

Mobility Needs, activity patterns and activity flexibility: How individuals select transportation mode

Mikkel Thorhauge¹, Habtamu Kassahun², Elisabetta Cherchi³, Sonja Haustein¹

¹ Department of Management Engineering, Technical University of Denmark

² Griffith University

³ School of Engineering, Newcastle University

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1 Introduction

Despite Denmark, and Copenhagen in particular, is one of the world leading places in terms of bicycle infrastructure and bicycling demand (Center for Transport Analytics, 2017; Haustein and Sick Nielsen, 2016; Hunecke et al., 2010; Pucher and Buehler, 2012), still a large share of commuters in the Greater Copenhagen Area uses the car on a regular or semi-regular basis. This has two main negative effects: First, the high volume of cars with traditional combustion engines produces severe consequences for the environment, adding to local air and noise pollution as well as greenhouse gas emissions (e.g., De Vlieger et al., 2000). Second, the current demand often exceeds the road capacity and leads to congestion, which in turn means even higher levels of pollution and time lost for people stuck in traffic. It has been estimated that approximately 130,000 hours are wasted being stuck in traffic every day in the Greater Copenhagen Area, which equals 800 million Euros per year (Municipalities, 2008). These effects are even more evident in other cities around the world, where the number of inhabitants/commuters are much greater than Copenhagen, while on the other hand bicycling is not as common (or even non-existing) leading to much more severe congestion levels.

Thus, cities around the world are still struggling with severe congestion problems as many commuters are reluctant (or unable) to switch to alternative transport modes. Studies have shown that mode choice is one of the least in-elastic day-to-day travel decisions individuals make (Hendrickson and Planke, 1984; Hess et al., 2007). This makes it even more important and interesting to understand why individuals choose as they do. While mode choice has been explained by a variety of factors and models, this paper focusses specifically on the effect of activities and constraints. Here, previous research has mostly focussed on the effect of activity patterns and trip chain complexity from an objective perspective, while constraints have so far mostly been considered from a subjective perspective. In this paper, we combine both perspectives, which to our knowledge has not been done before.

Haustein and Hunecke (2007) extended the TPB by the construct of perceived mobility necessities (PMN). The background for this addition was that the operationalisation of PBC mainly focus on transport-related constraints (e.g, trip distance, car/bike availability, transport infrastructure, see Bamberg, 2012), while

constraints related to the personal living situation are only captured indirectly. PMN were introduced to directly account for the mobility-related consequences of the personal living circumstances (e.g, having children, a full-time job, complex daily routines) and turned out to improve the model fit when being added to a TPB model as a predictor of the use of alternative transport modes to the car (Haustein and Hunecke, 2007). In-depth interviews additionally revealed that women with high PMN often had a job and children and felt a high necessity to escort their children to several activities. The missing flexibility and long travel times made it feel impossible for them to use public transportation instead of the car, also as their (or their children's) typical destinations were often located less central. Constraints and demands created by family and household responsibilities have also been identified as barriers of car use reduction in studies on (e.g., Bonham and Wilson, 2012; Pooley et al., 2013).

While it has been shown that PMN are related to socio-demographic variables, like having children or a job, and to perceived time pressure, it so far remains unclear what exactly it is that makes people perceive high mobility needs and to what extent this is related to the character of their specific daily activities. However, previous research on the effect of trip/tour characteristics and activity patterns mainly focussed on the influence of travel time (e.g., Limtanakool et al., 2006) and the complexity of trip chains (e.g., Ye et al., 2007). Specific constraints in relation to activities and related trips have, however, not been considered – probably also as this information is generally not included in travel diaries.

This research is motivated by the need to better understand how, and to what extent, mode choice decisions are influenced by our everyday activities and their temporal, spatial or social constraints and the perception of these constraints. More specifically, we have the following hypotheses:

- (1) Commuters who have a more complex everyday life (indicated by the complexities of their activities) are less likely to choose public transportation, and more likely to select the car. Other than in low cycling countries, where cycling is hampered by family and household related demands (e.g. Pooley et al., 2013), we expect that a high number of activities in the cycling city of Copenhagen not only favours car use but also cycling.
- (2) The effect of activities on mode choice is even stronger, when activities are characterised by temporal, spatial, social and/or compulsory constraints.
- (3) Commuters with high Perceived mobility necessities (PMN) are more likely to choose individual transport modes (car and bike), and less likely to choose public transportation.
- (4) Perceived mobility necessities are positively influenced by the number of daily activities individuals engage in.
- (5) That the Perceived Mobility Necessities is higher for individuals who are constrained and cannot change or cancel scheduled activities.

