	6	31	30	0	9
	50–66% straightlining	0	0	10	18	0	2
	> 66% straightlining	0	0	8	28	0	3
	Dropped out	0	0	0	0	100	
Binary logit out-of-home activity (%)	Not flagged	95	93	94	93	0	94
	Flagged	5	7	6	7	0	6
	Dropped out	0	0	0	0	100	
Speeding (predicted vs observed) (%)	> 3 times as fast	0	0	0	7	0	1
	2–3 times as fast	0	12	0	45	0	6
	1.25–2 times as fast	18	69	20	45	0	34
	1.25 times slower–1.25 times faster	46	18	46	2	0	35
	> 1.25 times slower	36	2	33	0	0	24
	Dropped out	0	0	0	0	100	–
Attrition	In panel	100	100	100	100	0	–
	Dropped out	0	0	0	0	100	–
Inactive covariates							
Reported immobility (%)	14	19	18	33	20	17	
Gender (%)	Male	46	46	46	50	46	46
	Female	54	54	54	50	54	54
Age (%)	12–24 years	16	18	20	31	28	18
	25–44 years	29	32	28	32	29	30
	45–65 years	36	35	34	27	33	35
	65 + years	19	15	18	10	11	17
Education level (%)	Low	28	29	37	49	37	31
	Mid	37	38	39	34	37	37
	High	35	33	24	17	26	32
Work status (%)	Paid work	53	56	51	47	53	53
	No job	3	3	4	4	4	3
	Retired	18	14	16	9	10	16
	Student	13	15	15	23	22	15
	Other	13	12	15	17	11	13
Household composition (%)	Single	20	16	21	14	11	19
	Adult household	29	28	27	18	20	28
	Household with children	50	55	51	66	67	52
	Other	1	1	1	3	1	1

**LR* Low risk, *SP* Speeders, *SL* Straightliners, *HR* High risk, *DO* Dropouts

**This column shows the overall mean without class 2

Table 11 Transition probability matrix five class latent transition analysis (MPN 2014, 2016, 2018)

		Class* [t−1]				
		LR	SP	SL	HR	DO
Class* [t]	LR	0.56	0.06	0.00	0.00	0.00
	SP	0.02	0.51	0.00	0.02	0.00
	SL	0.01	0.03	0.51	0.08	0.00
	HR	0.00	0.00	0.07	0.36	0.00
	DO	0.41	0.39	0.42	0.55	1.00

**LR* Low risk, *SP* Speeders, *SL* Straightliners, *HR* High risk, *DO* Dropouts

fast as expected when filling out the survey. Respondents in this class also show the lowest level of reported immobility. In terms of sociodemographics, this class is consistent with the sample average, with a slightly higher share of high educated people.

Respondents in the second class ('Speeders', 20% of the sample) often do not straightline, similar to the first class. However, they are flagged more often in the out-of-home activity model and they are often faster than expected when filling out the survey. Their reported level of immobility is higher than respondents in the first class. Compared to the first class, there are slightly less elderly in this group. Correlated with that, there are more respondents with a paid job and respondents are more often part of a household with children compared to the first class.

The third group ('Straightliners', 9% of the sample) are respondents with an above-average share of straightlining. Just over 90% straightline at least one of their grid questions, with approximately 50% straightlining more than 25% of their grid questions. They score similar as the first class on the indicators of the out-of-home activity model and speeding. The reported level of immobility in this group is higher than the first class, but lower than the other two classes. This group differs clearly from the first (low risk respondents) and second (speeders) group in education level, as highly educated people are underrepresented.

The fourth and smallest class ('High risk', 5% of the sample) is clearly a high-risk group in terms of soft-refusal. This class has the highest share of straightlining and speeding and the share of respondents who are flagged by the out-of-home activity model is similar to that in the third class. The reported level of immobility in this class is almost double the average. This class also has a distinct sociodemographic profile. Young people are overrepresented in this class and as a result there is a high share of less educated people, a high share of students and a high share of respondents living in a household with children.

The fifth class ('Dropouts', 28% of the sample) represents respondents who dropped out of the panel. Similar to the high-risk class, young people and people from a household with children are overrepresented in this class. This indicates that the attrition rate among young respondents from households with children is higher than average.

