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Incorporating psychological needs in commute mode choice modelling: A hybrid choice framework

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Abstract

This study proposes an integrated choice and latent variable model (ICLV) for commute mode choice that incorporates satisfaction of human needs and perceived functional and psychological barriers to using certain modes. The modelling framework is validated by data from a survey of commuters in the Greater Copenhagen area, which has large numbers of car users, public transport riders and bicyclists. The model results suggest that higher bicycle use is correlated to positive cycling self-concepts. Similarly, the commute choice of driving is positively correlated with car self-concepts and negatively correlated with functional difficulties in car use. Respondents with a strong focus on functional travel needs are most likely to commute using a car and least likely to use public transport. Evaluation of the effects of improving conditions for bicycles showed that the latent variables had a large influence on the potential mode shifts, highlighting that the mode choice of travellers is largely associated with mode-specific perceptions and fulfilment of travel needs rather than solely level-of-service characteristics. By analysing the mode shifts across the latent variables, further insights on the motives for travel behaviour decisions were obtained, thereby highlighting the superiority of ICLV models to simple multinomial logit models (MNLs). Furthermore, the study also revealed that socio-economic variables could explain mode choice both directly and indirectly through their impact on the latent variables. This means that a given policy might have a different impact according to the present ICLV model than when estimated by traditional models.

Keywords

[public transport; bicycles; mode choice; travel needs; sustainable transport; hybrid choice models]

1 Introduction

Transport mode choice affects mobility, congestion levels and emissions, especially during peak demand periods in metropolitan areas, in which the road network capacity is typically exceeded. Modelling mode choice decisions is important for evaluating traffic policies such as road pricing, bus priority and cycling infrastructure. Hence, it is crucial to ensure that important parameters are included in mode choice models.

Many factors contribute to individuals' mode choices. The literature has mainly investigated the influence of directly observable, quantifiable parameters, including level-of-service characteristics (e.g., travel time and travel costs) and travellers' socio-economic characteristics. While these variables are uncontested, they do not fully explain motivators of travel behaviour, which are suggested to be governed by a holistic experience comprising perceptions, emotions, past experiences, attitudes and social climate (Abou-Zeid et al. 2012; Susilo and Cats 2014). Studies have shown that travellers associate travel mode choice with both relatedness (sense of belonging with significant others) and personal growth (self-actualisation, self-identity and fulfilment of inner potential), which are essential human needs (Ingvardson et al. 2020; Ingvardson et al. 2017). Driving is associated with travel independence and self-image through status and prestige, thus highlighting personal growth considerations in mode choice (Sigurdardottir et al. 2014). Public transport is also associated with functional and psychological needs of relatedness and growth (Perone et al., 2005) and is correlated with self-esteem and respect for others through perceived travel mode fairness (Kaplan et al. 2014), 'relational value' through 'social climate appreciation' (Salvá et al. 2015), and the perceived importance of travelling in an environmentally friendly way (Ingvardson and Nielsen 2019). Similarly, cycling is related to facets of self-esteem such as self-identity, life-values, self-concepts (Spotswood et al. 2015), self-confidence and empowerment (van der Kloof et al. 2014).

The experience and thus mode choice of travellers therefore arises from a wide spectrum of needs (Ingvardson et al. 2020; Mateo-Babiano 2016; Taniguchi et al. 2014). Popuri et al. (2011) found that the choice of public transport for commuting was positively correlated with individuals' perceived importance of public transport and their desire for a reliable and stress-free commute, but negatively correlated with a need for privacy, perceived safety and having a dynamic work schedule. Similarly, Paulssen et al. (2014) found that commuter mode choice is highly influenced by personal values, including power and hedonism. Kamargianni et al. (2014) found a strong influence of social interaction on mode choice, e.g., the influence of parents' preferences on mode choice to school, suggesting the importance of incorporating social elements in the context of mode choice. The importance of social norms was also confirmed by Sottile et al. (2015), who found that using park-and-ride facilities at public transport stations was influenced by feelings of obligation due to the behaviour of others. Also, Kamargianni et al. (2015) found that the impact of personal beliefs related to a green lifestyle and physical activity were highly significant on public transport use and bicycle use, respectively.

While these studies have incorporated important aspects of social norms and self-perceptions into the choice context, only one study has focused on the importance of needs satisfaction using a framework that considers both lower-order functional needs and higher-order personal needs associated with self-identity and social interactions (Ingvardson et al. 2020). However, that study dealt with travel satisfaction rather than mode choice and did not consider mode attributes. Hence, this paper extends the work of Ingvardson et al. (2020) with the objective of studying the interrelationships between psychological beliefs and quantitative measures of travel characteristics in commute mode choice.

We adopt the coherent framework for analysing travel behaviour proposed in Ingvardson et al. (2020) and apply it to the mode choice context focusing on commute trips. The framework is based on the ERG theory of needs (Alderfer 1969) and incorporates relevant travel difficulties. The ERG theory is developed from

Maslow’s hierarchical theory of motivation (Maslow 1943) and is based on a three-fold conceptualisation of human needs: 1) *Existence* (e.g., material and physiological needs), 2) *Relatedness* (e.g., interpersonal relations with significant others), and 3) *Growth* (e.g., self-actualisation, fulfilment of inner potential and life opportunities). It relaxes the assumptions that needs are satisfied independently and hierarchically making it more appropriate for travel behaviour, as individual travel choices are often trade-offs among a multidimensional spectrum of attributes.

The relationship between the theory of human needs and motivational theories was extensively discussed and demonstrated by Alderfer (1969) and more recently Hagger et al. (2006). The theory of human needs emphasizes the role of universal and innate psychological needs underlying modern motivational theories. Behavioural motivation theories such as the theory of self-determination (Deci and Ryan 2000) and the theory of planned behaviour (Ajzen 1991), as well as the Normative, Gain and Hedonic framing theory (Lindenberg and Steg 2007) are based on the basic proposition that human motives and behaviour are aimed at satisfying both functional needs and innate psychological needs of relatedness and growth. While the aforementioned motivational theories are applicable across a range of actions, they provide situational- and contextual-level motivational constructs, underlying situational motivation rather than global reasoning. In contrast, the theory of needs, while more difficult to employ, provides the underlying global reasoning driving situational motivation. For example, utility maximisation derives from functional needs. Attitudes of self-esteem and self-actualisation are formed to answer the need for growth. Conforming with subjective norms provides a sense of belonging, and is thus a symptom of the need to satisfy the relatedness domain. While norms have been heavily studied and found to influence mode choice decisions due to relatedness needs, an explicit focus on relatedness needs is novel. Hence, integrating need satisfaction into motivational theories is advantageous because it can explicitly account for the role of satisfying global psychological needs by goal-directed situational behaviour (Alderfer, 1969; Hagger et al. 2006).

The framework adopted here allows for considering preferences that show how well each mode fulfils the needs of users, which is not usually taken into account in mode choice models, while also accounting for explicitly perceived travel difficulties as obstacles towards the use of certain modes. In order to study the relationships between satisfaction of travel needs, perceived travel difficulties and mode choice, we utilize an Integrated Choice and Latent Variable (ICLV) model to simultaneously model individual latent constructs and mode choice. The ICLV framework allows for a detailed user segmentation analysis of the latent constructs to understand the differences in mode choice perceptions across user groups. We also explore resulting policy implications using case study data from the Greater Copenhagen area, a region where driving, public transport and cycling each have large modal shares, hence allowing the framework to be validated in a multimodal setting. Specifically, we investigate how the framework can be used to model the impact of transport policies that improve bicycle conditions on commuting mode choice. The policy scenario is evaluated by segmentation of the latent variables across user groups, thereby providing insights on the motives behind mode shifts.

The rest of this paper is organised as follows. The model framework is described in Section 2. The survey data is described in Section 3, which also includes summary statistics and discussion of data limitations. The results of the integrated choice and latent variable model are reported in Section 4, and the benefits of the proposed framework are demonstrated by analysing differences in travel behaviour across user groups. Section 5 presents a policy scenario analysing the effects of bicycle travel time reductions on mode shares. Section 6 provides conclusions and policy implications.

2 Methodology

2.1 Model framework

The proposed model framework incorporates traditional level-of-service characteristics into the ERG theory of needs satisfaction, as illustrated in Figure 1. Since satisfaction of travel needs and perceived travel difficulties are not directly observable, these are modelled as latent variables. Thus, in order to jointly model the latent variables and the choice of mode, we utilize the Integrated Choice and Latent Variable (ICLV) model framework (Walker 2001; Walker and Ben-Akiva 2002). Mode choice is hypothesised to be influenced by all three ERG needs: existence, relatedness and growth. However, perceived mode-specific barriers are also important to mode choice as perceived difficulty of performing an action in terms of perceived behavioural control (Ajzen 1991). Thus, functional and psychological barriers due to specific perceptions of travel difficulties complement the ERG theory.

