Understanding the Decision-making Process of Discrete Choice Modellers: One database but many workflows

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Discrete choice modellers usually involve a mixture of formal behavioural theories and statistical methods with their own judgements to do their research. Therefore, choice modelling is often considered an art and involves several phases in which the choice modeller must make numerous decisions, large and small, from what method to use in data collection, how to specify and estimate the model to how to interpret the outcomes.

The multiple ways of carrying out the phases of the descriptive analysis, modelling specification, estimation process, and outcome comparison across models account for the variability of workflows in the field of discrete choice modelling. Moreover, the decisions made by those involved, motivated by their theoretical knowledge, subjective judgements and the methodologies considered, lead to a trial-and-error process that could lead to different outcomes. This situation creates a non-transparent environment that complicates the understanding of both the underlying data generation process and the factors influencing the choice situations studied.

A recent line of research has developed optimization algorithms that assist in the modelling process by providing model specifications subject to goodness-of-fit constraints (Paz et al., 2019; Ortelli et al., 2021; Beeramoole et al., 2023). However, these algorithms have certain limitations such as (i) focusing on few random utility maximization models, which avoids the exploration of other decision rules; (ii) not reflecting the actual choice made by modellers by neglecting their subjective judgments, other criteria, and prior knowledge consistent with the literature; (iii) not addressing the need for pre-processing the choice database; (iv) nor being capable of replacing variable selection to be included in the algorithm, potentially including variables that are not causal to the actual data generation process. Therefore, these efforts do not help to resolve the remaining uncertainty about the "degrees of researcher freedom" (Simmons et al., 2011) within this field and how "forking paths" (Gelman and Loken, 2013) can influence the results or interpretations that can be obtained from a specific investigation, and even from the same database."

To close this gap, this study aims to analyse the workflows inherent in discrete choice modelling. This paper focuses on the collection and analysis of the sequential decisions made by discrete choice modellers from the reception of a particular research question and database to the selection of the most appropriate model according to their criteria. A serious game design and implementation within the discrete choice modelling community is conducted. These games are used as learning tool, as they provide immediate feedback to players about decisions they have made, allowing participants to see the consequences of their choices in a more didactic way to improve their decision-making skills (Corti 2006; Squire, 2003). Indeed, the proposed serious game will allow us to collect evidence and capture all the sequential decisions respondents make to understand their behaviour throughout the process (van Dijk et al 2021).

Methodology and data collection

In the spirit of Silberzahn et al. (2018) and Botvinik-Nezer et al. (2020) methodologies, the serious game starts by providing a contextualisation of the study, a stated preference database based on an actual study together with an ex ante hypothesis to investigate (name omitted for research purposes). Subsequently, participants will be faced with five blocks representing some modelling phases, such as "Descriptive Analysis", "Model Specification", "Estimation Outcomes", "Outcomes Validation", and finally, "Model Selection". It is important to note that respondents will be able to iterate through each block as many times as they deem necessary before moving on to the next, thus capturing the intrinsic trial-and-error phenomenon of the process.

Using the sequence of decisions, it will be possible to identify the methodologies carried out in each of the phases of the modelling process considered, and the time and number of iterations will be able to account for the importance or complexity of each of them. We hope to analyse the relationship between the model selection results reported by modellers and the analytical decisions taken. This will allow us to shed light on the most significant methodological decisions at each stage of the process, highlighting which specifications are considered, and allowing us to analyse individual differences between participants and how the workflows performed by the modellers lead to different results or different interpretations. In addition, this data would allow us to compare the specifications considered consistent by the modellers with those delivered as a solution of the two-stage optimisation algorithms.

Work in progress

The proposed serious game design is ongoing, we are considering the most relevant methodologies of the modelling phases mentioned above. Mainly, we are focused on including the specifications of the different families of models that can be estimated from the analysed choice situation. The pilot test of the experiment is planned to be carried out in the coming months. At the conference, we intend to present an overview of the multiple results that emerge considering different workflows and how they affect policy implications.

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