Soft-refusal over time

Besides the different behavioral patterns and their profiles, the latent transition analysis allows to examine how respondents shift between patterns over time. Table 11 shows the probabilities for respondents in each class to either stay in the same class, or transition to another class over time. The first thing that stands out, is that the probability to transition to the dropout class is very similar for the first three classes (the low risk respondents, speeders and straightliners). Only when respondents are identified as possible soft refusers on multiple indicators, this is predictive for attrition, as can be seen from the higher probability for the high-risk group to drop out.

When respondents do not dropout, they tend to stay in the same class over time, as can be seen from the diagonal. There is only a small probability that respondents transition to another behavioral class. If they do, we see that the low risk group primarily transition to the speeder group and vice versa, while the straightliners primarily transition to the high-risk group and vice versa. In other words, speeders may transition to a more reliable class, while straightliners may transition to a worse class in terms of soft-refusal. This implies that straightlining is a better indicator of poor response behavior than speeding. This makes sense intuitively, as one has to make a conscious choice to straightline grid questions (i.e. if a respondent straightlines more than a plausible share, this has to be done on purpose), while speeding could be plausible behavior, for instance because a respondent is a fast reader compared to other respondents.

Conclusion and discussion

We presented three different methods to identify possible soft-refusal in a longitudinal travel behavior panel, based on: 1) predicting out-of-home activity 2) straightlining, and 3) speeding. We used these methods to explore soft-refusal and attrition in a multi-year mobility panel. While this study indicates that the vast majority of respondents respond correctly to a survey, all methods seem to be able to identify respondents with poor response behavior in a travel behavior context (i.e. a suspiciously high level of reported immobility). While the first method (binary logit out-of-home activity model) is directly aimed at identifying reporting days on which respondents incorrectly report no trips, it was found that also speeding and straightlining in a questionnaire are strongly related to reported immobility in the travel diary. Similar to Kitamura and Bovy (1987) we found that attrition is correlated with reported immobility. Furthermore, we found that attrition itself is an additional indicator of reported immobility in the final wave of participation. In other words, the three presented methods likely do not capture all soft-refusal.

While the presented methods all seem to identify respondents who have a higher probability of wrongfully reporting to stay at home, this points at an important limitation to this research. Since the ground truth is often not known in a travel behavior panel, there is no possibility to statistically test the effectiveness and reliability of the presented methods in identifying true soft refusers. While it would be easy for travel behavior panels to include a question to directly ask whether respondents reported their true travel behavior, this information would probably also be biased as soft refusers might use this question to justify their reported immobility. As a result of the ground truth being unknown, it may be difficult to decide when a respondent is considered to score poorly on a certain indicator (i.e. how fast should a respondent be to be speeding too much and what percentage of straightlining is plausible and/or acceptable).

Due to the inability to test effectiveness and reliability of the methods, it is not recommended to use just a single method to identify soft refusers as this will likely result in a high number of false positives, i.e. respondents who are wrongfully identified as a soft refuser. While soft refusers may bias a data set, removing true respondents will also introduce a bias. Since the indicators on soft-refusal in this study are (strongly) related to reported immobility, there is a risk of wrongfully removing respondents who have a low level of immobility. Because people with a low mobility level may be part of a vulnerable group of society (especially if this low level of mobility is involuntarily), the costs of removing false positives may be higher than keeping false negatives in the dataset. We therefore recommend to use a combination of indicators as this will lower the chance of wrongfully identifying respondents as soft refusers. See for example how being flagged by several indicators at once appears to be a strong indicator of subsequent attrition, compared to just a single flag.

The latent transition analysis showed that there are four distinct behavioral patterns in terms of soft-refusal behavior (plus a fifth class to represent dropouts). The largest class consists of respondents who are overall not identified as a possible soft refuser, followed by a class who seem to be speeding and a class with a higher share of straightlining. While their level of reported immobility is higher than the first class, there are only a few differences in their sociodemographic profiles. Only the fourth class (the high-risk soft-refusal class with a very high level of reported immobility) has a distinct sociodemographic profile. Knowing a priori which type of respondents have a higher risk of showing soft-refusal provides the possibility to account for this by oversampling these groups. In the case of the MPN, that would be young and less educated people.