Bahamonde-Birke et al. (2017) emphasise the importance of differentiating between attitudes and perceptions in choice modelling for correct model identification. While global needs are innate individual-related intrinsic constructs, the ability to satisfy needs embeds alternative-related perceptions. Hence, incorporating needs into discrete choice models for predicting behaviour may provide additional sensitivity to psychological constructs. Notably, human needs are individual-specific latent attributes. Similarly to general attitudes or those related to specific alternatives (Bahamonde-Birke et al. 2017), human needs are innate global and general constructs independent of the choice environment (e.g. relatedness needs), but their satisfaction may be alternative-related or not. For example, relatedness can be achieved through a variety of modal choices, but self-actualisation of an athletic, green and healthy self-concept can be better achieved by cycling than by other modes. Hence, embedding human needs into hybrid models is similar to modelling attitudes (e.g. Bahamonde-Birke et al., 2017). Level-of-service characteristics include travel time and travel costs associated with public transport and driving and travel time for cycling. Finally, respondents' socio-demographic characteristics are explicitly considered in mode choice as influencing the latent variables related to the constructs of ERG and travel difficulties.

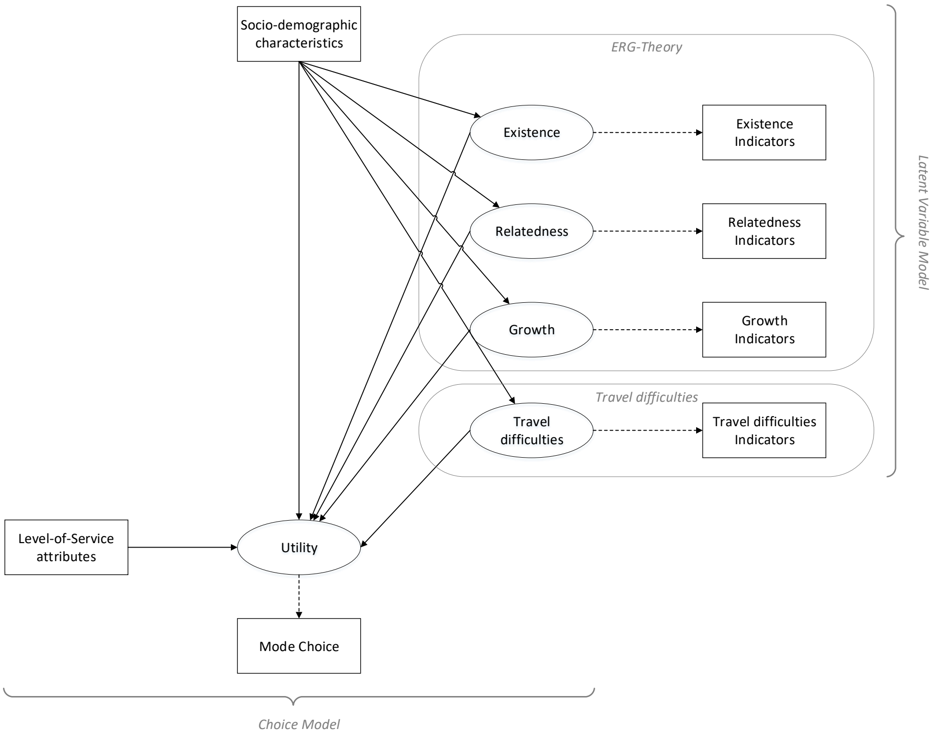

Figure 1 Model framework incorporating the ERG theory, travel difficulties, traditional level-of-service attributes and users' socio-economic characteristics.

2.2 Model specification and estimation

The Integrated Choice and Latent Variable (ICLV) model consists of a set of structural and measurement equations for both the latent variables and the choice model, as described in the following. The structural equations are linear. The measurement equation for the choice model has a logit kernel. As the indicator responses are rated on a (5-point) Likert scale, their measurement equations treat them as ordered variables.

Structural equation for the latent variables:

Each latent variable *m* for individual *q* is defined by a structural equation given by:

$$X_{qm} = \alpha_m + \lambda_m^S \cdot S_q \ + \gamma_m^n \cdot n_q \ + \omega_{qm} \qquad \forall m \in M \tag{1}$$

Where

- X_{qm} is (the value of) the latent variable *m* for individual *q*.
- S_q is a vector of socio-demographic characteristics for individuals *q*, and λ_m^S its corresponding vector of coefficients for latent variable *m*.
- n_q is a vector of (lower level) latent variables for individuals *q*, and γ_m^n its corresponding vector of coefficients for latent variable *m*.

- α_m is a constant for latent variable *m*.
- ω_{qm} is a normally distributed error term for latent variable *m* with zero mean and covariance matrix Σ_ω.

Structural equation for the choice model:

The utility function for alternative *j* in the full choice set J_q for individual *q* is given by:

$$U_{jq} = V_{jq} + \varepsilon_{jq}$$
$$V_{jq} = C_j + \beta_j^Z \cdot Z_{jq} + \sum_{m=1}^{M} \beta_j^X \cdot X_{qm} + \beta_j^S \cdot S_q \tag{2}$$

Where

- U_{jq} is the utility of alternative *j* for individual *q*, while V_{jq} is the systematic utility.
- C_j is the alternative specific constant for alternative *j*.
- Z_{jq} is a vector of level-of-service characteristics of alternative *j* for individual *q*, and β_j^Z its corresponding vector of coefficients.
- X_{qm} is latent variables *m* for individual *q*, and β_j^X its corresponding vector of coefficients.
- S_q is a vector of socio-demographic characteristics for individuals *q* and β_j^S its corresponding vector of coefficients.
- ε_{jq} is a typical i.i.d. Extreme Value (EV) type I error term.

Measurement equations for the latent variables:

The measurement of the latent variables is given by a set of *R* measurement equations, corresponding to the number of indicators for each LV. Given *M* latent variables we define a total of $\sum_{m=1}^{M} R_m$ measurement equations. As the indicator responses are rated on a (5 point) Likert scale, the measurement equations are specified as ordered discrete outcomes in which the probability that the latent variable X_{qm} lies within a range that gives the observed response $I_{qrm} = k$ defined by cut-off points $\tau_{rm,k-1}$ and $\tau_{rm,k}$:

$$P\left(I_{qrm} = k \middle| X_{qm}; \theta_{rm}, \tau_{rm,k}\right) = \Phi\left(\tau_{rm,k} - \theta_{rm} \cdot X_{qm}\right) - \Phi\left(\tau_{rm,k-1} - \theta_{rm} \cdot X_{qm}\right) \tag{3}$$

Where

- I_{qrm} is the indicator *r* of the latent variable *m* for individual *q*.
- X_{qm} is (the value of) the latent variables *m* for individual *q*, and θ_{rm} its corresponding coefficient.
- Φ is the cumulative density function.

For practical application, we specify the model as an ordered logit model, as shown in eq. 4, to obtain the conditional distribution of the indicators:

$$f\left(I_{qrm} \middle| X_{qm}; \vec{\theta}; \vec{\tau}\right) = \left(\frac{1}{1 + e^{\theta_{rm} \cdot X_{qm} - \tau_{rm,k-1}}}\right) - \left(\frac{1}{1 + e^{\theta_{rm} \cdot X_{qm} - \tau_{rm,k}}}\right) \tag{4}$$

Measurement equations for the choice model:

$$y_{jq} = \begin{cases} 1 & if\ U_{jq} = max\{U_q\} \\ 0 & otherwise \end{cases} \quad , \quad j \in J_q = Car, Bike, Public\ Transport \tag{5}$$

Where y_{jq} is a vector that equals one if *j* is the alternative chosen by individual *q*.Given the specifications of the structural and measurement equations, we can specify the functional probability form. For the choice model we assume logit probabilities; thus, the probability of individual *q* choosing mode *j* is given by:

$$P(j|Z_j\ ,X_q\ ,S_q\ ;\vec{\beta}) = \frac{\exp\ (V_{jq})}{\sum_{j=1}^{J} \exp\ (V_{jq})}\ \ ,\quad \forall j \in J_q$$

Where $\vec{\beta}$ designates all the unknown parameters to be estimated in the choice model of equation 2, i.e. $\vec{\beta} = \{C_j, \beta_j^Z, \beta_j^X, \beta_j^S\}$.

Only the distribution of the latent variables are known. Let Φ be the standard Normal distribution function. Assuming independence among the LVs, the distribution of the latent variable and the indicators are:

$$f(X_{qm}|S_q;\vec{\lambda}) = \prod_{m=1}^{M} \frac{1}{\sigma_m^{\omega}} \varphi\left(\frac{LV_{qm} - (\alpha_m + \lambda_m^S \cdot S_q)}{\sigma_m^{\omega}}\right) \qquad \forall m \in M \tag{6}$$

Where $\vec{\lambda}$ designates all the unknown parameters to be estimated in the structural equations of the latent variable (equation 1), i.e. $\vec{\lambda} = \{\alpha_m, \lambda_m^S, \Sigma_\omega\}$.

