

Game and Choice Based Simulation

The design of a methodological framework using the case of the Physical Internet inspired “Freight Transportation Game”

S.J. Caminada¹

¹ Faculty of Technology, Policy and Management, Delft University of Technology

Abstract

Serious games have the potential to be used as an innovative data collection method. Combining this with Discrete Choice Modelling (DCM) could create a methodology that provides insight into the player's behaviour and allows for creating a realistic simulation. This innovative Game and Choice Based Simulation (GCBS) methodology has been conducted and evaluated using the case of the Physical Internet inspired “Freight Transportation Game”. The bidding behaviour of players is analysed using DCM. Using the insights obtained from the estimated choice model, a decision support tool for carriers is defined as a policy to optimise the system's performance. Hereafter, the DCM is implemented into a simulation based on the gameplay, creating a realistic simulation of the PI inspired transportation market. By conducting a simulation experiment with this innovative simulation, the policy could be successfully evaluated. Considering this case of application, the GCBS methodology proved its potential. Using insights obtained during the research, a framework for GCBS has been designed explaining when and how to conduct the methodology. More research needs to be done to test the (external) validity of the decision support tool and to test and extend the methodological framework in order to increase its robustness.

Keywords: Serious Gaming, Discrete Choice Modelling, Simulation, Collecting Choice Data, Physical Internet, Freight Transportation Market, Decision support tool

1. Introduction

When designing in socio-technical systems, developing products and services, or creating policies, a profound understanding of user behaviour, user demand, and the user response is desirable. What are the best business models for upcoming new technologies as bike-sharing and electric vehicles? Buy, rent or lease? Do people prefer price over range or travel time over comfort? And what is the effect of tax breaks, free services and other regulations on the purchasing behaviour of people? All these types of questions are relevant in the numerous sectors. From transportation and logistics to energy and environment, from marketing to business administration, and from health to political science. To cope with these questions, quantitative, statistically rigorous answers, beyond psychology are needed (Chorus, 2018). Herefore, choice models are used to understand and be able to

forecast (new) systems and predict the effects of policies. In the western world, choice models form a crucial pillar on which transport models and policies are built (Chorus, 2018).

Conventionally the choice data by which the choice models are estimated is collected using two methods (Krabbe, 2016). At first, the data is often gathered by observing choices in real life, so-called Revealed Preference (RP). Secondly, choice data is often retrieved by conducting advanced surveys; the so-called Stated Preference (SP) method. RP data portrays the world as it is, with all its complex and human interaction, and therefore usually results in reliable and valid choice data. However, because of these interactions, inherent relationships between attributes occur in the RP data. Additionally, the effect of non-existent or future alternatives can not be observed using RP and often only one observation per respondent is possible, making it a time-consuming method (Louviere, Hensher, & Swait, 2000). On the other hand, using

SP surveys, the effect of nonexistent alternatives can be studied, relationships between attributes can be controlled by the design of the survey and multiple observations per respondent is possible Louviere et al. (2000). However, because the recorded choices are only based on (perfect) information provided by the survey, complex interactions between individuals and their environment are neglected, and consequences of (nonexistent) alternatives are not felt. Therefore, respondents may show other behaviours than they would show if the choices were made in real life.

A solution to the drawbacks the RP and SP data collection methods could be found by using an innovative data collection method: Serious Gaming. In Serious Games, a simplified representation of a complex (future) reality can be created (Duke, 1975) in which the human factor and dynamic relationships are addressed (Bradley, Hax, & Magnanti, 1977). Herewith choices are made in a real-life inspired experimental setting with interacting players and changing in-game environments. Additionally, nonexistent alternatives can be included, and multiple observations per individual are possible. This way of collecting data, therefore, has the potential to form a more valid and reliable method than SP and a more accurate and time-efficient method than RP.

By estimating a discrete choice model (DCM) based on this collected game data, insight into the behaviour of players can be obtained. Additionally, the estimated choice model could be implemented into a simulation model that is based on the game. Herewith a simulation with modelled human decisions is conceived, creating a realistic simulation that incorporates the human dynamics of the system it represents. So, herewith a gaming model of the real world is used to estimate a discrete choice model, which is then implemented into a simulation model to create a realistic simulation of that same world. Eventually, the simulation model offers new possibilities for conducting experiments in a time-efficient and isolated way.

However, little is known about this methodology of combining serious gaming and DCM. To the best of the author's knowledge, only Karampelas (2018) ones used DCM to create a simulation based on a serious game. However, his work focussed more on the multi-model approach (gaming, simulation and optimisation). Although his insights are used, the conducted research described in this paper focussed more on the methodological combination of serious gaming and DCM, which will be further referred to as Game and Choice Based Simulation (GCBS). To create more knowledge, experience and to evaluate this innovative GCBS methodology, a methodological framework for GCBS is designed using a combination of qualitative research, and a performed modelling study that uses the GCBS methodology. This paper will present the main findings and insights of this research. Eventually, this paper can act as structured guidance and example for further research using GCBS methodology.

