Learning about the unobservable

The role of attitudes, measurement errors, norms and perceptions in user behaviour.

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Doctoral thesis in Transport Science

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To Fátima.

"There is only one good, knowledge, and one evil, ignorance"

Socrates

Abstract

Unobservable factors are important to understand user behaviour. Moreover, they contain information to help design services that will solve today's challenges. Yet, we have barely scratched the surface of the underlying mechanisms ruling user behaviour. For decades, user behaviour analysis has focused on the capabilities of observable variables, as well as assumptions of regular preferences and rational behaviour to explain user choices; and amalgamated unobservable factors into "black-box" variables. As a response, the field of behavioural economics has produced an array of so-called *choice anomalies*, where people seem not to be fully rational.

Furthermore, as a consequence of the "digital revolution", now we harvest data on an unprecedented scale -both in quantity and resolution- that is nurturing the golden age of analytics. This explosion of analytics contributes to reveal fascinating patterns of human behaviour and shows that when users face difficult choices, predictions based only on observable variables result in wider gaps between observed and predicted behaviour, than predictions including observable and unobservable factors.

Impacts of the "digital revolution" are not limited to data and analytics but they have filtered through the whole tissue of society. For instance, telecommunications allow users to telework, and telework allows users to change their travel patterns, which in turn contributes to increase the overall system complexity. In addition to the new world dynamics facilitated by Information and Communications Technology, megatrends such as hyper-urbanization or increase demand of personalised transport services are imposing pressures on transport networks at a furious pace, which also contributes to increase the complexity of the choices needed in order to navigate the networks efficiently.

In an effort to alleviate these pressures, new mobility services such as electric and autonomous vehicles; bicycle and car sharing schemes; mobility as a service; vacuum rail systems or even flying cars are evolving. Each of these services entails a different set of observable variables like travel time and cost, but also a completely different set of unobservable ones such as expectations, normative beliefs or perceptions that will impact user behaviour. Hence, a good understanding of the impact of underlying, unobservable, factors -especially when services are radically different from what users know and have experienced in the past- will help us to predict user behaviour in uncharted scenarios.

Unobservable factors are elusive by nature, hence to incorporate them into our models is an arduous task. Furthermore, there is evidence showing that the importance of these factors might differ across

time and space, as user preferences, perceptions, normative beliefs, etc. are influenced by local conditions and cultures. As a consequence, we have witnessed a surge of interest in behavioural economics over the past two decades, due to its ability to increase the explanatory and predictive power of models based on economic theory by adding a more psychologically plausible foundation.

This thesis contributes to the existing body of literature in *Transport Science* in the areas of user perceptions, measurement errors, and the influence of attitudes and social norms in the adoption of new mobility solutions. The work builds on the behavioural economics theoretical framework, underpinned by economic theory, discrete choice analysis -rational behaviour and random utility maximization-, as well as social and cognitive psychology. Methodological contributions include a framework to systematically test differences in user preferences for a set of public transport modes, relating to observed and unobserved attributes; and a framework to assess the magnitude of unobservable measurement errors in the input variables of large-scale travel demand models. On an empirical dimension, findings support the existence of a *"rail factor"*, the impact of modelling assumptions on parameter estimates of hybrid choice models, the presence of larger measurement errors in the cost variables than in the time variables, -which in turn translates into diluted parameters that under-estimate the response to pricing interventions-, and that the model with the best fit does not guarantee better parameter estimates.

Therefore, I expect this thesis to be of interest not only to modellers, but also to decision makers; and that its findings will contribute to the design of the mobility solutions that users need and desire, but also that will benefit society as a whole.

Sammanfattning

Ej observerbara faktorer är viktiga för att förstå människors beteende. I sådana faktorer bär på information som kan bidra till att designa tjänster som kan lösa dagens utmaningar. Trots det är vi bara i början av att förståde underliggande mekanismer som styr mänskligt beteende. I årtionden har analyser av användarbeteende fokuserat på att förklara människors val med hjälp av observerbara faktorer och antaganden om reguljära preferenser och rationellt beteende. Ej observerbara faktorer har relegerats till feltermer. Som ett resultat har forskningsfältet beteendeekonomi kunnat visa på en rad anomalier i människors val som tycks visa på irrationellt beteende.

En konsekvens av digitaliseringen är att vi idag samlar in data i en skala som aldrig tidigare setts och det har skapat något av en guldålder för dataanalys. Den här explosionen av dataanalys bidrar till att avslöja fascinerande mänskliga beteendemönster, men också till att prediktion baserad enbart på observerbara variabler visar sig ge större avvikelser från observerbart beteende än när den inkluderar både observerbara och ej observerbara faktorer.

Digitaliseringens inverkan begränsas inte bara till data och dataanalys utan den påverkar också hela samhället. Till exempel, informations- och telekommunikationsteknik (ICT) låter människor distansarbeta, och distansarbete gör det möjligt att ändra resmönster, med resultatet att hela systemets komplexitet ökar. Förutom att ICT ändrar dynamiken så bidrar megatrender som hyper-urbanisering till att öka efterfrågan på personligt anpassade transporttjänster, vilket sätter press på existerande transportnätverk, vilket bidrar till att det blir allt mer komplext för människor att navigera transportnätverken effektivt.

Som ett svar på den ökande pressen på transportnäten utvecklas i snabb takt nya tjänster, som till exempel cykel- och bildelningstjänster, elektriska och självkörande bilar, mobilitetstjänster, vacuumtåg eller till och med flygande taxifordon. Varje sådan tjänst har sin egen uppsättning observerbara variabler som t.ex. restid och kostnad, men också helt egna ej observerbara faktorer som till exempel förväntningar, normativa uppfattningar, eller upplevelser som alla påverkar beteendet. Därför behövs en god förståelse för underliggande, ej observerbara faktorer för att kunna förutse människors beteende – särskilt när de nya tjänsterna skiljer sig radikalt från de tjänster människor känner till och har upplevt själva.

Ej observerbara faktorer är sin till natur svåra att få grepp om så att inkludera dem i modeller är en grannlaga uppgift. Det finns också

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indikationer på att betydelsen av dessa faktorer kan variera över tid och plats, för att preferenser, upplevelser, normativa uppfattningar etc. påverkas av t.ex. lokala och kulturella förutsättningar. En konsekvens är ett ökat intresse för beteendeekonomi de senaste två årtiondena då den bidrar till att förbättra ekonomiska modellers förklaringsvärde både för utforskande analys och prediktion genom att lägga till en psykologisk grund.

Den här avhandlingen bidrar till den existerande litteraturen inom *transportvetenskap* på områdena användarupplevelser, mätfel, och attityder och sociala normers inflytande på upptaget av nya transporttjänster. Arbetet bygger på ett beteendeekonomiskt teoretiskt ramverk, och bottnar i ekonomisk teori, diskreta val – rationellt beteende och stokastisk nyttomaximering – såväl som social- och kognitiv psykologi. Metodmässiga bidrag inkluderar ett ramverk för att på ett systematiskt sätt testa skillnaden i användarpreferenser mellan olika kollektiva färdmedel, och ett ramverk för att uppskatta storleken på ej observerbara mätfel från variabler i storskaliga transportmodeller.

Empiriska resultat i avhandlingen stödjer existensen av den så kallade *"spårfaktorn"*; visar på betydelsen av modellantaganden på parameterestimat i hybridvalmodeller; att mätfelet är större i kostnadsvariablerna än i tidsvariablerna – vilket i sin tur leder till en underskattning av responsen vid prisförändringar; och att modeller med den bästa överensstämmelsen med observerat beteende inte garanterar de bästa parameterestimaten.

Därför hoppas jag att den här avhandlingen inte bara är intressant för modellerare utan även för beslutsfattare och att resultaten bidrar till att mobilitetslösningar kan utformas så att de inte bara uppfyller användarnas behov och önskemål utan även är till nytta för samhället i stort.

Nyckelord: Attitudes; Measurement errors; Discrete choice analysis; Latent variables; Model misspecification; Normative beliefs; Rail factor; User perceptions; Social norms; and Value of travel time savings.