As the latent variables are associated with each individual *q* and do not vary among the choice set, the unconditional joint probability is given by:

$$\begin{aligned} &P(j, I|Z_j\ ,X_q\ ,S_q\ ;\vec{\beta},\vec{\lambda},\vec{\theta},\vec{\tau}) \\ &\qquad = \int_{X_q} P(i|Z_j\ ,X_q\ ,S_q\ ;\vec{\beta})\ \ f\big(X_{qm}\big|S_q;\vec{\lambda}\big)\ \ f\big(I_{qrm}\big|X_{qm};\vec{\theta};\vec{\tau}\big)\ \ dX_q \end{aligned} \tag{7}$$

The log-likelihood function is then given by the sum of the logarithm of the unconditional probability:

$$LL = \sum_q \sum_j y_{jq} ln\left(P(j, I|Z_j\ ,X_q\ ,S_q\ ;\vec{\beta},\vec{\lambda},\vec{\theta},\vec{\tau})\right) \tag{8}$$

To guarantee the model's identifiability, we defined $C_1=0$, $\delta_{1m}=0$ and $\theta_{1m}=1$, while all the other coefficients were estimated using the software package Biogeme (Bierlaire, 2016).

3 Data

To analyse the influence of human needs on transport mode choice, two data sources are used: i) an online survey covering ERG needs and travel difficulties; and ii) mode-specific level-of-service characteristics from the Danish National Traffic Model.

3.1 Latent variable data collection

The data are based on a tailor-made online survey designed to analyse the relationships between the ERG dimensions and commute mode use frequency. The survey included four parts: i) general travel habits and commute characteristics; ii) the ERG dimensions, iii) mode-specific travel difficulty statements, and iv) individual socio-economic characteristics. The survey statements were based on the mode choice context of commuting trips within the Greater Copenhagen area[1]. The data were collected by distributing online questionnaires to firms listed in the Danish Bureau of Statistics as located in the area and having more than five employees. The final sample contained responses from 1,481 respondents. The survey is briefly described below. A full description of the survey design and data collection can be found in Ingvardson et al. (2020).

Respondents were asked about their travel habits, including the frequency of each travel mode (car, bicycle, public transport, and public transport with bicycle) measured on an ordinal scale of rarely, 2–3 times monthly, once weekly, 2–3 times weekly and daily. The respondents were also asked about their usual travel time to and from work using their preferred mode. We used respondents who used the same mode every day and reported their origin and destination in the survey, since these are required to obtain level-of-service attributes for the non-chosen alternatives. We excluded multi-modal commuters. This reduced the number of observations to 1,097. Descriptive statistics for the full sample of respondents from Ingvardson et al. (2020) and the sub-sample of observations used for this study are shown in Table 1**Error! Reference source not found.**. As shown, there were no significant differences between samples for any of the variables, thus ensuring similarity across respondent and trip characteristics.

The statements measuring human needs (ERG dimensions) were based on a thorough literature review of the most important requisites of travel satisfaction (van Lierop et al. 2018; de Oña and de Oña 2014; Susilo and Cats 2014; De Vos et al. 2016) and measured on a 5-point Likert scale: ‘strongly agree’, ‘agree’, ‘neutral’, ‘disagree’ and ‘strongly disagree’. They were phrased in accordance with the approach suggested by Chiu and Lin (2004) to measure ability to satisfy needs when travelling, from both individual and service quality perspectives. We included both mode-specific needs, such as positive self-concepts as a result of cycling or driving (e.g.,‘I feel good about myself when I cycle’) and intrinsic needs such as travel safety (e.g., ‘It is important for me to arrive safely’), which can be satisfied by any mode. *Existence needs* included functional needs when travelling, such as time and monetary savings (non-alternative related attitudes). *Relatedness needs* were related to interpersonal relationships, such as travelling together with friends, colleagues or family members, or being united with other people in a sense of togetherness related to travelling (non-alternative related attitudes). *Growth needs* covered higher-order personal needs, including developing self-concepts, self-identity or self-esteem, such as social status or prestige (alternative related attitudes). Finally, 4-5 statements related to *travel difficulties* for each mode were formulated, such as perceived accessibility and service quality of public transport, bicycling being too difficult due to weather, distance or hilliness, or travelling by car being prone to congestion or parking difficulties (alternative-specific perceptions).

The distribution of the responses for the 46 ERG and travel difficulty statements used for the formation of the latent variables and the factor loadings from the exploratory factor analysis are reported in Table 2. Note that the factor loadings are marginally different from those reported in Ingvardson et al. (2020) due to the difference in sample size. Finally, the type of ERG need-satisfaction and travel difficulties (TD) are reported for each factor.

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[1] The Greater Copenhagen Area is defined as the commuting region, which includes the Region of Copenhagen and a few municipalities of the Region of Sealand.

		Full sample [%]	Mode choice sample [%]	Difference between samples	
		(N = 1,481)	(N = 1,097)	X^2	*p*
Gender	Male	44.6	43.3	0.713	.398
	Female	55.4	56.7		
Age	18-29	13.0	13.3	0.649	.885
	30-45	37.2	36.1		
	46-65	47.2	47.9		
	66+	2.6	2.7		
Car accessibility	Yes	68.4	68.0	0.080	.778
	No	31.6	32.0		
Family status	Single	14.3	14.8	0.978	.913
	Couple	31.3	30.8		
	Single with children	4.7	4.6		
	Couple with children	40.0	39.4		
	Other	9.7	10.4		
Employment status	Full time	87.6	87.1	0.336	.845
	Part time	7.6	7.7		
	Other	4.9	5.2		
Monthly income [$]	0-3000	6.0	6.1	12.290	.266
	3000-4500	15.6	15.7		
	4500-6000	35.0	34.7		
	6000-7500	23.0	23.1		
	>7500	20.3	20.5		
Education level	Elementary only	1.8	1.7	1.268	.867
	High-school	5.4	5.5		
	Tertiary	23.3	24.6		
	Bachelor	22.4	22.2		
	Graduate	47.2	46.0		
Commute origin	Copenhagen city	32.8	34.2	1.484	.476
	Suburbs	33.7	32.1		
	Rural	33.5	33.7		
Commute destination	Copenhagen city	43.4	43.4	0.158	.924
	Suburbs	43.9	43.9		
	Rural	12.7	12.7		
Commuting distance [km]	0–4.9	17.3	18.9	2.914	.713
	5–9.9	21.4	20.3		
	10–19.9	25.5	24.3		
	20–29.9	13.8	13.8		
	30+	22.1	22.7		

Table 1 Descriptive statistics of the survey data for the full dataset including 1,481 observations and the sub-sample of 1,097 observations for which the mode choice could be uniquely identified.

Statement	Factor loading*	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
F1 Positive cycling self-concepts (G) (0.915)						
I feel on top and with good energy when I cycle	0.89	6%	9%	31%	33%	22%
I feel mentally strengthened when I cycle	0.87	6%	8%	32%	33%	21%
I feel good about myself when I cycle	0.85	5%	5%	25%	40%	26%
I enjoy challenging myself physically when I cycle	0.74	8%	18%	38%	22%	14%
I feel good about contributing to the environment when I cycle	0.65	6%	7%	32%	31%	24%
It is important for me to get exercise	0.48	11%	13%	28%	25%	23%
It is important for me to get fresh air	0.47	11%	13%	29%	26%	22%
F2 Relatedness needs (R) (0.897)						
It is important for me to talk about a shared hobby related to travel mode	0.87	35%	29%	27%	7%	2%
It is important for me to exercise by bicycle with friends	0.85	36%	29%	28%	5%	2%
It is important for me to be part of a bicycle culture	0.80	37%	28%	28%	5%	1%
It is important for me to travel with my colleagues	0.78	40%	28%	28%	3%	1%
It is important for me to spend quality time together with others on the way	0.74	36%	30%	27%	4%	3%
It is important for me to participate in Bike-to-Work campaigns	0.72	33%	26%	28%	10%	3%
It is important for me to bring/collect others on the way	0.50	30%	23%	26%	13%	8%
F3 Car use functional difficulties (TD) (0.763)						
Driving a car is too stressful for me	0.76	22%	26%	22%	18%	11%
Searching for parking takes too long for me	0.66	17%	24%	31%	21%	7%
Driving a car is too unreliable (congestion) for me	0.65	22%	25%	23%	15%	15%
Driving a car is too dangerous for me	0.59	32%	34%	26%	5%	3%
It is important for me to avoid worrying about parking	0.54	9%	22%	30%	24%	16%
Driving a car is too expensive for me	0.51	11%	9%	29%	22%	28%
It is important for me to avoid road congestion	0.47	24%	19%	23%	19%	15%
It is important for me to avoid driving stress	0.44	7%	12%	32%	30%	20%
It is important for me to save money	0.43	8%	16%	35%	24%	17%
I believe it is important not to contribute to congestion	0.40	7%	12%	44%	25%	11%
Public transport is inaccessible to me	–0.33	25%	30%	20%	15%	9%
F4 Positive car self-concepts (G) (0.909)						
Driving a car makes me feel optimistic and high-on-life	0.88	29%	24%	33%	10%	4%
Driving a car is a cool way to travel	0.83	28%	25%	33%	9%	5%
Driving a car makes me feel that I get the most out of every situation	0.75	26%	21%	29%	17%	8%
I live life to the fullest when I drive my car (e.g. by listening to music)	0.67	16%	16%	32%	24%	12%
I feel more independent when I drive a car	0.61	16%	13%	21%	32%	18%
F5 Satisfying functional needs (E) (0.751)						
It is important for me to arrive on time	0.60	1%	1%	7%	32%	59%
It is important for me to carry my things	0.59	3%	5%	19%	41%	33%
It is important for me to arrive safely	0.55	5%	6%	17%	33%	38%
It is important for me to save time	0.54	3%	4%	20%	40%	33%
It is important for me to avoid having to change transport mode/line	0.54	5%	10%	29%	31%	24%
It is important for me to go wherever and whenever I want	0.50	1%	3%	11%	28%	57%
It is important for me to avoid congestion in public transport	0.49	2%	4%	15%	29%	50%
It is important for me to have privacy during my transport	0.28	19%	21%	30%	20%	10%
F6 Cycling functional difficulties (TD) (0.779)						
Biking is difficult for me because of the terrain	0.70	32%	29%	28%	7%	4%
Biking is difficult for me because of the distance	0.68	27%	17%	9%	17%	31%
Biking is difficult for me because of the weather	0.61	22%	28%	30%	15%	5%
Biking is dangerous for me due to other traffic	0.48	22%	28%	30%	15%	6%
F7 Functional difficulties in public transport (TD) (0.751)						
Public transport is too crowded for me	0.71	1%	10%	31%	36%	[illegible]
Public transport is unreliable	0.66	2%	15%	28%	33%	[illegible]
Public transport is too expensive for me	0.57	3%	7%	19%	41%	[illegible]
Public transport is too slow for me	0.55	5%	15%	15%	36%	[illegible]