The game that is used to apply the GCBS methodology on is the Physical Internet (PI) inspired "Freight Transportation Game". The current world of transport and logistics is inefficient and unsustainable (Montreuil, 2011). The innovative future concept of a decentralised, PI inspired, transportation market has the potential to increase efficiency and sustainability within the transport and logistics sector (Ballot, Montreuil, & Meller, 2014). To research the dynamics and performance of this non-existing market, the "Freight Transportation Game" is developed at MINES ParisTech - PSL (Lafkihi, Pan & Ballot, 2019). Experiences with game sessions show that the players behave sub-optimal, and the potential of the market can be utilised better. A DCM based on the game data is created to gain insight into the behaviour of players. Using these insights, a policy to optimise the behaviour is defined and tested in an experiment. The experiment is conducted using a simulation that is based on the structure of the gameplay, at which players' behaviour is imitated through the DCM. One could argue that experiments could have also be conducted by playing the game. However, for this research, it was chosen to use a game and choice-based simulation, because the aim was to create more knowledge about the innovative GCBS methodology. Additionally, DCM provides more insight into the attributes that affect people's decision making, which helps to find and endorse a policy that can improve this behaviour. By creating a simulation based on the game, a clean (*ceteris paribus*) comparison in performance between different settings of the simulation can be made as well. Finally, more game rounds can be simulated than in a typical game session, and multiple games can be simulated in far less time than by playing the game in real life.

This paper will have the following structure. In chapter 2, the conducted research approach is explained. Hereafter, in chapter 3, a brief overview of background literature is presented. In chapter 4, the first design of the methodological GCBS framework is described. This contains the opportunities of the methodology and a structure for conducting it. In chapter 5, the context and motive of the game are elaborated on. Additionally, the fit between the GCBS methodology and the application case is motivated. In chapter 6, the conduction of the GCBS methodology on the "Freight Transportation Game" is described. Based on the insights of chapter 6, the methodological GCBS framework of chapter 4 is evaluated and adjusted in chapter 7. Finally, in chapter 8, the conclusion and recommendations of the research are given.

2. Research Approach

In order to create the design of a methodological GCBS framework, design requirements are defined based on general methodological characteristics, as stated in the work of Ishak, & Alias (2005). The design requirements are determined as follows; the methodological GCBS framework should:

1. Provide insight into the opportunities of the methodology.
2. Help to provide insight into the behaviour of players.
3. Provide structured guidance on how to conduct the methodology.
4. Contribute to the creation of a valid game based discrete choice model.
5. Help to create a realistic simulation based on the gameplay, including human behaviour.
6. Use a combination of serious gaming, DCM and simulation.

Using these design requirements and based the argumentation of the introduction and a literature review on, a first design of the methodological framework is created. Hereafter a modelling study that uses the GCBS methodology is performed. Using insights obtained from this modelling study and by evaluating the first framework, eventually, an improved, final framework is created.

So, the final design of the methodological GCBS framework is to a significant extent based on insights obtained from applying the GCBS methodology on the case of the "Freight Transportation Game". For this modelling study game data and discrete choice, modelling is used to analyse the behaviour of players. Together with practical and theoretical knowledge, this formed the basis of a new policy that could optimise the system's and the player's performance. Hereafter, the policy is tested in a simulation experiment. Therefore, a simulation based on the gameplay is created (GCBS), at which DCM is used to include the current behaviour of players. Eventually, the generated results of the simulation experiment show to what extent the policy is a success.

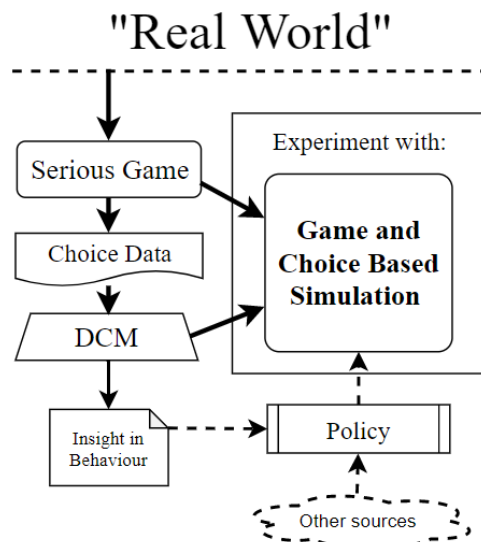


Figure 1, Conducting the GCBS methodology

3. Background literature

3.1 Data collection methods for DCM

Discrete choice modelling is focused on explaining choice behaviour. By using the modelling technique, the relative

merit of a phenomenon can be computed as it makes it possible to estimate the relative importance of these attributes and even to estimate overall value for different combinations of attribute levels (Krabbe, 2016). DCM is applicable when individuals can choose between two or more distinct ("discrete") alternatives. Because this conceptual requirement is common in our daily life (everyone makes choices between distinct alternatives every day) and because of its explanatory and predicting power DCM is a popular method used in all kinds of sectors. As mentioned in the introduction, conventionally the choice data by which the choice models are estimated is collected using two methods; RP and SP (Krabbe, 2016).