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Contents

List of abbreviations

AIC	Akaike information criterion
ASC	Alternative Specific Constant
BIC	Bayesian Information Criterion
cMaaS	corporate Mobility as a Service
CTS	Centre for Transport Studies
DCA	Discrete Choice Analysis
EV	Extreme Value
HCM	Hybrid Choice Model
i.i.d.	independently and identically distributed
ITRL	Integrated Transport Research Lab
KTH	Kungliga Tekniska högskolan
LCLVM	Latent Class and Latent Variables Model
LCM	Latent Class Model
MaaS	Mobility as a Service
ML	Mixed Logit model
MNL	MultiNomial Logit model
NL	Nested Logit model
OL	Ordered Logit
PT	Public Transport
RP	Revealed Preferences
SEM	Structural Equation Model

List of papers

  I Varela, J.M.L., Börjesson, M., and Daly, A., 2018. Public transport: One mode or several?. *Transportation Research Part A: Policy and Practice*, 113:137–156.

  II Varela, J.M.L., Börjesson, M., and Daly, A., 2018. Quantifying errors in travel time and cost by latent variables. *Transportation Research Part B: Methodological*, 117:520–541.

 III Varela, J.M.L., 2018. Misspecified Hybrid Choice Models: An empirical study of parameter bias and model selection. *Submitted.*

 IV Varela, J.M.L., Susilo Y.O. and Jonsson, D., 2018. User attitudes towards a corporate Mobility as a Service. *Submitted.*

Declaration of contributions

- Paper I - The idea was proposed by Maria Börjesson. Juan M.L. Varela performed the analysis and wrote the paper. Maria and Andrew provided feedback to the major iterations of the paper and supervision.

- Paper II - The idea was proposed by co-authors. Juan M.L. Varela performed the analysis and wrote the paper. Maria and Andrew provided feedback to the major iterations of the paper and supervision.

- Paper III - Juan M.L. Varela proposed the idea, performed the analysis and wrote the paper.

- Paper IV - Juan M.L. Varela proposed the idea, performed the analysis and wrote the paper. Yusak provided feedback during the data collection period. Daniel and Yusak provided feedback to the major iterations of the paper and supervision.

Related work not included in this thesis

- Varela, J.M.L., 2018. Parameter bias in misspecified Hybrid Choice Models: an empirical study.*Transportation Research Procedia*, 33:99 - 106. XIII Conference on Transport Engineering, CIT2018.

- *Paper V*, Objective vs subjective travel time. What rules behaviour in user mode choices?

- *Paper VI*, Value of travel time savings calculation from national survey data in Stockholm, after accounting for measurement errors.

- Multimodal route planner for Mobility as a Service. *SWECO - Stiftelsen J. Gust Richerts Minne (2018)*

- *DEMOPAN* - Demand model estimation based on a combination of active and passive data collection.

Figure 0.1: Work timeline
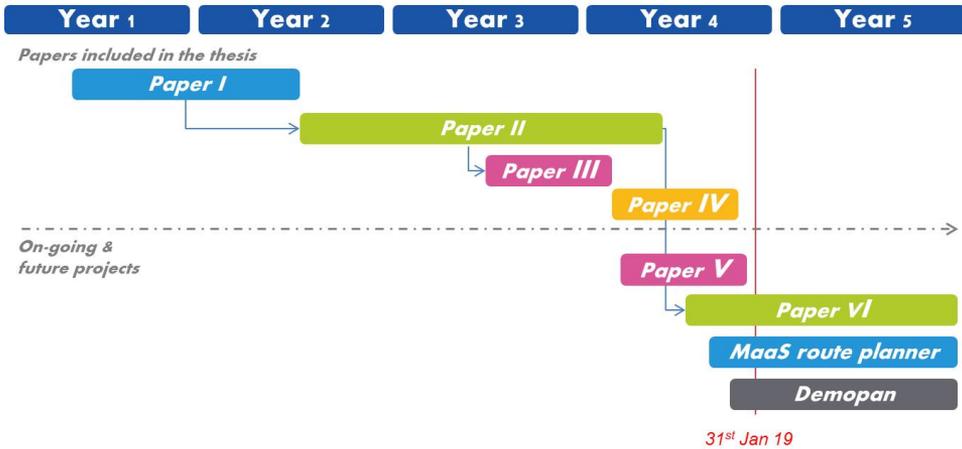
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Introduction

User behaviour, and in particular the choice process, has been object of study by disciplines such as economics, psychology, marketing, or transport planning. As a consequence, there are different perspectives and theories that help us understand user behaviour. Nevertheless, a common tool to all the disciplines is the use of models. A model, in essence, is a representation of a complex problem that can help us build our understanding about the problem in question, and even be used to make predictions. This makes mathematical models of a complex problem valuable. As models are representations, certain simplifications will be used. These simplifications will depend on the type of model, the purpose of the model, available information, etc. Hence, no one-size-fits-all solution exists.

User behaviour analysis have long recognised the role of observable variables. Variables such as age, place of residence, family situation or visited websites are normally used to classify users into categories that are later targeted by tailored strategies. Hence, market segmentation based on observable characteristics has served as a proxy to model unobservable variables; such as preferences, attitudes and social norms, which influence user decisions.

Transport user behaviour models have normally focused on few core attributes of the transport alternatives to explain user choices. Nevertheless, user travel needs are rarely an end product per se, but rather a by-product

of engaging in other activities. Hence, explaining user travel behaviour in isolation by looking only at the core attributes of the transport alternatives results in a myopic approach that makes some of the observed decisions seem irrational.

Previous studies in the transport field have demonstrated the importance of individual preferences, attitudes and normative beliefs, and started to integrate theories and methods from social and cognitive psychology across several empirical contexts. Some examples include: travel mode choice [Anable, 2005, Kamargianni et al., 2014], car ownership [Belgiawan et al., 2014, Kim et al., 2014a], or public transport (PT) use [Bamberg et al., 2007];[Zhang et al., 2016], as cited by [Krueger et al., 2018].

These unobservable factors (preferences, attitudes and normative beliefs) are elusive by nature, hence the task of incorporating them into our models present several challenges. First, we do not know a priori what factors are important. Second, how to measure these unobservable factors is not straightforward, hence it is likely that measurement errors are introduced during the measuring process. These errors might differ depending on the adopted measuring strategy and the nature of the factors. Third, even if we know what factors are important for a specific situation and how to measure them, empirical evidence might differ across transport networks and over time, as user preferences, perceptions and beliefs are influenced by local conditions and cultures, [Scherer, 2010].

Despite of the challenges, the use of unobservable factors in behavioural models is on the rise, as an increasing amount of research evidence shows model explanatory power improvements when such variables are introduced. Because of this, efforts to collect information about unobservable factors have increased over the past decades to the point where surveys about population attitudes have become normal practice. As an example, the British Social Attitudes survey is an annual statistical survey conducted in Great Britain by the National Centre for Social Research (NatCen) since 1983, [NatCen, 2018]. Among the different survey elements, the survey includes a transport section, but also related areas such as climate change attitudes that provide information about unobservable factors that are intimately related to transport behaviour. Furthermore, if done right, these surveys also provide a longitudinal dimension that will help understand how user attitudes evolve over time.

Despite of these actions, current efforts in quantifying unobservable factors are still fragmented as survey questions and methods are not stan-

dardised. Each country, or even study, employs different sets of questions which leads to other problems, such as: reference dependency and gain-loss asymmetry in responses due to question framing. This situation makes identification of trends across time and geographic location difficult to spot.

At the same time that transport modellers face these challenges, mega-trends such as climate change, hyper-urbanization, and societal changes are imposing pressures on transport networks at a furious pace. In an effort to alleviate these pressures, new mobility services that reduce the externalities of private car usage are emerging, such as electric cars and bikes or car and bike sharing schemes. Furthermore, we live in the *Digital Age*, which is characterized by technological evolution and an explosion of information. This environment has nurtured a series of innovative solutions that facilitate the integration of services, building on the new modes and the developments in information and communication technologies.

Electric vehicles [Langbroek et al., 2017a], Mobility as a Service (MaaS) [Kamargianni et al., 2018], autonomous vehicles [Fagnant and Kockelman, 2015], vacuum rail systems [Taylor et al., 2016], or flying cars [CBSNews, 2018] are some of the new mobility solutions that might change the mobility paradigm. These alternatives that only a few years ago might have been perceived as futuristic are now under the spotlight and they need to be consistently evaluated in order to understand, and predict, the market appetite for such solutions. As it is sensible to think, these new mobility solutions cannot only be evaluated using traditional factors such as trade-offs between time and cost, or emissions. All those components will still need to be considered, but to understand how attractive these new alternatives will be, we should also consider more subtle things; such as trust towards autonomous vehicles, or human-machine interaction. In words of [Cunningham and Johnson, 2007];

> "The perception that something is good or bad, positive or negative, or pleasant or unpleasant is critical to almost any behaviour. Indeed, the processes of evaluation and associated behavioural choice are ubiquitous though often invisible in daily life. Yet, as is increasingly clear, even simple evaluations are often the integrated outcome of multiple affective and cognitive component processes."