Table 2 Summary statistics of the survey questions. All items measured on the 5-point Likert scale. N = 1,097, Cronbach's alpha in parenthesis. For each factor the link to type of needs satisfaction (ERG) and travel difficulties (TD) in parenthesis. *Only factor loadings from the highest-scoring factor are presented.

Commented [s1]: in this table F3, F6, F7 all get the abberviation TD which is quite confusing, also because they are different factors.Shouldnt we have different avverviations or did you consider them together in the policy analysis?

Commented [JBI2R1]: I believe that we operate within the four categories of E, R, G needs, and travel difficulties. And these three factors are all within the travel difficulty domain. I therefore gave them the same abbreviation. I'm not sure how to otherwise group them.

3.2 Mode attributes

The choice model was estimated using level-of-service characteristics, such as travel time and cost, for the chosen (observed) mode and the non-chosen alternatives. The Danish National Transport Model (NTM) provided (in-vehicle) travel times and cost for all modes. For public transport, NTM also provided access/egress time, waiting time, transfer time, headway, and number of transfers. Since revealed preference (RP) data were used for the estimation, we decided to estimate a single parameter for the (generalised) total travel time (TTT) for public transport, to facilitate model estimation and avoid correlation among level-of-service attributes. As transfers are perceived by passengers to be more onerous than actual travel time, this was taken explicitly into account. A recent study found that transfers in the Greater Copenhagen area on average equalled 5–20 minutes of in-vehicle travel time, dependent on locations and types (i.e., bus-bus, bus-train, train-bus, and train-train), with an overall average of 10 minutes (Anderson et al. 2017). Hence, a general transfer penalty of 10 minutes in-vehicle travel time was included when calculating the generalised TTT. As the survey data did not include specific departure times for the commute trips we used level-of-service variables for an average weekday. We considered using values from the morning peak period, but since 42% of commuting trips depart outside the morning peak period (7–9 AM), this was not ideal (Christiansen and Skougaard 2015).

3.3 Data limitations

While the survey and data collection were designed to generate important insights on the underlying motives for travellers' mode choices, it does have some limitations.

First, the study is based on cross-sectional data, which do not allow for determining cause and effect. Hence, the study mainly analyses correlations between mode choice, fulfilment of ERG needs and perception of travel difficulties. Specifically, respondents may simply affirm their mode choice decision when answering the mode-specific survey questions on travel difficulties. The same circular association occurs between mode choice and observed variables such as travel time, as improved travel time or cost saving can reinforce the behaviour, thus creating travel habits. Nevertheless, while past mode choice can shape the feeling of need satisfaction, current need satisfaction shapes future mode choice decisions, since experiences from one trip contribute to motivational intentions towards the next.

Secondly, while the survey includes detailed questions on fulfilment of self-concept needs for bicycle and car modes, this was not included for public transport. Although the previous literature has sometimes emphasised considerations in public transport related to the self-identity of passengers, such as the environment or social equity (Kaplan et al. 2014), De Vos et al. (2020) suggested that actual use frequency is more influenced by economic considerations. This suggests that the motivation for public transport is due more to functional needs, which is indeed analysed in this study.

Thirdly, multi-modal travellers were excluded in this study even though the framework allows for them. Using a combination of modes needs to be treated as a specific choice, but this was not possible here since we cannot estimate level-of-service for multi-modal travellers without travel diary data, which were not included in the questionnaire due to survey length limitations.

Finally, the survey considered mode choice for commuting by either bicycle, public transport or car. Commuting was chosen because commute trips constitute 19.4% of trips and 24.0% of total mileage in the Greater Copenhagen area, which is higher than any other trip purpose (Christiansen and Skougaard 2015). Similarly, the study considered the main commuting modes car (46%), bicycle (31%) and public transport (17%), which combined represent 94% of commute trips (Christiansen and Skougaard 2015). Travellers might emphasise certain aspects more for different trip purposes, such as functional needs for shopping trips (being able to carry things) or relatedness or growth needs for leisure activities such as visiting friends, restaurants or attractions. However, as the proposed framework is general in terms of trip purpose, it is expected that similar results will be obtained across trip purposes. In addition, most of the survey items relate to general needs satisfaction, which is independent of mode. Travel difficulties on the other hand are mode-specific, thus requiring adaptation in travel cultures where other modes are dominant. Most importantly, walking will be important to consider in some countries, possibly instead of cycling, which was included in this specific case due to the highly developed bicycle culture in Denmark. Due to the similarity between these two modes in terms of needs satisfaction several of the travel difficulty aspects can thus easily be adopted in such a setting.

4 Results

The latent variable and choice models were estimated jointly in order to obtain consistent and more robust parameter estimates. Multiple model specifications were tested based on the relationships between needs satisfaction and mode use frequency identified in Ingvardson et al. (2020). As travel costs for non-motorised modes are negligible (i.e., bicycle), only a single combined cost coefficient was estimated for public transport and driving. Two traditional Multinomial Logit (MNL) mode choice models were also estimated for comparison. The first (MNL I) was based on the same specification as the ICLV model, excluding the latent variables, whereas the second (MNL II) was based on estimating the best possible model using the information available, i.e., not considering the model specification of the ICLV model. The value of time (VoT) of public transport and driving derived from the ICLV model results is 128 DKK/hour (approx. €17 per hour) and 126 DKK/hour (approx. €17 per hour) and 140 DKK/hour (approx. €19 per hour) for models MNL I and MNL II, respectively. These are all reasonable compared to Danish value-of-time studies (Fosgerau et al. 2007; Transport DTU 2019).

4.1 Model estimation results

The main results for the three choice models are shown in Table 3. For the ICLV model, Table 4 reports the influence of socio-economic characteristics on the latent variables as well as latent variable mediator effects. The internal structure of how the LVs enter the choice model is illustrated in Figure 2, which also includes level-of-service characteristics (time and cost) as well as socio-demographic characteristics (gender, age, job type, etc.).

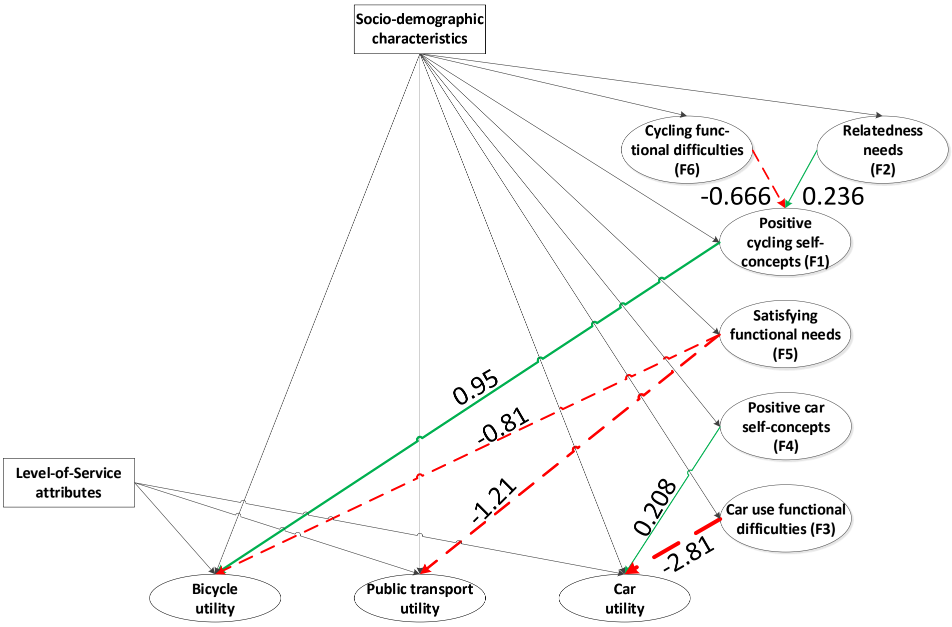

Figure 2 Final ICLV model structure (Green solid lines denote positive relationships and red dashed lines denote negative relationships. Black lines are used for representing the level-of-service and socio-demographic characteristics, which include multiple attributes.)