2 Methodology and data

To test our hypotheses, we utilize an Integrated Choice and Latent Variable (ICLV) model (Walker, 2001; Walker and Ben-Akiva, 2002), which consist of two components: a mode choice model and a latent variable model. The mode choice model is specified as a function of the activity patterns, activity constraints and perceived mobility needs (in addition to the typical alternative specific Level-of-Service attributes and individuals socio-demographic characteristics). We specify the perceived mobility necessity (PMN) as a latent variable explained by both the complexity of the activity patterns and the constraints. Figure 1 depicts the modelling framework.

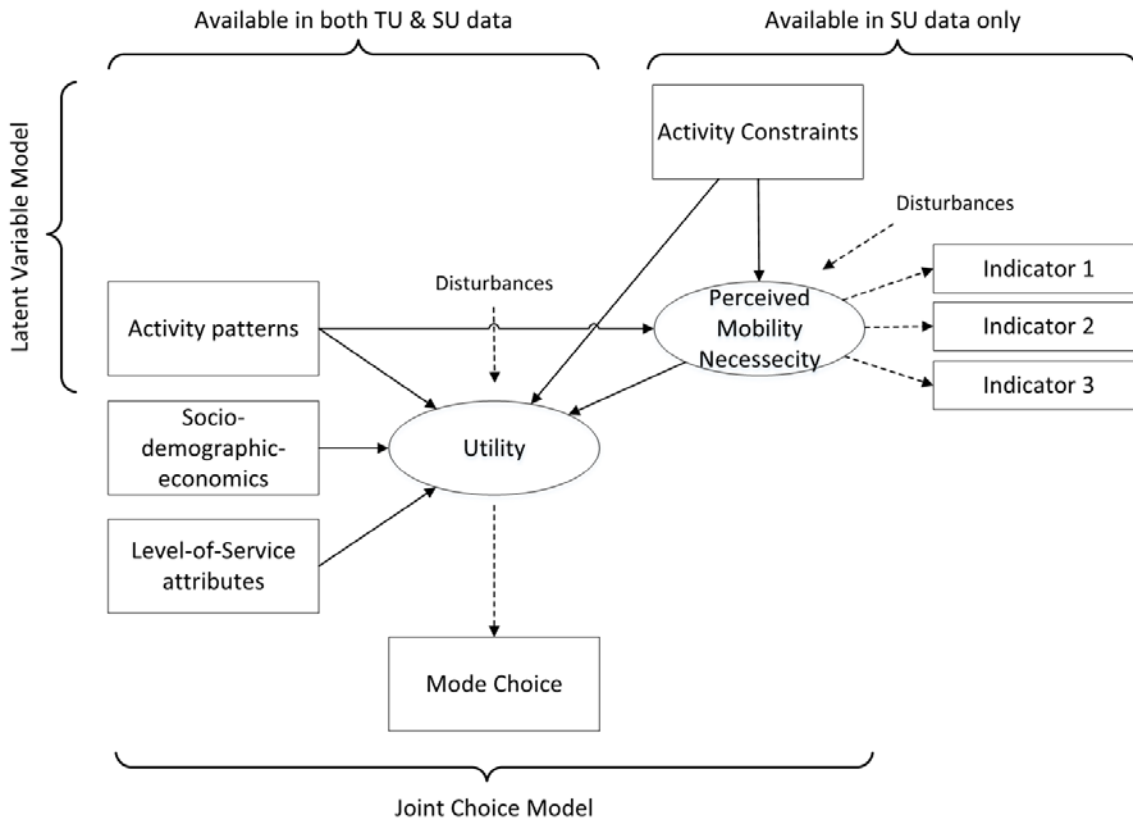


Figure 1: Overview of the model framework for the Integrated Choice and Latent Variable model.

To estimate the model we rely on two main data sources: The first is the Danish National Travel Survey, *Transportvane-undersøgelse* (TU). The second data source, *Special-undersøgelse* (SU), is a customized version of TU that (also) collects detailed information on activity constraints and travel-related attitudinal constructs (Thorhaug, 2015).