Therefore, methods that allow us to understand what unobservable factors are relevant for transport-related decisions need to rise to the current chal-

lenges, and help policy-makers identify potentially disruptive technologies before they begin to exert their disruptive powers in the economy and society.

This thesis is methodological in nature, and the methods developed can be applied to other fields. Nevertheless, the different case studies focus on the econometric modelling to predict the behaviour of transport users, whilst incorporating findings from other disciplines into transport analysis. The case studies contribute to the current state-of-the-art of the *Transport Science* literature in the areas of user perceptions, quantifying and controlling for unobservable measurement errors, and the influence of attitudes and norms in the adoption of new transport solutions. Hence, I expect this thesis to be of interest not only to modellers, but also to decision makers; and that the methods hereunder presented will contribute to the design of the mobility solutions that users need and want, but also that will benefit society as a whole.

1.1 Research objectives

The objective of this thesis is twofold: to bridge the gap between industry and academia by showing how familiar methodologies can answer new questions; and when this is not possible, to develop state-of-the-art methodologies to deal with the new challenges ahead. The following minor research objectives are addressed in this thesis:

1. Develop a methodology for testing and implementing differences in preferences for a set of public transport modes, relating to observed and unobserved attributes in state-of-practice large-scale travel demand models. Particularly focus is put on unobserved shared attributes among alternatives that can create correlations. *(Paper I)*

2. Develop a methodology to assess the magnitude of the measurement errors in travel time and travel cost by latent variables, in a large-scale travel demand model. *(Paper II)*

3. Investigate the extent of parameter bias in misspecified hybrid choice models. *(Paper III)*

4. Assess how modelling assumptions of hybrid choice models impact the parameter estimates of the choice model. *(Papers II and III)*

5. Investigate current user attitudes and expectations towards corporate Mobility as a Service (cMaaS) solutions, and how modality styles might impact the adoption of such systems. *(Paper IV)*

1.2 Thesis structure

This thesis is structured as a compilation of papers and has two parts: the overview and the papers. The overview is structured into five chapters. The first and current chapter, Chapter 1, introduces the research and outlines the research objectives. Chapter 2 provides a small literature review for each of the areas covered in the case studies. Chapter 3 describes the key theories underpinning the methodology used. Chapter 4 summarises the contributions and limitations of the current research, and Chapter 5 presents some reflections about current practices in the field and future work directions.

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Literature review

Unobservable factors are difficult to quantify, and sometimes even so complex that it is not clear how or what needs to be evaluated. Nevertheless, failure to control for unobservable factors results in biased estimates of the effects of the observed factors.

> *"The concern does not arise from the possibility of omitting relevant factors. This general criticism can be made of every empirical study. Rather, the concern arises from the widespread neglect of unobservable factors that strategic theory and empirical evidence highlight as central to the topic under analysis."* [Jacobson, 1990]

In what follows, I present the unobservable factors that will be the focus of the case studies. The topics were chosen by focusing on a mixture of presence in current public debates and critical importance in model estimation. Each of the topics is motivated by findings in the current literature and its importance for understanding travel user behaviour is highlighted, as well as identified needs in the state-of-the-art approaches to overcome current obstacles.

2.1   User preferences and rail-based modes

The term *rail factor* relates to the idea that public transport users frequently consider rail-based alternatives to be superior to bus systems, even in cases where quantitative hard factors, such as travel time, cost, availability, etc., are equal. This concept is frequently employed to express a higher attraction in terms of higher ridership of rail-based public transport in contrast to bus services. [Axhausen et al., 2001];[Ben-Akiva and Morikawa, 2002];[Vuchic, 2005];[Scherer, 2010];[Scherer and Dziekan, 2012].

Moreover, property developers often claim that metro investments increase the land values over and above what a bus system with equal capacity and travel times would. Hence, the *rail factor* argument is frequently used as a political instrument that makes decision makers prone to support rail-based public transport alternatives over bus services.

A higher preference for rail-based public transport modes is to some extent supported by studies in psychology, transport modelling and economics. For instance, [Eliasson et al., 2016] found that accessibility by metro increases the property prices of apartments in Stockholm more than accessibility by bus. In the transport field, [Axhausen et al., 2001] studied the effects of replacing old trams and tracks with modern busses within a section of the city of Dresden network. This study reported evidence to the contention that there is a rail bonus, but they also indicate that it might be small. [Ben-Akiva and Morikawa, 2002] explored differences in the preference for rail and bus services in two case studies. They found that there are systematic preferences for the metro alternative, followed by bus and commuter train. It is worth to highlight that whilst commuter train is a rail-based mode, it was found to be less preferable than bus alternatives, being quantitative hard factors ceteris paribus. [Scherer and Dziekan, 2012] includes a meta-analysis of German and Swiss studies focusing on user perceptions and mental representation of train, tram, and bus. They also conclude that there is a *rail factor* that is loaded with emotional and social attributions.

As previous studies show, the existence of the *rail factor* is widely accepted among experts. Nevertheless, little evidence exists about the reasons why public transport users have different preferences for different transport modes. From the evidence reviewed we see how differences are not linked to the modelled quantitative hard factors, neither to the fact that modes are rail-based per se, as we have seen evidence that bus alternatives

can be preferred over rail-based alternatives as presented in [Ben-Akiva and Morikawa, 2002]. Rather, differences in the perception of each particular transport mode seem to be highly loaded with emotional factors, based on experiences and habits, [Scherer and Dziekan, 2012]. Then, if travellers' preferences differ among public transport modes, the treatment of them as the same mode in transport models translates into biased parameter estimates and model predictions. Such bias would then propagate to all types of policy analyses including Cost Benefit Analysis. Hence, there is a need to develop a methodology to systematically test and implement differences in user preferences for a set of public transport modes, relating to observed and unobserved attributes in travel demand models.

2.2 Measurement errors

Measurement errors go hand in hand with revealed preference (RP) data. RP data are measurements of real-world behaviour from which it is possible to estimate underlying user preferences.

Measurement errors have been an object of study by researchers for a long time, and there is a large amount of literature on measurement errors, particularly within the econometric literature. For instance [Buzas et al., 2005] is a review article on measurement error where the authors describe different types of measurement error, their consequences, and potential solutions. Nevertheless, although considerable research has been devoted to measurement errors in the econometric literature, far less attention has been paid to measurement errors in discrete choice modelling and transport, [Walker et al., 2010]. Moreover, within the transport sector, measurement errors in the time and the cost variables are one major reason for collecting stated preference data for *value of travel time*[1] estimation, leading to other problems, such as reference dependence and gain-loss asymmetry. [De Borger and Fosgerau, 2008, Börjesson and Eliasson, 2014, Börjesson and Fosgerau, 2015, Hess et al., 2017].

Parameter bias due to measurement errors in input variables has been highlighted as a substantial problem in the appraisal of policy. "Measurement error is a type of endogeneity bias and disregarding the measurement error will lead to inconsistent estimates of the parameters" [Walker et al.,

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[1]The *value of travel time* is the trade-off between travel time and travel cost implied by a travel demand model,[Ben-Akiva et al., 1985].

2010]. For instance, there are reasons to expect that travel cost variables in transport demand models have substantial errors, which attenuate the cost parameters in transport models and lead to under-estimation of the response to pricing measures in appraisal.

In this thesis, as in [Walker et al., 2010]; [Díaz et al., 2015]; and [Vij and Walker, 2016], measurement errors are defined as the difference between the observed value of a variable, provided by the indicator, and the unobserved "exact" value, normally represented by a *latent*[2] variable. Hence, measurement errors are frequently unobservable, apart from rare exceptions where experiments are set-up to also collect precise measurements.

How measurement errors give rise to endogeneity is discussed extensively in [Walker et al., 2010, Díaz et al., 2015, Vij and Walker, 2016]. To reduce bias arising from measurement errors, statistical models that can accommodate errors in explanatory variables have become increasingly popular. These methods include but are not limited to the Control-Function method [Petrin and Train, 2003]; the Multiple Indicator Solution [Guevara and Polanco, 2013]; or the integration of Latent-Variables, [Walker et al., 2010]; and among them, the Hybrid Choice Model (HCM) is the modern workhorse in discrete choice analysis.