Commented [s3]: Change travel togetherness into relatedness needs

Commented [JBI4R3]: Done.

Commented [s5]: Jesper, F7 is missing from figure 2 and table 3 and 4 - was it not significant? we should have a comment on it.

Commented [JBI6R5]: Yes, it was insignificant. I have added a brief comment on this.

	ICLV		MNL I		MNL II	
Variable	Values	t-value	Values	t-value	Values	t-value
Travel characteristics / LoS						
Travel time [min]	–0.0386	(–4.72)**	–0.0362	(–4.25)**	–0.0317	(–3.47)**
Travel costs [DKK] (car, PT)	–0.0181	(–5.70)**	–0.0155	(–7.41)**	–0.0151	(–7.24)**
Latent (needs) factors						
Cycling self-concepts (F1) (bicycle)	0.945	(7.88)**	-	-	-	-
Car use functional difficulties (F3) (car)	–2.81	(–6.23)**	-	-	-	-
Car self-concepts (F4) (car)	0.208	(2.18)*	-	-	-	-
Functional needs (F5) (bicycle)	–0.813	(–2.94)**	-	-	-	-
Functional needs (F5) (public transport)	–1.21	(–3.35)**	-	-	-	-
Socio-economic characteristics						
Workplace location, city centre (bike)	2.07	(5.94)**	2.00	(9.08)**	2.57	(6.52)**
Workplace location, city centre (PT)	1.85	(5.40)**	1.90	(7.91)**	1.93	(7.68)**
Education, graduate (car)	–0.693	(–2.36)*	–0.655	(–3.28)**	–0.623	(–2.97)**
Monthly income, $0–3000 (PT)	1.10	(3.32)**	0.697	(2.62)*	-	-
Couple with children (bike)	0.725	(2.72)**	0.644	(3.37)**	0.581	(2.88)**
Age, 30–44 (PT)	-	-	-	-	–0.673	(–2.55)*
Age, 45–64 (PT)	-	-	-	-	–0.879	(–3.33)**
Education, vocational (PT)	-	-	-	-	0.645	(2.31)*
Car availability (bicycle)	-	-	-	-	0.554	(2.34)*
Home location, city centre (bicycle)	-	-	-	-	0.659	(3.41)**
Workplace location, suburbs (bicycle)	-	-	-	-	0.774	(2.01)*
Alternative-specific constants						
Car (reference alternative)	-	-	-	-	-	-
Bicycle	–8.05	(–5.30)**	–1.42	(–5.51)**	–2.74	(–6.50)**
Public transport	–3.79	(–2.15) *	–1.79	(–4.56)**	–1.42	(–2.86)**

Table 3 Results of the DCM based on proposed ERG-framework (Model II). * p<0.05, ** p<0.01.

Dependent (mediator) variables	Explanatory variable	Values	t-value	p-value	
Cycling self-concepts (F1)	Intercept	4.19	16.2	<0.01	**
	Relatedness needs (F2)	0.236	8.03	<0.01	**
	Cycling functional difficulties (F6)	–0.666	–6.14	<0.01	**
	Sigma	1.49	11.7	<0.01	**
Relatedness needs (F2)	Intercept	0.416	2.39	0.02	*
	Education, high school	1.46	3.67	<0.01	**
	Sigma	2.97	11.6	<0.01	**
Car use functional difficulties (F3)	Intercept	2.64	19.4	<0.01	**
	Male	–0.103	–1.42	0.15	
	Home location, city	0.449	5.77	<0.01	**
	Work location, city	0.534	6.21	<0.01	**
	Car availability	–0.440	–5.39	<0.01	**
	Sigma	0.720	11.2	<0.01	**
Car self–concepts (F4)	Intercept	2.25	9.80	<0.01	**
	Car availability	1.51	5.49	<0.01	**
	Home location, city	–1.10	–4.67	<0.01	**
	Sigma	2.31	16.1	<0.01	**
Functional needs (F5)	Intercept	3.81	17.9	<0.01	**
	Car availability	0.565	4.64	<0.01	**
	Couple with children	–0.296	–2.49	0.01	*
	Sigma	1.09	7.89	<0.01	**
Cycling functional difficulties (F6)	Intercept	2.86	15.3	<0.01	**
	Home location, city	–2.00	–7.80	<0.01	**
	Home location, suburb	–0.844	–4.42	<0.01	**
	Sigma	–1.62	–11.7	<0.01	**

Table 4 The influence of explanatory variables on the latent variables (ICLV only).

The ERG-theory constructs are significant in explaining the commute mode choice, either directly or indirectly as mediators. The choice of bicycle correlates positively with cycling self-concepts, which suggests that respondents are more likely to choose a bicycle commute if they feel it contributes to their personal values of having an active lifestyle, contributing to a better environment, etc. Cycling functional difficulties is a significant negative mediator for improved self-concepts. That is, experiencing difficulties in commuting by bicycle correlate negatively with positive cycling self-concepts, thus contributing to a lower likelihood of choosing cycling. Relatedness needs have a small indirect positive effect on bicycle mode choice, possibly due to cycling creating a strong relationship with peers, such as through bike-to-work campaigns or shared bicycle hobbies. This is not surprising given the extensive bicycle culture in Denmark, and especially within the greater Copenhagen area. On the other hand, respondents emphasising a short commute time are less likely to choose cycling.

Respondents who strongly emphasise satisfying lower-level functional needs, such as travel time, comfort and travel freedom, are more likely to choose driving. Furthermore, respondents who perceive driving as burdensome, for example, due to congestion or difficulties finding parking, are less inclined to drive. This highlights the importance of considering perceived personal travel difficulties in a travel behaviour context. A driving commute also has a higher utility if commuters feel that it satisfies higher-order needs related to self-identity and personal image. This result suggests that the choice of driving is due not only to its functional advantages, but is also highly motivated by self-image, as also highlighted by Steg (2005).

Public transport and cycling choices are negatively correlated with satisfaction of functional needs. Furthermore, respondents with a strong focus on travel time and comfort seem to prefer driving to cycling, and cycling to public transport. Finally, functional difficulties in public transport was not found significant in the model.

Commuters working in the city centre are more likely to commute by bicycle and public transport than by car, which is not surprising given road congestion and limited parking in city centres, as well as better public transport and bicycle infrastructure in city areas. Lower-income commuters are more inclined to use public transport, which confirms its value in ensuring social equity and mobility for all users. In line with Carse et al. (2013), respondents with graduate university degrees are less likely to choose driving for their commute, which could be due to a stronger focus on environmental issues. Finally, living as a couple with children is correlated with choosing a bicycle commute. This may seem surprising given that families with children in the Greater Copenhagen area have more car accessibility than other household types (Christiansen and Skougaard 2015). However, in Copenhagen many families also use bicycles for their (short) commutes. This finding could also be influenced by whether, out of the two partners, the driving commuter or the commuter using other modes answered the questionnaire.

In addition, a rich set of socio-demographic data explains the latent constructs, and thereby in turn indirectly impacts the choice through the ERG-constructs. Again, being located in the city is correlated with more functional difficulties with driving (e.g., congestion, difficulties finding parking, etc.) and fewer functional difficulties with cycling (e.g., better bicycle infrastructure and less hilly terrain). Residents in the city centre are also less likely to have car-related self-concepts, which might be related to less driving and thus less focus on the freedom and image related to this mode. Having access to a car is correlated with a stronger focus on functional needs, which is not surprising considering that cars are often faster and more convenient. Similarly, car availability is negatively correlated to perceptions of functional difficulties in driving. Finally, only respondents having finished high school as their main education were significant in explaining relatedness needs.

Since the impact of cost is often relative to income, we also tested income-specific cost-parameters in various ways, but did not find any significant effect. We tried including error terms to capture unobserved effects; specifically, we tested error components (to test normally distributed constants) as well as systematic heterogeneity on the Level-of-Service parameters (to test random taste heterogeneity assuming normal distributions), but still did not find any error terms to be significant.

Elasticities by mode for the three models are presented in Table 5, including comparison to values from the Danish National Transport Model (NTM) (Rich and Hansen 2016), which are representative of the entire Danish population. They are based on model simulations with a 10% increase in the corresponding variable, i.e., total travel times and total travel costs. Elasticities are highest for the MNL I model. In general, the elasticities resulting from the ICLV model are in line with the NTM numbers, thus supporting the validity of the model results.