The first dataset has been collected ongoing since 2006 with about 1000 interviews per month (approx. 80% by telephone and 20% on the internet), and currently consist of 150,000 individuals between 10-84 years old. The survey is administered by the *Center for Transport Analytics* of the Department of Management Engineering at the Technical University of Denmark. TU collects a full trip diary of all trips and (out-of-home) activities during a 24H period (starting and ending 3:00 a.m.), and collects information about trip length, departure time, travel time, mode, purpose at destination as well as area codes at both ends of the trip. Furthermore, TU collects various (socio-demographic-economic) characteristics of the individual, the household (family members, location, and car ownership), the work place (location and parking facilities), as well as the transport possibilities (have a driver's license, holds a season pass, has a bike). For more information about TU we refer to Christiansen & Warnecke (2018) and Christiansen & Skougaard (2015)

The second dataset was collected in 2013 (and later re-released in 2017), and is collected as a detailed special survey based on TU. This special survey contains all the same components (as well as data structure and variable codes) as TU but is modified to collect additional information about activity and trip constraints as well as latent variables. Firstly, a set of questions was defined regarding detailed information about the flexibility for each trip reported in the trip diary and/or the activity tied to the specific trip. More specifically, following the typical literature in time geography (Hägerstrand, 1970) three types of constraints were considered in this study: temporal, spatial and social constraints. Additionally we also considered whether the

activity were compulsory. Thus, the questions on trip and activity constraints used in this specific study are listed below. For more details we refer to Thorhauge et al. (Thorhauge et al., 2016a).

1. *Spatial constraints*: Could you have carried out this activity at another location? (yes/no).
2. *Temporal constraints*: Were there any restrictions to how early you could have departed? (yes/no¹)
3. *Social constraints*: Did you decide yourself when to depart? (yes/partly/no)
4. *Compulsory constraints*: Could you have omitted this trip/activity? (yes/no)

Secondly, we also collected 24 indicator statements designed to capture various latent construct thought to be relevant for transport related decisions (especially departure time, but also more general latent construct). Of particular relevance for this study is the perceived Mobility Necessity as defined by Haustein and Hunecke (2007). The indicators were ranked on a 1-5 Likert scale (Likert, 1932) showing the respondents agreement with the statements presented, where 1 is complete disagree, and 5 is complete agree. The indicators statements are presented in Table 1. For more we also refer to Thorhauge et al. (Thorhauge et al., 2017, 2016b, 2014).

| Indicators | Mean | Std. Dev. | 10th Pctl | 25th Pctl | 50th Pctl | 75th Pctl | 90th Pctl |
|---|------|-----------|-----------|-----------|-----------|-----------|-----------|
| 1. The organization of my everyday life requires a high level of mobility | 3.22 | 1.29 | 1.00 | 2.00 | 3.00 | 4.00 | 5.00 |
| 2. I have to be mobile all the time to meet my obligations | 3.11 | 1.32 | 1.00 | 2.00 | 3.00 | 4.00 | 5.00 |
| 3. My work requires a high level of mobility | 2.86 | 1.26 | 1.00 | 2.00 | 3.00 | 4.00 | 5.00 |

Table 1: Indicators for the latent variable *Perceived Mobility Necessity*.

From the surveys we had detailed information about (all) the trips individuals performed, such as mode, travel time, purpose, etc., but no information about non-chosen alternatives was available. In order to estimate a discrete mode choice model, however, we need information about both the chosen alternative as well as the non-chosen alternatives. Thus, in order to obtain Level-of-Service (LoS) for each respondent we relied on the Danish National Transport Model (Rich, 2016). The National Transport Model (NTM) provides travel times, cost, and length among all combinations of OD-pairs for each mode and time period. We then cross-matched the information in NTM with our data to obtain LoS-data for each trip in the sample.

The final sample used in the study consists of 10,784 morning commuters travelling in the Greater Copenhagen Region between 6:00-10:00 A.M. using one of the following 5 modes: walk, bike, car driver, car passenger or public transportation.

3 Main findings

In this section we present the modelling results. All model estimations are done using PythonBiogeme 2.5 (Bierlaire, 2016). We estimated an integrated choice and latent variable (ICLV) model jointly across two RP-datasets containing. The results for the choice model are presented in table 3 (appendix A) while the results for the latent variable model are presented in table 2. In order to account for how constrained individuals were, we defined a constraint-score as the sum of 4 binary variables representing responses (1; constrained, 0; flexible) to the questions about flexibility. This constraint-score was included both directly in the choice model (for PT), and indirectly (for car drivers and bicyclist) through the latent variable.