The first application of the HCM to account for measurement errors can be found in [Walker et al., 2010], where a latent variable approach is introduced to deal with error-prone travel times. Using the same methodology, [Varotto et al., 2017] investigate how the time parameter changes when accounting for measurement errors. Furthermore, [Walker et al., 2010, Vij and Walker, 2016] use Monte Carlo experiments to show that the estimated parameters converge to their "true" value as the model accounts for measurement errors in the input variables.

However, these studies do not treat cost variables as latent, or model more than one latent variable at a time; and, to date, no study on large-scale transport models has explored the extent of measurement errors in both, time and cost, dimensions simultaneously. These variables are particularly important in transport demand models as travel time and travel cost are key variables for deriving the *value of travel time*; hence, there is a need to expand the existing body of work to multiple variables and multiple indicators, as important biases could have not been detected.

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[2]Throughout the thesis, the terms *latent* and *unobserved* are synonyms.

2.3 Model misspecification

The use of HCMs has grown exponentially during the last decade. This situation is motivated not only by the capabilities of the model to account for measurement errors, but by findings from the social sciences that support that unobserved variables such as attitudes, norms, and perceptions can often override the influence of observable variables on disaggregate behaviour.

The problem is that to make HCMs operational requires several modelling assumptions, which include the specification of structural and measurement equations. See for instance [Walker et al., 2010, Varela et al., 2018b]. Through these assumptions, the modellers postulate theories in the form of statistical models and test how well the theories model the observed data. Frequently, and especially when working with real datasets, the postulated theories may not be accurate and result in misspecified models; hence, nearly all models are to some degree structurally misspecified, [Browne and Cudeck, 1992]. As a result, most of the ideal properties of the maximum likelihood estimator need not hold in the real world, [Bollen et al., 2007]. Following this line of reasoning, [Kolenikov, 2011] dealt with the problem of quantifying the degree to which parameter estimates in a Structural Equation Model (SEM) can be biased when structural relationships were not specified correctly and proposed a framework to assess the degree to which the parameter estimates may be biased.

Whilst thorough research in structural misspecification bias has been carried out in SEM, structural misspecification has been the focus of very little research in hybrid choice models. For instance, [Walker et al., 2010] used synthetic data to test the capabilities of the HCM framework to correct measurement errors in explanatory variables; and found that the HCM framework was able to accurately estimate the true value of the parameters without knowing the "true" travel time. Nevertheless, the estimated HCM was correctly specified and matched the formulation used for the data generating process. A more recent study [Vij and Walker, 2016] systematically evaluated the benefits of the HCM framework in comparison with a more traditional choice model without latent variables. In this study, the authors carried out a detailed analysis of goodness-of-fit and bias of the parameter estimates through different Monte Carlo experiments with synthetic data. Among these experiments, the HCM in experiment III had a misspecified utility function, whilst the HCM in experiment IV had misspecified structural equations. Unfortunately, the focus of those experiments was the

goodness-of-fit of the HCM compared to a reduced form mixed logit, and parameter estimates were not discussed, neither provided. Furthermore, in their discussion of measurement error bias, results from another Monte Carlo experiment were given, but the structural and measurement equations of the HCM tested were not only correctly specified, but also the structural equation included an extra parameter. In other words, the model tested was more flexible than the one used for the data generation. In their analysis, the hypothesis that the mean parameter estimates were equal to the true values could not be rejected.

Whilst these exercises provide useful insights into the HCM capabilities to correct for measurement errors, misspecification effects expected from the complexity of real datasets, where the specified HCM is not flexible enough to model the data generation process, might not have been captured. Hence, there is a need to investigate the extent of parameter bias in misspecified HCMs.

2.4 Modality styles and adoption of new mobility solutions

The concept of modality style describes the part of an individual's lifestyle that is characterised by the repeated use of a certain set of transport modes, [Krueger et al., 2018]. This manifested behaviour, the repeated use of a certain set of transport modes, has been hypothesised to reveal latent psycho-social constructs about the user, [Ohnmacht et al., 2009]; hence, if modality styles and user latent psycho-social constructs are connected, individuals with different modality styles are likely to have different reactions to policies and infrastructure initiatives aimed at changing users behaviour, [Vij et al., 2013]. Previous studies such as [Heinen and Chatterjee, 2015, Olafsson et al., 2016, Prato et al., 2017], to cite some, provided evidence that sustains the aforementioned hypothesis, and argued that it is important to understand how modality styles are distributed among the population to accurately evaluate possible responses to policy interventions. Furthermore, [Salomon and Ben-Akiva, 1983, Simma and Axhausen, 2001, Walker and Li, 2007] showed that modality styles impact mobility related decisions, independently of being long-term or short-term choices.

Modality styles can be modelled in different ways. For example, [Diana and Mokhtarian, 2009, Heinen and Chatterjee, 2015] used cluster analysis

based on a "multimodality index", [Molin et al., 2016] applied latent class cluster analysis, and [Vij et al., 2011, Vij et al., 2013] used a latent class model approach. [Krueger et al., 2018] went a step further, and explored the interconnections between modality styles and social norms; and proposed an integrated conceptual framework that combines elements of the two literature streams. In their framework, modality styles are hypothesised to be a function of normative beliefs, and observed behaviours a function of modality styles. The model structure is defined as a Latent Class and Latent Variables Model (LCLVM) and it combines latent class with hybrid choice models. Using this approach, they found statistical significance effect of normative beliefs in user modality styles, suggesting that soft policy interventions that appeal to individuals' normative beliefs have the potential to induce a modal shift, and they could be used as mobility management tools and for specific mode promotion, [Olafsson et al., 2016].

Nevertheless, all these studies focused on the interaction among observed behaviour, normative beliefs and modality styles within existing modes, and other latent psycho-social constructs, such as desires and expectations, were barely discussed. Inspired by the findings mentioned in the previous paragraph, the framework proposed by [Krueger et al., 2018] could potentially be used to explore the effect of other latent psycho-social constructs, such as user expectations and desires. These insights might provide important information to improve current mobility solutions as well as to help design future services. Understanding the factors that influence adoption intention for new services can help providers decide on the segmentation and positioning strategies, [Wang et al., 2008].

3

Theoretical framework

This section introduces, at a high-level, the fundamentals of neoclassical economic arguments underpinning the methodology used in this thesis.

3.1 Discrete choice analysis

To explain user behaviour we need to understand how users make choices. The basic problem analysed by Discrete Choice Analysis (DCA) is the modelling of choice from a set of mutually exclusive and collectively exhaustive alternatives, [Ben-Akiva et al., 1985]. Furthermore, the neoclassical microeconomics paradigm makes choices the central focus of mainstream economics, [Karlström, 2014], hence DCA is taken as the starting point.

DCA origins can be traced back to the late 20's, [Thurstone, 1927], with the axiomatic approach developed by [Samuelson, 1938a, Samuelson, 1938b] as cited by [Karlström, 2014]. Since then, tremendous progress has been made, with an explosion of transport related applications of discrete choice models starting from the 60's. Discrete choice model applications in connection with transport have focused on a broad range of topics. For instance, the estimation of the *value of travel time*, [DeSerpa, 1971, Jara-Díaz and Guevara, 2003, Fosgerau, 2006] , development of policy-sensitive models for market share predictions [Langbroek et al., 2017b], car-ownership models, [Jong et al., 2004, Kim et al., 2014a], residential location combined with

transport accessibility, [McFadden, 1978], travel satisfaction ,[Kim et al., 2017, Abenoza et al., 2017], mode choice, [Daly et al., 1990, Rich et al., 2009], etc. During this maturing process, discrete choice models have been incorporating findings from other disciplines, such as economic theory and psychology, that have expanded the capabilities of DCA. In what follows I present the core building blocks of DCA; rational behaviour, random utility and behavioural economics.