	ICLV			**MNL I**			**MNL II**			**NTM**	
	Car	**PT**	**BC**	**Car**	**PT**	**BC**	**Car**	**PT**	**BC**	**Car**	**PT**
BC TT 10%	0.066	0.200	–0.243	0.121	0.271	–0.346	0.106	0.236	–0.301	-	-
Car TT 10%	–0.181	0.347	0.055	–0.263	0.505	0.098	–0.225	0.440	0.084	-0.253	0.785
PT TT 10%	0.229	–0.989	0.196	0.280	–1.397	0.221	0.245	–1.200	0.195	0.066	–1.050
Car TC 10%	–0.125	0.266	0.023	–0.160	0.361	0.036	–0.155	0.352	0.033	–0.163	0.403
PT TC 10%	0.061	–0.219	0.039	0.072	–0.288	0.041	0.069	–0.275	0.039	0.054	–0.762

Table 5 Elasticities and cross elasticities, including values for the Danish National Transport Model (NTM).

Finally, the fit indices of the models are reported in Table 6. In terms of the Akaike information criterion (AIC) (Akaike 1974), the discrete choice model fit for the ICLV is worse than that of the MNL models, and the MNL II has the best fit. Although this might seem counterintuitive, there are several explanations for this. First, MNL II includes more socio-demographic parameters in the choice model, which were not significant in the ICLV model. This is probably due to the inclusion of the LVs in the choice model, which then includes the indirect effect of the socio-demographics (cf. Table 4). Second, the ICLV uses the same information to jointly explain both the choices and the indicators, whereas in the MNL the same information is used only to explain the choices. Hence, for the HCM some of the fit is sacrificed to also explain the indicators, so that the combination of indicators and choice is optimal. The fit is also worse than in MNL I, which is mainly due to noise from the error terms of the LVs.

	ICLV	MNL I	MNL II
N	1,097	1,097	1,097
No of parameters	14	9	14
Final log-likelihood	–585.41	–572.08	–555.99
AIC	1,198.82	1,162.17	1,139.99
BIC	1,268.82	1,207.17	1,209.99

Table 6 Model fit indices.

4.2 Mode share segmentation

The main advantage of the ICLV model is the possibility of analysing differences in perceptions across user groups. This can be illustrated by comparing the dependence of the mode shares across groups on users' emphases on the various latent variables. Using the parameter estimates from the utility function of the ICLV model we computed the level of the latent variable for each individual. Based on this level we segmented the respondents into three groups of equal size using tertiles, i.e., the lowest, the medium and the highest third of the sample population. Hence, for each of the latent variables three groups of equal size were defined, which then consisted of i) the third with the lowest emphasis, ii) the third with the intermediate score, and iii) the third scoring the highest on that given latent variable. This enabled us to analyse how different perceptions, i.e., varying emphases on the latent variables, influence mode choice preferences.

Commented [s7]: did ypu segment the population instead of by the factor scores by the socio-economic characteristics explaining the factor? you could have done it directly with the factor scores.

Commented [JBI8R7]: Yes, we used the model. I propose to stick to this since it was done for all latent variables.

The overall mode shares from the sample are 47% drivers, 31% cyclists, and 21% public transport users, in line with the modal shares of 45%, 32% and 18% reported in the National Travel Survey[2] (Christiansen and Skougaard 2015). However, Figure 3 shows that when segmenting the respondents based on their computed LV-scores, the latent variables strongly influence the mode shares. Note that LV2 on relatedness needs is not included since it is not well explained by the model specification due to only being explained by a single socio-economic characteristic, which has little variation over the respondents.

Commented [JBI9]: Is this comment okay? I added a bit more details in the response letter.

Among users with strong preferences for positive cycling self-concepts, the bicycle mode share is 58%, whereas it is 5% among users that do not focus on cycling self-concepts in their commute mode choice. The corresponding car mode shares are 74% for those with the lowest focus on positive cycling self-concepts and 19% for those with the highest. Similarly, 76% of car users with a strong focus on car self-concepts choose driving for their commute compared to only 11% of those with a weak focus on car self-concepts. The corresponding bicycle mode shares are 11% and 54%, respectively. These results suggest that modes that fulfil needs related to individuals' self-image are more attractive. Hence, it is also important to consider higher-order needs in a mode choice context.

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[2] The remaining 5% are other modes, such as walking.

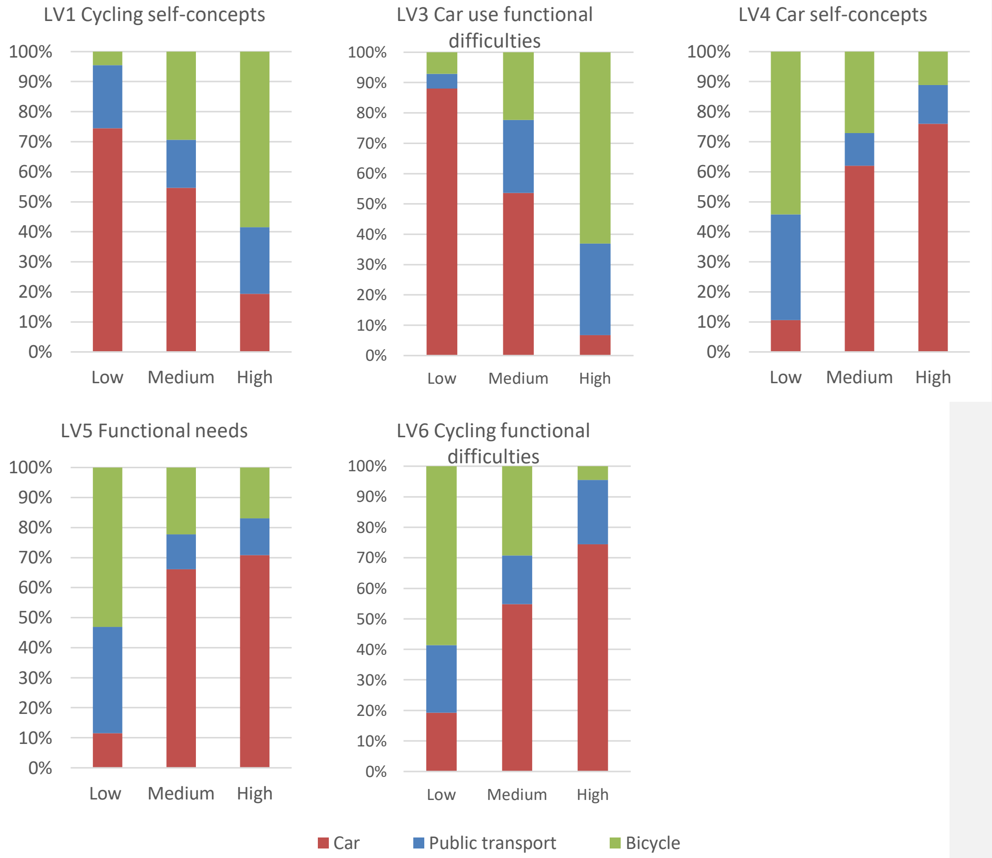


Figure 3 Mode share segmentation based on the six latent variables.

Commented [s10]: Change travel togetherness into relatedness needs

Commented [JBI11R10]: I have removed the figure for LV2.

Increased functional difficulties related to car use (LV3) is associated with lower rates of driving and larger use of other modes, especially bicycle. Notably, the mode share of driving drops from 88% among users with low functional difficulties with driving to only 7% among those with high perceived travel difficulties of driving. Similarly, the bicycle mode share decreases with individuals' functional difficulties with cycling (LV6). Hence, among the one third of respondents emphasising the most cycling difficulties, the bicycle mode share is 4%, which increases to 59% among the third with lowest level of cycling functional difficulties. Simultaneously, car mode share is reduced from 74% to 19%. These results confirm that mode-specific travel difficulties are an important aspect for commuters.

For respondents with a strong focus on satisfying functional needs (LV5), the preferred mode choice is driving (71% and 66% of respondents in the high and medium group), whereas the mode shares of cycling and public transport is much lower, although these are much higher among respondents who place less emphasis on satisfying functional needs. Hence, it is apparent for this LV that respondents that choose cycling or public transport are in general less focused on satisfying functional needs. These modes are most often slower, so the choice is based on other aspects than pure travel time considerations.

Mode choice therefore correlates strongly with individuals' perception of whether the modes fulfil specific user needs, which are not strictly limited to level-of-service characteristics. By incorporating latent variables related to needs satisfaction, the ICLV model includes explicitly factors that traditional MNL models do not. Moreover, the model results show the importance of considering the influence of such factors in mode choices.

5 Policy analysis

We tested the implications of transport policies through forecasting scenarios to illustrate how the ERG-constructs impact individuals' choices. Forecasting can reveal differences across user groups when travel characteristics are changed, because the ICLV model incorporates individuals' perception of how the transport modes fulfil various needs. We tested the model with a policy scenario that promotes sustainable transport. In the City of Copenhagen, 43% of commuters biked to work or education in 2016, and the goal is to increase this share to 50% by 2025 (City of Copenhagen 2018). We therefore tested a policy scenario in which cyclists are given priority through green waves, improved bicycle paths, shortcuts, etc. This is currently being prioritised in the Copenhagen area, which has implemented several 'bicycle superhighways', which focus on creating safe, comfortable and more direct routes for cyclists. We approximated such a scenario by assuming a general 20% travel time reduction for cyclists.