The mode choice model includes several dummies for individuals performing different types of activities (escort, errand, and leisure) during different times during the day (morning, afternoon and evening). The transit

¹ If “yes” what is the earliest possible departure time?

mode is used as references, and in line with hypothesis 1 all parameters (with the exceptions of a few insignificant parameters) are positive, indicating that if individuals are engaging in escort, errand and/or leisure activities either during home-work, work-home and/or in the evening after returning back home from work then they are more likely to select other modes than public transportation. We believe this is due to the nature of timetable-based transport modes since every new activity involves access/egress trips as well as waiting time at every stop, making it a slow and inefficient way to facilitate complex activity patterns.

In addition to that, we find that individuals who are constrained in their activities during the morning commute are less likely to select PT (and thereby more likely to select individual modes), which confirms hypothesis 2. We believed this is due to the fact that PT is a relatively rigid (and sometimes unreliable) mode of transportation, thus would suit individuals with (higher degree of) flexible schedules in order to adapt to the predefined timetables and stopping locations of public transportation (all else equal). Furthermore, we also accounted for PMN, and we find individuals with high(er degree of) PMN favour individual mode of transportation, such as car and bike, where it is relatively easier to get around and engage in various activities. This confirms hypothesis 3.

| Structural Equation | Value | t-test |
|------------------------------|--------------|---------------|
| Intercept | 2.69 | 14.93 |
| Number of daily activities | 0.08 | 2.29 |
| Constraint-score *** | 0.10 | 1.73 |
| Sigma | 0.04 | 0.96 |
| Measurement equations | | |
| LV_PMN_Ind1_sig | -0.33 | -4.47 |
| LV_PMN_Ind2_ASC | -0.10 | -0.49 |
| LV_PMN_Ind2_alfa | 1.00 | 17.03 |
| LV_PMN_Ind2_sig | -0.23 | -3.61 |
| LV_PMN_Ind3_ASC | 0.09 | 0.53 |
| LV_PMN_Ind3_alfa | 0.86 | 15.36 |
| LV_PMN_Ind3_sig | -0.18 | -3.39 |

Table 2: parameter estimates for the Latent variable model.

The latent variable Perceived Mobility Necessity (PMN) is explained by two (observable) components; the number of daily activities performed by the individuals, as well as a constraint-score to capture how constrained individuals are during the commute trip from home to work. We find that perceived mobility need increases as both the number of activities and the constraint-level increases, which confirms hypotheses 4 and 5. The fact that PMN increases the more constrained individuals are is reasonable because inflexible activities cannot be rescheduled, changed and/or cancelled, thus the (perceived) need for mobility is higher since the scheduled activities cannot be altered, oppose to flexible activities, which can be altered or cancelled, thereby making the need for mobility less strict. In line with the existing literature, we also tested various socio-demographics (in particular related to the presence of children and the need of escorting them to/from activities) as explanatory variables for PMN, as well as including the total distance travelled in order to represent a spatial element of their activity pattern, but found none of these effects to be significant when also including the number of activities and constraints as explanatory variables. Since PMN has a positive impact on the utility for car drivers and bicyclist, it means that individuals who have many daily activities and/or have a high level of constraints is more likely to select car or bike to address their needs and engage in activities required of them. This is consistent and in line with direct effects confirmed for hypothesis 1 and 2 above.