Rational behaviour

Under this new paradigm, it is important to understand that individuals are not trying to maximize the total satisfaction received from consuming a good or service, in other words, their utilities. However, if they adhere to a few regularity axioms, then they will behave *"as-if"* they were utility maximizers. Therefore for preferences to be representable we need them to be consistent and transitive. Consistent in the sense that if an user is presented more than one time with the same choice, he or she will always make the same choice; and transitive meaning that if alternative A is preferred to alternative B, and alternative B is preferred to alternative C, then alternative A is preferred to alternative C. This is known as the *"as-if"* assumption of neoclassical economics. In [Karlström, 2014] words,

> *"the beauty of this approach is that we do not have to know any-thing about what the decision process actually is, and what men-tal deliberation goes on inside the brains of individuals; as long as people have coherent and regular preferences, all we need to study is their choices."*

Finally, under this approach, it is assumed that preferences are fixed, so it is not within the power of the policy-maker to affect the preferences of individuals, [Karlström, 2014].

Random utility models

The concept of random utility was formalised by [Manski, 1977]. It is based on a perfectly rational individual, who always choose the alternative with the highest utility. The concept of random utility was born in order to solve the problem that not all decision makers have the same set of preferences, hence it is impossible to specify and estimate a model that will always succeed

in predicting the chosen alternatives for all individuals. These observed inconsistencies in choice behaviour are taken to be a result of observational deficiencies on the part of the analyst, [Ben-Akiva et al., 1985], resulting from:

1. unobserved attributes

2. unobserved taste variations

3. measurement errors

4. use of intrumental (or proxy) variables

In random utility, the true utilities of the alternatives are considered random variables, so the probability that an alternative is chosen is defined as the probability that it has the greatest utility among the available alternatives. The random utility concept is then formulated as follows: The utility of alternative j to individual n is U_{jn}, and it is fully known for the user that makes the choice. From the economic perspective, U_{jn} is an indirect utility function. In this way, individual n will choose alternative i if and only if

$$U_{in} > U_{jn} \, \forall \, i \neq j \tag{3.1}$$

Nevertheless, the analyst does not know, for each individual, neither all the variables that influence the choice nor the exact way on how they influence it. For this reason, the utility of an alternative is divided into two components. An observable part that we call V_{jn}, and an unobservable component that will be treated as a random error component, ε_{jn}.

$$U_{jn} = V_{jn} + \varepsilon_{jn} \tag{3.2}$$

The deterministic or systematic part of the utility, V_{jn}, is a function of observable attributes of the alternatives and socio-economic characteristics of the individuals. These observable variables are normally represented as x_{jn}, and this function will require for its calibration some parameters β_{jn}.

$$V_{jn} = f(x_{jn}|\beta_{jn}) \tag{3.3}$$

The majority of discrete choice models use linear functions in parameters to model the deterministic part of the utility, V_{jn}. Then, depending on the assumptions regarding the parameters, β_{jn}, and the error components, ε_{jn}, we will have different types of models. Further details regarding the assumptions behind each of the models used in this thesis are presented in Section 3.2.

Behavioural economics

Despite the consistent theoretical framework of DCA based on assumptions of rationality, we observe that individuals' choices sometimes deviate from predicted rational behaviour. In words of [Samson, 2014], the field of behavioural economics suggests that;

> *"Human decisions are strongly influenced by context, including the way in which choices are presented to us. Behaviour varies across time and space, and it is subject to cognitive biases, emotions, and social influences. Decisions are the result of less deliberative, linear, and controlled processes than we would like to believe."*

Behavioural economics can be described, in simple terms, as the field that tries to explain why consumer choices and actions deviate systematically from neoclassical economic assumptions of rationality, [Frederiks et al., 2015]. The origins of behavioural economics can be traced back to [Simon, 1955]. Nevertheless, it was not until the last two decades, when we have witnessed a surge of interest in behavioural economics due to its ability to "increase the explanatory and predictive power of economic theory by providing it with more psychologically plausible foundation", [Angner and Lowenstein, 2010]. Behavioural economics has been applied in diverse areas such as energy consumption, [Momsen and Stoerk, 2014]; low-carbon mobility adoption, [Schwanen et al., 2012]; or policy-making, [Dolan et al., 2010, Economides et al., 2012], just to cite some. In the field of travel behaviour, [Avineri, 2012] refers to the main findings of behavioural economics presented in [Dawnay and Shah, 2005]. These findings are:

1. other people behaviour matters,

2. habits are important,

3. people' self-expectations influence how they behave,

4. people are loss-averse and hang on to what they consider *"theirs"*,

5. people are bad at computation when making decisions,

6. people need to feel involved and effective to make a change

As evidence that users do not behave as complete rational individuals accumulates, it becomes apparent that the modelling of choices can be better addressed by incorporating theories and insights from behavioural economics into econometric frameworks, [Ben-Akiva et al., 1985]. As a result, behavioural economics has become a cornerstone piece of DCA.

3.2 Modelling unobservable factors in discrete choice analysis

This section provides an overview of the models used in the papers. In what follows, I present the key differences among the models, with a particular focus on their capabilities to model unobservable factors. For the interested reader, more detailed explanations and discussions about how to better estimate these models are available in the thesis papers, and the cited literature. [Ben-Akiva et al., 1985, Walker, 2001, Train, 2009, Vij and Walker, 2016].

Multinomial logit

The multinomial logit model (MNL) is a classification model that generalizes logistic regression to multi-class problems. In MNL models the utility of alternative j for individual n is normally expressed as

$$U_{jn} = V_{jn} + \nu_{jn} \tag{3.4}$$

with

$$V_{jn} = f(x_{jn}|\beta_{jn}) \ and \ \nu_{jn} \sim EV(i.i.d.) \tag{3.5}$$

where the disturbances ν_{jn} are:

1. Independently and identically distributed *(i.i.d.)*

2. Gumbel-distributed with a location parameter η and a scale parameter $\mu > 0$.

As explained in [Ben-Akiva et al., 1985], the assumption of a constant η for all alternatives, or $\eta = 0$, is not restrictive as long as each systematic utility, V_{jn}, has a constant term. Furthermore, the assumption that the term ν_{jn} is Gumbel-distributed is an approximation to the normal density used for analytic convenience.

However, the assumption that the disturbances are *i.i.d.* represents an important restriction, as it constrains all the disturbances to have the same scale parameter μ. This implies that the variances of the random components of the utilities are equal, and as we will see, this assumption might be difficult to defend in some situations.

As mentioned above, it is normal that all utility functions for the alternatives include a constant term, the alternative specific constant(ASC)[1]. The ASC amalgamates all the effects of the variables not explicitly modelled in the utility function. A high ASC is normally interpreted as a sign of a limited explanatory power of the variables in the utility function to explain the choice. Nevertheless, a symmetric interpretation when the value of the ASC is small cannot be made. A small ASC does not necessarily mean that all the variables that explain the choice have been included in the utility function; it can also mean that the variables not modelled will cancel each other out, in average.

The capabilities of MNL models to model unobservable factors are limited to the value of the ASC, and the β parameters.

Nested logit

The nested logit (NL) model is a generalization of logit that allows for a particular pattern of correlation in unobserved utility. This model is designed to explicitly capture the presence of shared unobserved attributes; hence a NL model is appropriate when the set of alternatives faced by a decision-maker can be partitioned into subsets, *nests*, in such a way that the following properties hold, [Train, 2009] :

1. For any two alternatives that are in the same nest, the ratio of probabilities is independent of the attributes or existence of all other alternatives.

2. For any two alternatives in different nests, the ratio of probabilities can depend on the attributes of other alternatives in the two nests.

The basic idea is to partition the universal choice set C into M mutually exclusive and collectively exhaustive subsets,*nests*, denoted by $C_1, ..., C_M$.

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[1]In practice, for identification purposes the ASC of one of the alternatives needs to be constrained to a fix value, normally zero,[Ben-Akiva et al., 1985].

Each alternative belongs to one and only one nest. That is

$$C = \bigcup_{m=1}^{M} C_m, \tag{3.6}$$

with

$$C_m \cap C_l = \emptyset, \ \forall \, m \neq l \tag{3.7}$$

For each individual n, the choice set C_n is partitioned into nests $C_{1n}, ..., C_{Mn}$, where C_{mn} is the intersection between the nest C_m and the individual specific choice set C_n.