A 20% decrease in bicycle travel time results in an increase in the mode share of bicyclists from 30.8% to 32.4%, with equally many being former car (–0.8%) and public transport users (–0.8%). However, the ICLV model reveals that the changes vary notably across user groups, as shown in Figure 4.

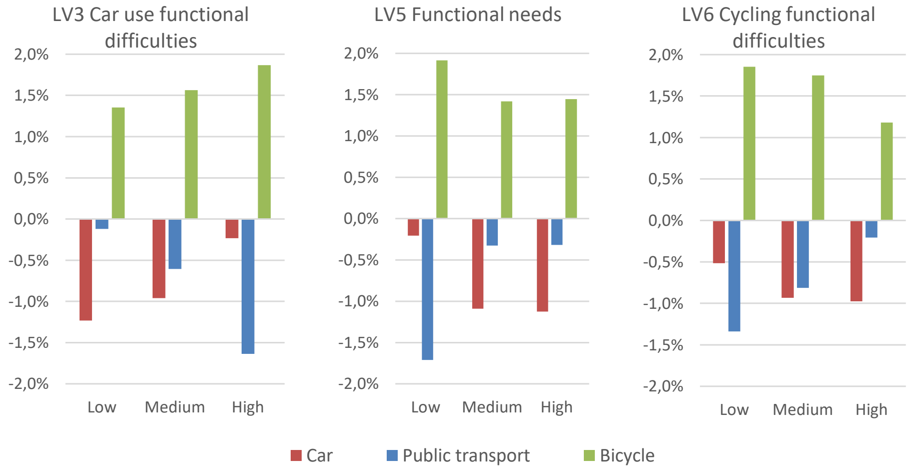


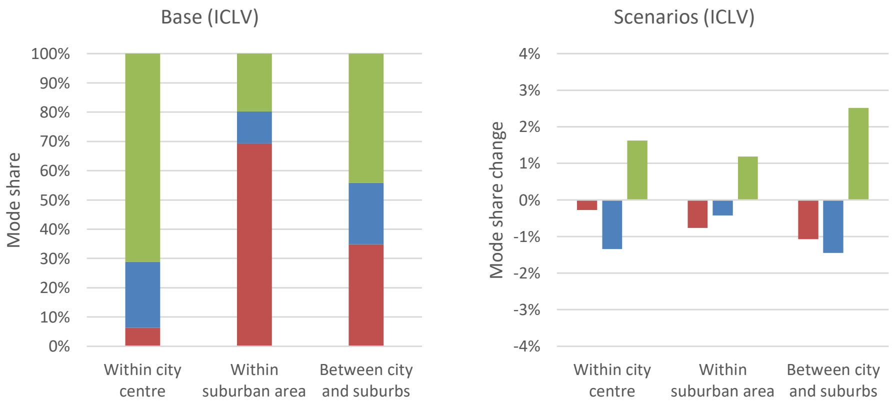
Figure 4 Changes in mode shares dependent on the three latent variables related to travel difficulties and functional travel needs.

The largest mode shifts are among respondents that focus the least on satisfying functional travel needs (1.9%), as compared to those with medium and strong focus on this (1.4%). This is as expected, as a 20% travel time reduction for cyclists does not necessarily result in cycling being the fastest mode choice in a given situation. Driving will often be the fastest alternative in the Greater Copenhagen area, whereas cycling is faster for short trips within the city centre. Similarly, the largest mode shifts are among the respondents with fewest (1.9%) rather than most (1.2%) cycling functional difficulties. Hence, commuters that experience less bicycle travel difficulties have a higher tendency to shift to cycling if it lowers travel time.

The mode shift is also larger among respondents with stronger (1.9%) rather than weaker (1.4%) functional difficulties with driving. This suggests that users that perceive a driving commute as inconvenient due to, for example, parking issues, car use expenses, traffic congestion, safety concerns or driving stress, are more likely to change mode if bicycle travel times are reduced. Among commuters with low functional difficulties with driving, the mode shift from driving is 1.2%, larger than the 0.1% coming from public transport, which might seem counter-intuitive. However, this should be compared to the significantly larger car market share among these respondents (see Figure 3). In relative terms, the 1.2% mode shift corresponds to 1.4% of drivers, whereas the 0.1% of public transport users corresponds to 2.5% of the public transport users.

We further analysed the capabilities of the ICLV model by creating three further forecasting scenarios where bicycle travel time reductions were only obtained for specific commuter groups based on travel pattern, hence allowing for possible spatial differences to be evaluated. This would be a more realistic scenario, where the focus is on improving bicycle conditions in specific areas of the Greater Copenhagen area. Hence, for each of the three scenarios, the 20% bicycle travel time reduction was only obtained for travellers commuting i) within the city centre, ii) within the suburbs, and iii) between the city and the suburbs. Commuters outside these areas (i.e., in rural areas) did not have any travel time reductions. The main results are shown in Figure 5, which shows the mode shares in the base scenario (left) and the changes to mode shares for the three scenarios (right) using the ICLV model (top) and the simple MNL model (bottom).

As previously suggested, travel patterns in specific areas strongly influence mode shares, as the bicycle mode share is much higher in the city centre than in the suburbs. This is probably due to shorter trip distances, which, combined with higher congestion levels for commuting by car, makes the bicycle an attractive choice. On the other hand, driving is the most popular choice in the suburbs, where travel distances are longer and average travel speed by car is higher. The largest effects are obtained when there are travel time reductions between the city centre and the suburbs. This is probably due to a combination of cycling being an attractive alternative when there is still a large potential for mode shifts. If improvements only focus on the city centre, the mode shift is smaller, as the majority is already cycling. These results also suggest that mode shifts require relevant and reasonable alternatives, which often require travel obstacles or restrictions for car traffic.



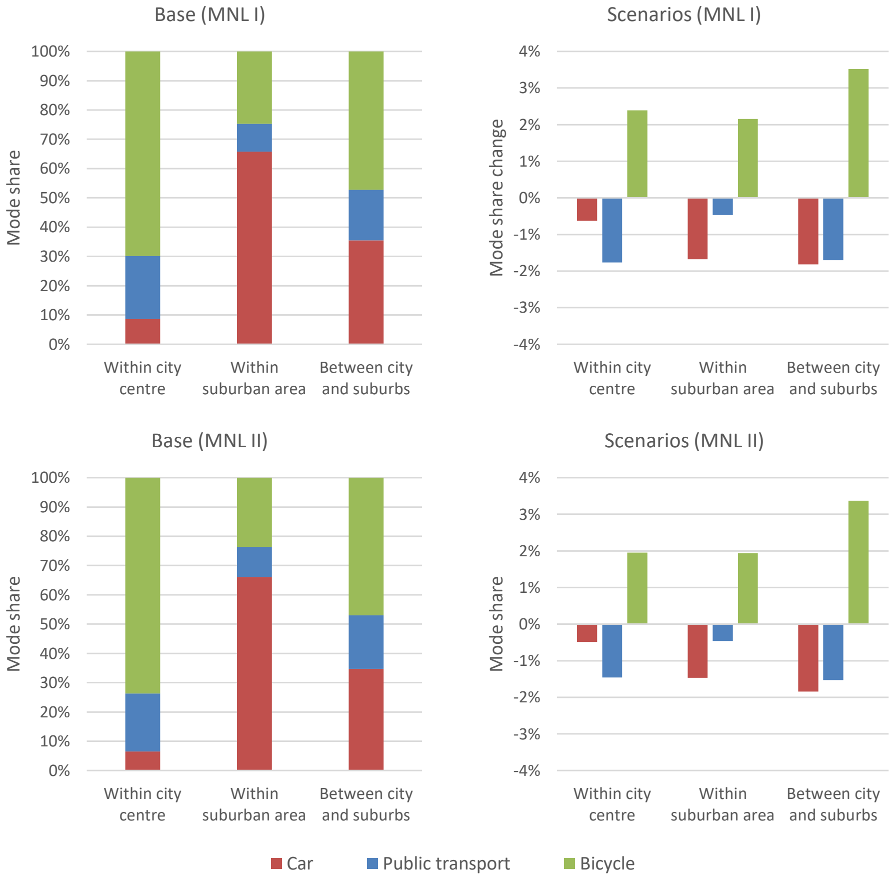


Figure 5 Changes in mode shares are dependent on whether bicycle travel time reductions are obtained within the city centre only, within suburbs only, or between city and suburbs only. Top: ICLV model. Bottom: MNL model.

Generally, the MNL model predicts larger mode shifts than the ICLV, but the trends are comparable. The main differences between the two model predictions lie in the possibility of revealing further behavioural insights when segmenting the results of the policy scenario on the latent variables, as shown in Figure 6. This illustrates that the segmentation of respondents based on the latent variable related to functional difficulties with driving is highly influenced by the spatial travel pattern. Among those respondents that have the lowest driving functional difficulties, none commute to or from the city centre, suggesting that those commuters do find driving inconvenient. Conversely, the car mode share is 84% among those commuting within the suburban area with low driving functional difficulties. Among respondents with higher driving functional difficulties, the driving mode share is much lower (6–7%), whereas the majority (61–71%) use bicycles for their commute. The mode share of public transport is lower within the city centre (23%) than for radial trips between the city centre and the suburbs (33%), where trip distances are longer, which favours public transport over cycling.