From the transition analysis we found that only when respondents are identified as possible soft refusers on multiple indicators (the high-risk class), the attrition rate is higher. Furthermore, if respondents do not dropout, they tend to stay in the same class over time. This implies that keeping respondents from the high-risk class in the panel will mainly result in these respondents providing the same poor data quality in subsequent measurements. It is therefore recommended to no longer invite such respondents in subsequent measurements of the panel. However, in the specific case of the MPN, removing a single respondent results in removing the entire household from the panel. Since most respondents from the high-risk class are part of a multi-person household, removing them would simultaneously remove more reliable respondents from the panel.

The extent of the impact that soft refusers will have on analyses with the data depends on the type of analysis. In light of longitudinal analyses (i.e., studying travel behavior changes), the finding that soft refusers from the high-risk class are likely to stay in that class over time can be considered a positive finding. Because they will likely be a soft refuser in all their waves, no (or only few) travel behavior changes will be observed (since they will likely always report a low level of mobility). While this may lead to an underestimation of effects, including soft refusers in longitudinal analyses will probably have a limited impact on the results. When doing cross-sectional analyses, the impact may be greater. Especially when doing research on low-mobility groups, soft refusers may (strongly) bias the results. However, also the high-risk class will likely include false positives. Removing this group entirely from the analyses, may also bias the results. Nevertheless, being able to identify respondents with a high-risk of being a soft refuser allows to study the effect of this group on the results (e.g. comparing results with and without these respondents included). It is recommended to always study the effect of the possible soft-refusers on the results before removing this group from the analysis entirely. This seems to be a relatively safe way to deal with potential soft-refusers in the data.

Future research

From the results, some recommendations for future research can be given. First, future research could focus on finding the ground truth in mobility panels. As already discussed, directly asking respondents whether they reported their true travel behavior will likely result in biased answers from soft refusers. A possible option would be to have respondent self-report their travel behavior and simultaneously passively collect the travel behavior (e.g., with a GPS tracker, or a smartphone app), a recommendation also given by Aschauer et al. (2018). This research should also study the impact of passively collecting data on the self-reporting of travel behavior (respondents may report more accurate data if they know the ground truth is known). Being able to compare self-reported and passively collected data would provide the possibility to test the effectiveness and reliability of the methods and help in determining thresholds for the methods e.g., what is the maximum allowed share of straightlining.

Studying the link between the soft-refusal indicators and underreporting of trips may be another interesting avenue for future research. The present research focuses mainly on the link between the soft-refusal indicators and reported immobility. Reporting no trips at all can be considered the most extreme form of underreporting trips. It may be that the indicators on soft-refusal are also related to less extreme forms of underreporting, i.e., reporting only a part of trips. To study this link, it may be interesting to estimate a model to predict the level of mobility in terms of number of trips or travelled distance and compare the outcome with the reported level of mobility. A high ratio between predicted and reported mobility would then indicate a high level of underreporting. Studying the correlation between this ratio and the other indicators of soft refusal (straightlining, speeding, attrition) would show to what extent these other indicators are indicative for underreporting trips.

A third direction for future research is to study if, and how, these soft refusers could be motivated to transition from the high-risk class towards a more reliable class. The need to study reasons for non-response was also highlighted in the ISCTSC workshop synthesis on dealing with immobility and survey non response (Lucas and Madre 2018). If it turns out soft-refusal is mainly the result of a lack of interest, the options to motivate these respondents are probably limited. However, if this is not the case, knowing how to motivate this specific group of soft refusers (e.g. with other types of incentives, or with more interaction) would help in solving (part of) the soft-refusal problem.

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Data availability Data from the Netherlands Mobility Panel (MPN) are, two years after data collection, available through https://www.mpndata.nl.

Code availability The models to identify soft-refusal are estimated using SPSS. The Latent Transition Model is estimated using the statistical software package LatentGold. Model codes are available on request.

Declarations

Conflicts of interest On behalf of all authors, the corresponding author states there is no conflict of interest.

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