The partition must be designed such that alternatives sharing unobserved attributes belong to the same nest. Once the nesting structure has been defined, the utility of alternative j in nest C_m can be expressed as

$$U_{jn} = V_{jn} + \varepsilon_{jn} \tag{3.8}$$

where the error term ε_{jn} has cumulative distribution:

$$exp \left(- \sum_{m=1}^{M} \left(\sum_{j \in C_m} e^{-\varepsilon_{jn}/\lambda_m} \right)^{\lambda_m} \right) \tag{3.9}$$

This distribution is a type of generalised extreme value (GEV) distribution. As explained in [Train, 2009], it is a generalisation of the distribution that gives rise to the logit model. In a logit model, each ε_{jn} is independent with a univariate extreme value distribution, but for this GEV, the marginal distribution of each ε_{jn} is univariate extreme value. However, the ε_{jn}'s are correlated within nests and uncorrelated among nests.

The parameter λ_m measures the degree of independence in unobserved utility among the alternatives in nest m. Thanks to the increased flexibility to model error components, among and within different nest, the degree of correlation can be explored. Hence, NL models solve one of the MNL model limitations.

Mixture models

Mixture models resolve the three limitations of standard logit by allowing for random taste variation, unrestricted substitution patterns, and correlation

in unobserved factors over time, [Train, 2009]. As a downside, by introducing flexible distributional forms, mixture models lose their closed form solution and need simulation techniques in order to be estimated. In what follows, I divided mixture models into two different categories to better explain their particularities. These are *mixed logit models* and *latent class models*.

Mixed logit models

In a Mixed Logit (ML) model the utility of alternative j for individual n is normally expressed as

$$U_{jn} = V_{jn} + \varepsilon_{jn} + \nu_{jn} \qquad (3.10)$$

with

$$V_{jn} = f(x_{jn}|\beta_{jn}) \; and \; \beta_{jn} = g(\lambda_{jn}) \qquad (3.11)$$

where β_{jn} is now a distributed parameter with probability distribution $g(\lambda_{jn})$; ε_{jn} is a random component that can have any functional formal, and ν_{jn} is an Extreme Value (EV) *(i.i.d.)* random component. Under this formulation, ML models can accommodate random preference variations through $g(\lambda_{jn})$ and unrestricted correlation patterns through ε_{jn}, whilst ν_{jn} adds tractability. The flexibility of ML model is better explained in [McFadden and Train, 2000], where the authors demonstrated that any random utility model can be approximated by a ML model.

Latent class models

Latent class models (LCMs) are a type of mixture models, where the mixing distribution $g(\lambda_{jn})$ is discrete, with β_{jn} taking a finite set of distinct values.

LCMs capture unobserved heterogeneity, and they can be used to represent different choice sets, decision protocols, tastes, model structures, etc.

Ordered models

Ordered models help us model responses that provide ratings of various kinds. The main characteristic of these type of variables is that the potential responses are ordered. For instance, a school performance rating of 4 is lower than 5 but is higher than 3. As explained in [Train, 2009], a standard MNL model could be specified with each potential response as an alternative. However, the MNL model's assumption of independent errors for each

alternative is inconsistent with the fact that the alternatives are ordered: with ordered alternatives, we expect an alternative to be similar to those close to it and less similar to those ranked further away.

Ordered models assume that the respondent has an opinion regarding the asked question. This opinion is modelled in an unobservable variable, U, where higher levels of U are associated with a higher position in the ranking, and vice versa. In terms of the school ranking example, a higher value of U represents that the person thinks the school is doing a better job and lower levels mean he or she thinks the school is doing a less better job.

The unobservable variable, U, is a continuous variable and can take many different values. Nevertheless, the question answer normally allows a few different categories; usually a five-point Likert scale, [Likert, 1932], is used. This means that even though the respondent's opinion can have many different values, the question allows only five possible responses. Then, we assume that the respondent chooses a response category on the basis of the level of his or her U, and a series of threshold values, which we label τ_k. The decision is represented as shown by Figure 3.1, where the threshold values, τ_k, will be estimated. Similarly to the MNL model shown above, the unobservable variable U can be decomposed into observed, V, and unobserved, ε, components.

$$U = V + \varepsilon \tag{3.12}$$

In this models, ε is also considered to be random. Hence the distribution of ε defines the probability of the different response categories. If we assume that ε is distributed logistic we have an ordered logit (OL) model.

Ordered models are especially helpful to model responses to attitudinal questions, as the structure of the model accounts for the ordinal nature of the indicators.

Figure 3.1: Distribution of opinion. Adapted from [Train, 2009]
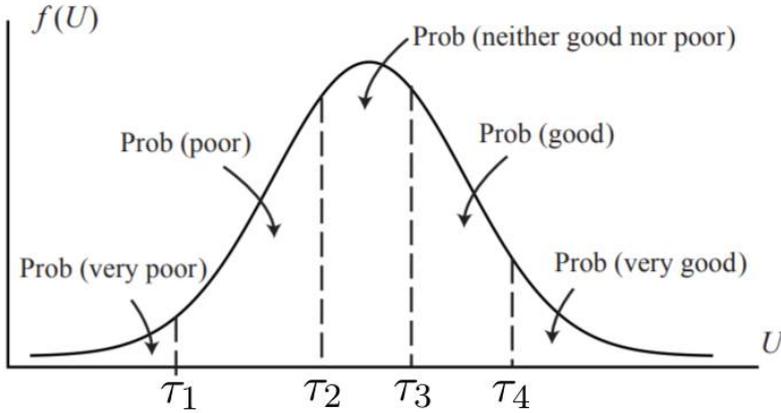
Hybrid choice models

Hybrid choice models (HCMs) appeared in the last two decades, [Walker, 2001, Ben-Akiva et al., 2002], and since then their use has exploded due to the great flexibility to model unobservable factors. The objective of this type of models is to explicitly model the choice behaviour relationships shown by Figure 3.2, [Ben-Akiva et al., 2002]. HCMs are motivated by findings in the social sciences, where evidence supports that latent variables (attitudes, norms, perceptions, etc.) can often override the influence of observable variables on disaggregate behaviour. In the past, the solid arrows in Figure 3.2 were mostly examined; now the dashed arrows have growing importance, [Ben-Akiva et al., 2002].

The quintessence of HCMs is that latent variables are modelled using observed indicators, which serve as proxies of the unobserved variables, and the estimated latent variables are added to the commonly used set of attributes in discrete choice models, [Kim et al., 2014b]. The framework for the HCM is depicted in Figure 3.3.

Making the HCM operative requires several modelling assumptions, which include; the functional form of the choice model, the definition of the structural equation for each latent variable, and the measurement equations. The functional form of the choice model refers to the type of model that will form the kernel of the HCM, types include the logit model, mixed logit, etc. The structural equation of a latent variable refers to the

Figure 3.2: Choice behaviour. Adapted from [Ben-Akiva et al., 2002]
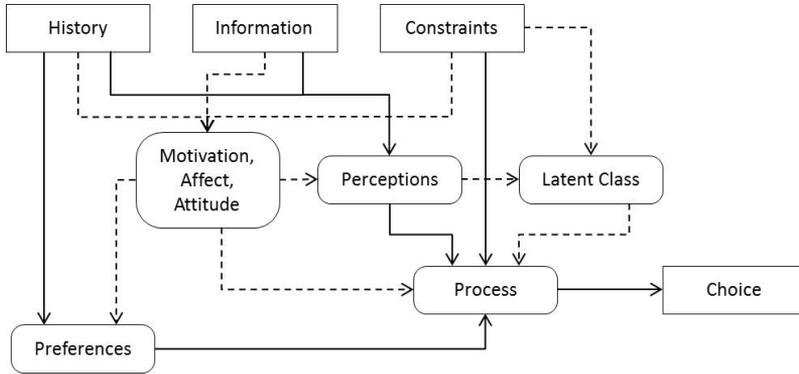
Figure 3.3: Hybrid Choice Model Framework. Adapted from [Walker, 2001]
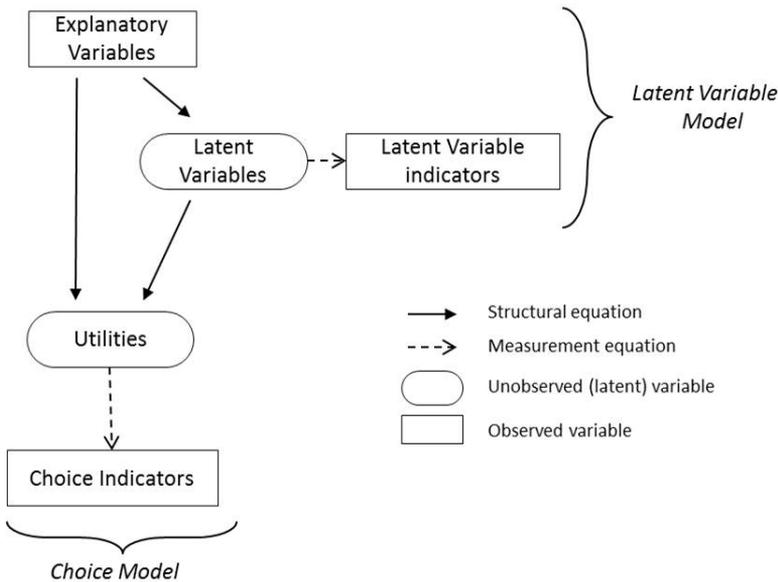
function that defines the components that build the unobserved attribute, the latent variable. Finally, the measurement equations link the value of the latent variable with the observed indicator. Through these assumptions, researchers postulate theories in the form of statistical models and test how well the theories model the observed data.