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Appendix A

| | Walk | | Bike | | Car driver | | Car passengers | | Transit | | Multiple modes | |
|--|--------------|---------------|--------------|---------------|--------------|--------------|----------------|--------------|--------------|--------------|----------------|--------------|
| | Value | t-test | Value | t-test | Value | t-test | Value | t-test | Value | t-test | Value | t-test |
| <i>Level-of-Service, ASC, scale, and error components</i> | | | | | | | | | | | | |
| ASC | 8.03 | 11.08 | 4.13 | 7.27 | | | -3.49 | -4.16 | -0.08 | -0.15 | | |
| Travel Time [1/min] | -0.34 | -15.40 | -0.26 | -13.47 | -0.10 | -9.49 | -0.09 | -7.04 | -0.04 | -4.66 | | |
| Waiting Time [1/min] | -0.20 | -3.25 | | | | | | | | | | |
| Access/Egress Time [1/min] | -0.04 | -4.49 | | | | | | | | | | |
| Hidden Waiting Time (Headway) [1/min] | -0.11 | -6.54 | | | | | | | | | | |
| Number of changes | -0.44 | -2.97 | | | | | | | | | | |
| Travel Cost/Income [1000DKK/DKK] * | | | | | | | | | | | -0.73 | -3.29 |
| Scale between TU & SU data ** | | | | | | | | | | | 0.98 | -0.08 |
| Error Component - Std. Err of ASC | | | 2.20 | 7.92 | | | 3.39 | 6.57 | | | | |
| Error Component - car driv. & car pass. | | | | | | | | | | | 2.05 | 7.24 |
| <i>Socio-demographics</i> | | | | | | | | | | | | |
| Household has 1 car | | | | | -0.93 | -2.13 | | | | | | |
| Household has 2+ cars | | | | | 1.34 | 2.96 | | | | | | |
| Parking Available at Work | | | | | 1.29 | 6.92 | | | | | | |
| Parking Free Work at Work | | | | | 1.66 | 8.34 | | | | | | |
| Age < 30 | 0.42 | 2.08 | | | | | 1.26 | 3.07 | 0.40 | 2.98 | | |
| Age >= 50 | | | | | | | 0.62 | 2.15 | | | | |
| Male | -0.55 | -3.13 | -0.32 | -2.28 | | | -2.17 | -6.99 | -0.70 | -5.37 | | |
| Education. University degree | 0.75 | 3.55 | 1.85 | 8.68 | | | | | 0.85 | 5.28 | | |
| Education. Elementary School | | | | | | | 1.17 | 3.09 | 0.85 | 4.51 | | |
| Education. High School | | | 0.96 | 4.46 | | | | | 0.97 | 4.81 | | |
| Work Hours Per week = 37H | | | 0.59 | 3.75 | | | | | 0.34 | 2.64 | | |
| Work Hours Per week < 37 H | 0.38 | 1.61 | 0.80 | 3.91 | | | | | 0.90 | 4.96 | | |
| <i>Activities and constraints</i> | | | | | | | | | | | | |
| Has Errand activity - Home-Work | 3.77 | 2.17 | 1.49 | 2.22 | | | 1.91 | 2.33 | | | | |
| Has Errand activity - Work-Home | | | | | 1.08 | 6.35 | 1.14 | 3.40 | | | | |
| Has Errand activity - After-Work | 0.31 | 1.38 | 0.70 | 4.11 | 0.27 | 1.53 | | | | | | |
| Has Escort activity - Home-Work | 3.76 | 6.07 | 0.67 | 2.37 | -0.64 | -2.46 | -0.67 | -1.41 | | | | |
| Has Escort activity - Work-Home | | | 0.29 | 1.31 | 1.10 | 5.07 | 0.78 | 2.28 | | | | |

| | Walk | | Bike | | Car driver | | Car passengers | | Transit | | Multiple modes | |
|---|-------------|-------------|-------------|-------------|-------------|-------------|----------------|--------|--------------|--------------|----------------|--------|
| | Value | t-test | Value | t-test | Value | t-test | Value | t-test | Value | t-test | Value | t-test |
| Has Escort activity - After-Work | | | 0.39 | 1.63 | 0.31 | 1.46 | | | | | | |
| Has Leisure activity - Home-Work | 4.67 | 4.89 | | | | | | | | | | |
| Has Leisure activity - Work-Home | | | 0.68 | 4.52 | 0.79 | 3.89 | | | | | | |
| Has Leisure activity - After-Work | 0.23 | 1.48 | 0.54 | 4.30 | | | | | | | | |
| <i>Only estimated using SU-data (information not available in TU)</i> | | | | | | | | | | | | |
| LV PMN | | | 0.26 | 1.99 | 0.21 | 1.67 | | | | | | |
| Constraint-score *** | | | | | | | | | -0.29 | -1.98 | | |

Table 3: Mode choice model parameter estimates. Parameters in bold and italic: 95% sign. Parameters in bold: 90% sign.

* Parameter is generic across car driver, car passenger, and PT.

** Parameter is generic across all five alternatives, T-test against 1

*** The constraint score is computed as a sum of the following four constraints variables, which represents temporal, spatial, social, and compulsory constraints:

- 1) Did you have any constraints in terms of how late you could arrive?
- 2) Could you have performed this activity at another location?
- 3) Did you decide yourself when to depart?
- 4) Could you have omitted this activity?