The changes resulting from the policy intervention suggest that the largest increase in bicycle mode share happens among respondents with medium and higher car use functional difficulties, and among commuters between the suburbs and the city centre. Thus, improving conditions for cyclists on the radial links linking the city centre jobs with the suburban residential neighbourhoods is also important. This has already been recognised in designing the ‘cycle superhighways’ in the Greater Copenhagen area (Capital Region of Denmark 2019).

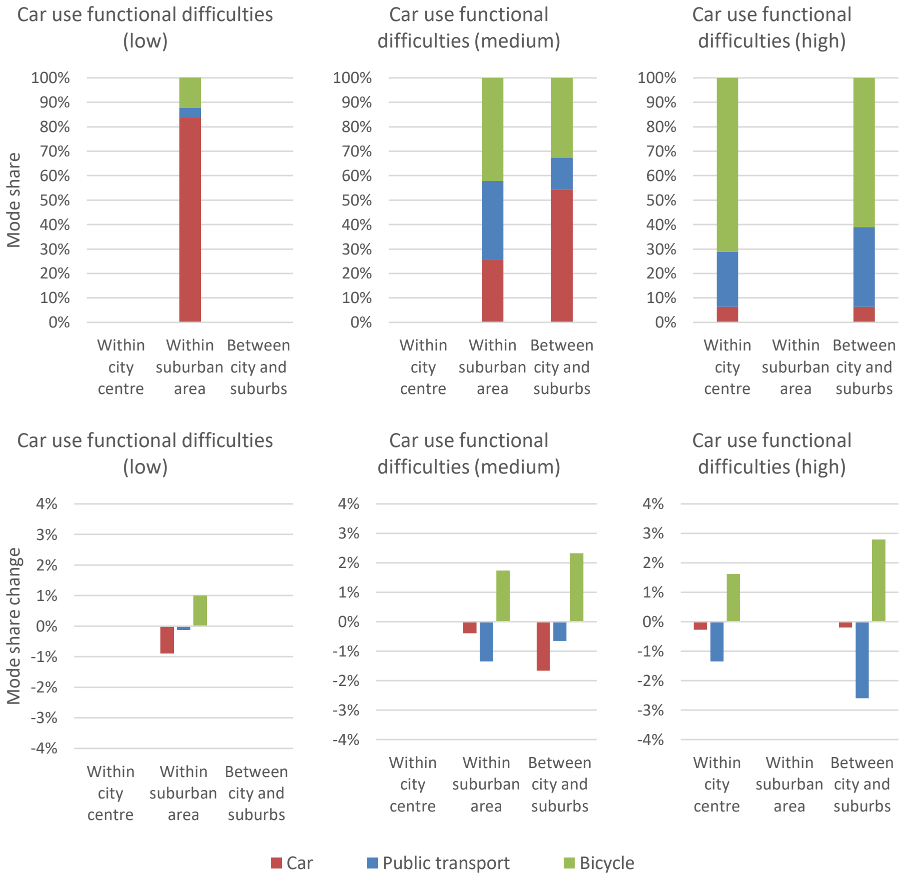


Figure 6 Results of the policy scenario reducing bicycle travel times by 20% in specific geographical areas, segmented across users with different perceived car use functional difficulties. Top: mode shares in base situation; bottom: mode share change.

It would have been interesting to also test a policy scenario focusing on higher-order needs, e.g., self-concepts for cycling or driving. However, such scenarios would require the implementation of measures directed at improving, or reducing, the level of satisfaction in self-concepts. While car manufacturers often focus on higher-order needs by creating perceptions among users that their products are aspirational (Douglas et al. 2011), such measures are much more difficult to define, estimate and quantify than functional needs. Hence, it was not possible to analyse such a policy scenario.

6 Conclusions

This study is the first exploration of how needs according to the ERG theory influence commute mode choice decisions. The results provide important general insights on the underlying motives for commuters' mode choices.

First, the results highlight the advantage of using an Integrated Choice and Latent Variable (ICLV) model approach, which allows for differentiating between commuters who focus differently on satisfying lower-order functional needs, higher-order growth needs and social aspects while also taking into account traditional mode-specific attributes, hence explicitly considering the heterogeneity of travellers. Specifically, mode choice was highly associated with fulfilment of higher-order needs. The choice of bicycle and car modes correlated with these modes being perceived as contributing to individuals' self-identify and self-concepts and by mode-specific travel difficulties and competencies. Furthermore, relatedness needs were significantly correlated with bicycle usage, however indirectly. Finally, commuters with a strong focus on lower-order functional needs were more likely to drive and least likely to use public transport.

Second, the ICLV model enabled an analysis of mode choices across user groups based on segmentation of the latent variables as well as on how these depend on various socioeconomic characteristics. While this is an important advantage of using ICLV models, it has not often been emphasised in recent literature. The results revealed strong associations between the latent variables and mode choice, e.g., users reporting strong identification with bicycle self-concepts had notably higher bicycle mode share than other users. Hence, this study highlights the importance of also considering such factors in the mode choice context.

Third, the results of policy scenarios analysing mode shifts when implementing improved conditions for bicycles showed that the latent variables were strongly related to the mode shifts. The latent variables relevant to reduced bicycle travel times were those related to functional needs and travel difficulties. The largest mode shifts were observed among users with the fewest cycling functional difficulties, the most driving functional difficulties and low focus on satisfying functional needs.

The study also revealed that socio-economic variables were associated with mode choice both directly and indirectly through the latent variables. This suggests that policy changes may have impacts that would not be captured by traditional models. Since socio-economic variables often vary spatially and latent variables influence mode choices, it may be the case that effects of policies also vary spatially. The policy scenarios in fact showed that bicycle mode shifts were larger when travel time reductions were obtained for trips between the city centre and the suburbs. On the other hand, mode shifts were smaller in the city centre (due to already high mode shares) and in the suburbs (due to car being the dominant mode). While similar findings might be obtained from a simple MNL model, it would not identify the underlying reasons. Hence, these policy analyses highlight insights on travel behaviour that can be extracted from ICLV models but not from simpler MNL models.

The results have important policy implications by suggesting that mode choice, and thus mode splits, are highly correlated to individual perceptions of travel modes. These are correlated both to the functional value assigned to the modes and to fulfilment of higher-order needs, which are strong motivators of travel behaviour and highly relevant in the mode choice context. Thus, policy interventions should consider both to ensure shifts towards more sustainable transport, through addressing both functional needs and higher-order needs. From the functional perspective, the study clearly shows the positive effect of the Danish long-term policy to prioritise bicycle infrastructure and public transport over road infrastructure, and to demotivate car use by restricting parking availability, increasing parking costs and informing the public about the actual costs associated with car use versus other modes. The policy analysis clearly shows that investment in cycling infrastructure has a long-term positive effect on reverting travellers from driving to cycling. When cycling is feasible, fast, and easy, car use difficulties will motivate a shift from driving to cycling. In terms of higher-order needs, the study shows that it is important to enhance positive cycling self-concepts and decrease positive car self-concepts. The study clearly shows that the long-term Danish concept of promoting cycling as an important transport mode and promoting the positive image of cyclists through campaigns, role models, and infrastructure allocation is effective. People with high cycling self-concepts will be more cycling-oriented and less car-oriented. Because the automobile industry is continuously investing in promoting car self-concepts through the media, transport authorities must promote positive cycling concepts by advertisement campaigns, role models, and the media. It is also important to invest in cycling infrastructure to signalise to the general public that cyclists are not a marginal group of road users but equal partners to other road users in terms of their road sharing rights. Because hybrid choice models allow incorporating such psychological needs into activity-based agent-based simulation models, psychological needs can have direct policy implications if they are embedded in the models. Moreover, satisfying psychological needs is a key to successful voluntary-behavioural change strategies (Dastjerdi et al. 2019) and promoting the market adoption of new transport technologies (see, e.g., Kim et al., 2014; Tchetchik et al., 2020). The current study offers a feasible tool for large-scale data collection and analysis of psychological needs. If such data collection about needs and attitudes is implemented in national travel surveys, it can then be embedded in activity-based and agent-based models. The population segmentation tool is useful in generating an agent-based synthetic population with a distribution of psychological needs representing the distribution in the actual population, in a similar manner to observed socio-economic variables. The model provides the necessary relationships between the psychological constructs and the actual choice. Both tools can be readily implemented in current activity-based, agent-based models for planning and policy analysis, and thus enhance the realism of human behaviour representation in activity-based models.

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Author contributions

All authors contributed to this study. The behavioural framework was developed by Sigal Kaplan. The survey design was developed by Sigal Kaplan and Jesper Ingvardson. The data analysis and ICLV modelling was performed jointly by Jesper Ingvardson and Mikkel Thorhauge with supervision and guidance by Sebastián Raveau. The paper writing was conducted mainly by Jesper Ingvardson, Mikkel Thorhauge and Sigal Kaplan, and assisted by comments from Otto Anker Nielsen and Sebastián Raveau.

Conflicts of interest statement

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

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