HCM can be used to model attitudes, correlations, norms, measurement errors, latent segmentation, etc. Due to their great flexibility, the HCM framework is the modern workhorse in discrete choice analysis.

4

Contributions

This chapter summarises the main contributions of the thesis to the current user behaviour/discrete choice research landscape. The thesis makes several contributions from a methodological and an empirical perspective.

Methodological

- *Paper I* provides a methodology to systematically test differences in preferences for a set of public transport modes, relating to observed and unobserved attributes, in state-of-practice large-scale travel demand models. The methodology tries to bridge the gap between academy and industry, hence it was designed with a focus on estimation speed and ease-of-implementation. It is based on simple models that are widely used by transport agencies all around the world, and have a closed-form solution for speed. The methodology was specifically designed to investigate the question of correlation among the random error of public transport alternatives and motivate the need to model, or at least test, whether different public transport modes should be modelled as different alternatives.

  Key differences between the proposed methodology and previous studies are that the proposed framework is designed as a systematic series of steps, and to make use of National Travel Survey (NTS) data. We

have chosen to use NTS data because it is a larger data set, conducted for many years in most countries doing transport modelling and appraisal. Moreover, countries conducting NTS surveys allocate large resources to the task and make sure that NTS data is representative for the population. Therefore, the methodology proposed offers a way to produce consistent comparisons, longitudinal and across different locations, to understand the evolution of the *rail factor* in time and space.

Limitations of the methodology in its current form include limited flexibility in the nesting structures that can be modelled, and in the evaluation of the effect of random preference variation. The case study used a Nested Logit model that has some limitations regarding the nesting structures that can be tested, but which has a probability with closed-form solution that makes the estimation of the large-scale models very fast. If desired, the methodology can be easily extended by using a Mixed Logit formulation that will allow any nesting structure and the evaluation of random preferences. The drawback, in this case, will be the increase in computation power needed, as Mixed Logit models do not have a closed-form solution, so the models will need to be estimated using simulation methods.

- *Paper II* developed a methodology to assess the magnitude of unobservable measurement errors in the input variables of large-scale travel demand models by latent variables. Parameter bias due to measurement errors in input variables has been highlighted as a substantial problem in the appraisal of policy. As a result, statistical models that can be used to accommodate errors in explanatory variables have become increasingly popular, but far less attention has been paid to the quantification of the measurement errors. The methodology developed in *Paper II* provides a framework to quantify the magnitude of the errors in input variables, and help identify the least reliable variables, aiding modellers to concentrate efforts where they are most needed. Another key contribution is that the methodology is also applicable in the case where only one indicator is available. This is an important advantage in the case of travel costs where it is normal to have a single indicator available. Said so, it is advisable from theoretical and empirical perspectives to use as many indicators as possible, when available.

Furthermore, the methodology shows that modelling measurement errors as factors, rather than absolute values, makes the estimated measurement error distributions directly comparable among indicators and variables, even when the variables are in different units such as time and cost. Moreover, we show that estimated parameters of the choice model are impacted by the modelling assumptions of the structural and measurement equations; and how a multiplicative error formulation can be applied to any variable which has support only on a semi-infinite interval, such as time, cost, income, etc.

A drawback of using advanced models such as the HCM formulations presented in this methodology is the increased difficulty to deal with confounding effects. For instance, the interaction between taste variations and measurement errors in the input variables remains unknown. In *Paper II* we defined measurement error as the difference between the observed value of a variable provided by an indicator, and the value of the latent variable. This definition is the same as in [Walker et al., 2010, Díaz et al., 2015, Vij and Walker, 2016]; nevertheless, in reality, this is a simplification, since the latent variable does not necessarily reflect the "true" value but only the one that the travellers perceive. Hence, the difference between the observed and the latent variables includes a measurement error but actually also the respondent's perception error. Note also that the perceived travel times reflected in the latent variables are different from the reported times that we use as one of the indicators. In the latter variable, there are also reporting errors. Hence, the more flexibility we build into our models the higher is the risk of undesired interactions, which are dangerous for two main reasons; first, we do not know their magnitude and second, data to help us evaluate them it is very scarce.

A second limitation of this methodology is the impossibility to estimate systematic measurement errors. Hence, it is not possible to make any claim about whether indicators are prone to over or under-predict the "true" values of the variables.

Another challenge derived from using HCMs is the lack of a robust framework to test the model performance. Results of traditional goodness-of-fit measurements, when used to evaluate HCMs, are only informative under special circumstances. Then, if modellers are not careful, goodness-of-fit measurements based on the final model

log-likelihood might yield counter-intuitive results. For instance, the Bayesian information criterion (BIC), [Schwarz et al., 1978], and the Akaike information criterion (AIC), [Akaike, 1974], might yield counter-intuitive results if used to compare models with different numbers of latent variables or indicators. Nevertheless, BIC and AIC results are consistent when comparing models with an equal number of latent variables and indicators.

Empirical

The following findings add to the empirical body of knowledge regarding user behaviour analysis in the areas of attitudes, norms, perceptions and preferences.

- *Paper I* finds that there are preference differences among public transport modes used for commute trips in Stockholm. Regarding the existence of a *rail factor*, findings support the hypothesis that rail-based modes have in fact a smaller time parameter (train) or higher alternative specific constant (metro), indicating that rail modes are preferable to bus, ceteris paribus. Surprisingly, we find no evidence for differences proportional to the in-vehicle time between bus and metro. Results also show that the *value of travel time* for train is lower than for bus and metro, and that it is higher for *auxiliary modes*[1] than for the main mode. This finding is interesting as normally the estimated *value of travel time* for train is higher than for bus and metro. Higher values of time for train are normally attributed to a self-selection effect, as the standard way of estimating the *value of travel time* is to use stated choice experiments to estimate car *value of travel time* on car drivers, bus *value of travel time* on bus users, and train *value of travel time* on train users. Then, the self-selection will impact mode differences because travellers with low marginal utility of income and high resource *value of travel time* for the trip under study will tend to choose faster but more expensive trips and vice versa. Because of self-selection train travellers (faster but more expensive) will often have higher *values of travel time* than bus users (slower and cheaper). This is also what is

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[1] *Auxiliary modes* are modes used during a multi-modal trip that are not the main mode. The main mode in a multi-modal trip is the most used for the longest distance, see *Paper I*.

found in the Swedish Value of Time study [Börjesson and Eliasson, 2014]. Nevertheless, the methodology in this thesis allows us to remove the self-selection effects when estimating the values of time for the different PT modes. As a result, we observe how the estimated value of time for PT modes is lower for train and higher for bus, in agreement with a priori expectations. Also, we find the dis-utility from auxiliary in-vehicle time to be highest for bus, and similar for metro and train.

Furthermore, we can reject the hypothesis that the PT modes have the same random error. This implies that, as long as we use MNL models, the model assuming that the public transport main modes are different alternatives outperforms the model assuming that they are the same alternative. In addition, we observe how the nested model outperforms the logit model with an identical utility specification, indicating that the error components of the PT alternatives are in fact correlated, confirming also a priori expectations.

- *Paper II* shows that parameter estimates differ substantially between models that account for measurement errors in explanatory variables and those that do not. Also, the estimated time and cost parameters depend on the modelling assumptions of the HCMs. I consider this finding particularly important, as other HCM applications in recent studies only consider one set of modelling assumptions without questioning whether they are adequate or not. Hence, we can increase the performance of our models, and our understanding of the magnitude of the error in the input variables, by testing different modelling assumptions of the latent variable distributions and the measurement error formulation. Also, we find that price elasticities for the HCM model, after accounting for measurement errors in time and cost variables, yield higher elasticities that a MNL model with an identical specification of the utilities. This finding is consistent with the results from [Varotto et al., 2017]. Also, our results indicate that when not accounting for measurement errors in the input variables, the estimated *values of travel time* based on revealed preference data are too high due to large measurement errors in the cost variables, which attenuate the cost parameter more than the time parameter in transport models. This leads to under-estimation of the response to pricing measures in appraisal.

Moreover, results suggest that measurement errors in our dataset are larger for the travel cost than for the travel time, and that measurement errors are larger in self-reported travel time than software-calculated travel time for car-driver and car-passenger, and of similar magnitude for public transport. Among self-reported travel times, car-passenger has the largest errors, followed by car-driver and public transport, and for the software-calculated times, public transport exhibits larger errors than car.

- Results from *Papers II* and *III* show that a multiplicative error formulation provides a better fit to the observed data for time and cost variables. The multiplicative error formulation seems particularly suitable for modelling travel times, as psychological research has found evidence suggesting that reported travel times follow a power function of the clock time, [Roeckelein, 2000]. This empirical finding is particular to the datasets used for the analysis, and a priori it is not possible to know for any given dataset whether the multiplicative error formulation will provide a better fit.

- *Paper III* shows that HCMs, even if misspecified, manage to recover better parameter estimates than simpler models such as a MNL when the input variables suffer from measurement errors. Another interesting finding is that all models tested, MNL and HCMs, seem to be able to isolate the source of the measurement error, and prevent the propagation of the bias to other parameter estimates. Furthermore, results show that parameter estimates of the choice model are robust to modelling assumptions of the HCMs. In terms of out-of-sample prediction accuracy, a simple MNL performed better than any of the more advanced HCM formulations.

- *Paper IV* finds that normative beliefs impact user decisions regarding mobility styles. In the particular case study examined, regarding a cMaaS solution, we find that "environmental mindset", "high expectations for the MaaS system", and "car affection" variables increase the explanatory power of the model. We also found evidence that supports the existence of a car ownership to car usership trend, as the majority of respondents in both classes expressed their interest in getting access to a car without owning one, and pointing out that car ownership costs are the key variable explaining this attitude. This

trend can lead to a reduction of congestion and driven kilometres due to a smaller number of privately own cars. Furthermore, we found that the need and feeling for flexibility is of paramount importance, and needs to be addressed for users to embrace a MaaS solution. Regarding user's preference to share a car journey with people they do not know, we observe two opposite trends suggesting that it might be appetite for both types of solutions, where users could choose between *private*[2] or shared journeys by car.

Limitations of these findings focus on the ability to extrapolate the results to a wider population, as the characteristics of the experimental setup, infrastructure and population demographics, might not be representative in other situations. For instance, the study was conducted among employees of a company that is implementing a cMaaS. These users have stable travel patterns for commute and intra-campus trips, as well as similar socio-economic variables in terms of education level, which has been shown that influences your environmental attitudes, [Scott and Willits, 1994, Tikka et al., 2000]. Furthermore, the cMaaS system only has one provider, the employer, which owns and operates all modes.

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[2]In this context, private means that the car journey is not shared with strangers, but does not necessarily imply that the car is privately own.

5

Reflections and future work

In addition to the contributions presented in Section 4, this chapter discusses current practices in the transport science field that sparked critical thoughts, as well as future research directions. The views and opinions expressed in this section are my own and do not necessarily reflect the position of any of my paper co-authors or supervisors.

Reflections on current DCA model analysis

In what follows I discuss some limitations identified on current practices within the DCA field, as well as potential benefits that could be achieved if such practices were updated.

Standardised model elasticities

An important part of the econometric analysis of user behaviour are the derived model properties that inform policy analysis, such as elasticities. In *Papers I* and *II*, a review of model elasticities was performed in order to compare the obtained results with currently accepted values. During that review, it became obvious the difficulty of comparing elasticity values, not only because people in different places have different preferences, the β parameters, but also because the variables associated with those parameters were different. So we were comparing elasticities among different things.

For instance, cost variables used in mode choice models can include different elements; One model might use the full cost, including vehicle depreciation, taxes, etc., whilst another model might include only fuel costs or fuel and congestion charge costs. The possible combinations of cost components to create the cost variable are nearly infinite. Then, how the cost variable is calculated will impact the estimated cost parameter which in the end will modify the model elasticities. Different studies will be interested in looking at the model elasticities in connection with a particular custom variable, and they can still do so in their particular application. Nevertheless, I feel that it might be useful to define a common framework where variables are defined consistently across studies. This *"variable standardisation"* will help to compare results across models, and might prove useful in identifying further data insights.

Goodness-of-fit of hybrid choice models

Another difficulty that became apparent during the studies of this thesis was the lack of a common framework to analyse the goodness-of-fit of advance DCA models, such as the models with latent variables used in *Papers II, III* and *IV*. This challenge is not particular to the DCA field, hence there is potential for DCA models to benefit from current practices in other fields. For instance, machine learning classification models have similar needs in terms of model performance evaluation. A common practice in machine learning classification models is to use out-of-sample[1] prediction metrics to evaluate model performance. I consider this a good practice that should be adopted at the core of DCA, especially when using advance models such as the HCM. Furthermore, out-of-sample model metrics might be useful not only to compare model performance but also to identify model over-fitting. Model over-fitting occurs when the estimated model is so flexible that "memorise" the data, risk that increases with advance DCA models such as the HCM. A model that over-fits will provide good estimations if evaluated on the data that was used for training the model but will struggle to perform at the same level when evaluated with a different dataset. At the moment, analysis of model over-fitting when using advance DCA models

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[1]Out-of-sample means to evaluate the model using a different dataset, a test set, to evaluate the model performance. When a test set is not available, the train set is normally split in two

is not receiving the attention that it deserves, and including this discussion might help generalise discrete choice model results.

Future work

In addition to the areas identified in the first part of Section 5, advances in connected fields, such as data collection, data privacy, or the need to evaluate future transport solutions, highlights the need to update current DCA models in order to cope with the challenges ahead. In what follows, I speculate on the future directions that are likely to prove fruitful in the near term.

New data sources

An issue that advance DCA models currently face is the need for high amounts of data in order to provide accurate forecasts for transport policy development. Nevertheless, [Prelipcean, 2018] highlights current trends on traditional survey response rates in Sweden, where the response rate of the national travel behaviour survey has dropped from 78% in 1994, via 68% in 2006, to 38% in 2015, [Trafikanalys, 2016], increasing the effective cost of surveys but more seriously raising concerns of bias. This problem is noted in Trafikverket's development plan chapter 7.2 Future forecast models, [Trafikverket, 2017]. This decrease in traditional paper and pencil surveys makes necessary new passive data collection techniques, [Prelipcean, 2018].

Due to the high market penetration that smartphones have, most of the new passive data collection techniques rely on smartphone data. Mobile phones can provide large amounts of data, with high accuracy, about positioning, timestamps, acceleration, etc., on an individual level resolution. These data from sensors will differ from our traditional data in multiple dimensions, such as type and volume of data. Hence, models need to be re-designed to extract the most useful information from the new data types, and estimation methods updated in order to cope with the new data volumes.

Furthermore, the focus of current legislation on data privacy and security will impose additional challenges. For instance, the new legislation in Europe, *"General Data Protection Regulation"*, [European Union, 2016], makes necessary the need to anonymise the collected data.

Nevertheless, in transport applications, particularly when working with trajectories, even individual level anonymised data might still provide sensitive information that violates data privacy laws. Hence, in order to provide the required data protection, data aggregation might be necessary. In that case, the data resolution might force modellers to infer some variables that are available in the data from surveys used today, such as origin and destination addresses or chosen travel mode. Therefore models will need to be able to account for these limitations in the input variables.

Discrete choice analysis, machine learning and economic theory

Machine learning methodologies that can extract the most information from big data are experiencing a boom. Currently, machine learning methodologies such as decision trees or neural networks are seen as a black box where model parameter interpretations do not have an economic meaning. Hence, another promising field is to investigate how econometric theory can be built into these methodologies. In this regard, some studies are starting to make the first baby steps, [Brathwaite et al., 2017, Van Cranenburgh and Kouwenhoven, 2018].

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