Using RP, choices are observed in a real-world context, herewith complex interactions between individuals and their environment are taken into account. This usually results in reliable and valid data. However, these interactions also cause a lot of inherent relationships between attributes making it hard to predict uncorrelated parameters. Using the carefully designed experimental surveys that usually form the basis of SP data, the correlations between attributes can be controlled by design, making it easier to estimate values for independent attributes. Additionally, SP is normally a much less time-consuming data collection method as taking a survey is easier than observing the behaviour and multiple choices can be observed per respondents. As has been argued in the introduction, using serious gaming data for discrete choice modelling could be an elegant method to combine the advantages of both RP and SP. By being a more valid method than SP and a more accurate and time-efficient method than RP.

The use of serious games or simulation games is a rather new but commonly used method in the field of transport and logistics (Kourounioti, Kurapati, Lukosch, Tavasszy, & Verbraeck, 2018). Within these games, players have the objective to win the game by managing their limited resources within the boundaries of certain rules (Greenblat, 1975). Simulation games are valuable as they provide the opportunity to effectively study complex systems that are future-oriented (Duke, 1975). Compared to experimenting in reality, gaming is a relatively easy and cheap way to study and experiment with a problem. Additionally, it makes a particular phenomenon more visible for observation and allows for the design of controlled experiments in a safe environment (Kurapati, Kourounioti, Lukosch, Tavasszy, & Verbraeck, 2018). An advantage compared to simulation model and an analytical model is that games take into account part of (important) human interactions that exist in the real world (Bradley et al., 1977). A digital game could be a potential source of loads of quantitative data (Lukosch, H. K., Bekebrede, Kurapati, & Lukosch, S. G., 2018). This data can be used to model the decisions of players as has been proposed by Kourounioti et al., (2018).

So, herewith serious games can obtain a new valuable function as a data collection instrument for discrete choice modelling, helping to analyse and simulate behaviour. The characteristics of this new Player Preference (a notion created for this research) data collection method in comparison to the RP and SP methods are summarised and compared in Appendix A.

3.2 Models

As mentioned before, using and creating models is central to the conducted research. A Discrete Choice Model is used to gain insight into players' behaviour and makes it possible to create a realistic simulation model, including human behaviour. The basis of this all is a serious game that in itself is also a model. The resulting innovative Game and Choice-Based Simulation is visualised in terms of modelling types in Figure 2, based on the modelling typology of Bradley et al., (1977). Using the GCBS methodology a game is used, based on the (future) real world (1), hereafter a DCM is created based on choice data of the game (2), then a simulation based on the structure of the gameplay is made (3) at which the DCM is used to imitate the behaviour of players (4). In this way, the human decision-maker is part of the simulation (in contrast to a conventional simulation) creating a modelling method with an increased degree of realism. So, a game and choice-based simulation can be seen as more realistic simulation type which retains its time efficiency quality.

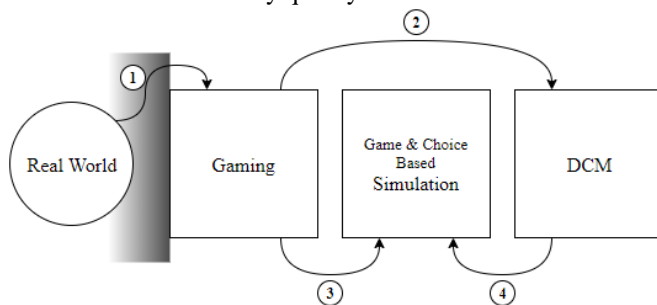


Figure 2, GCBS in terms of modelling types

4. First methodological GCBS framework design

Based on the argumentation of the introduction and the information of the background literature, a first version of the methodological GCBS framework is created. This design is focussed on requirements 1 and 3 of Table 1. So, it contains an elaboration on the opportunities if the GCBS methodology and a structure for conducting it.

4.1 Opportunities of the GCBS methodology

Gaming makes it possible to collect data with a so-called Players Preference method, which forms an alternative to the conventional RP and SP methods. The player preference method yields advantageous characteristics of both other methods. At first serious gaming makes it possible to gather

data about human behaviour validly and reliably as players, to a certain extent, feel connected to the system situation the game is representing. Additionally, a serious game takes into account interactions between people and their (game) environment. Especially when these interactions are important for the decision-making process of people, it should be included in the data collection method. Secondly, using the player preference method accurate data can be gathered in a time-efficient way. Because a serious game makes it possible to control the environment in which choices are made, a more experimental setting than real life is created. This makes it less likely that disturbing inherent relationships in the data occur, resulting in accurate data collection. A controlled setting also means a possibility to observe and analyse the behaviour in future environments, or real-life behaviour that is hard to observe in an efficient way (costly and complex). Using serious games, especially a digital one, multiple choices per player per round can potentially be collected and transformed into usable data, making it much more efficient than RP and when using digital games maybe even faster than SP.

By estimating a DCM based on a player preference data collection method, quantitative and statistically rigorous insight into the choice behaviour of these players can be obtained. This will help to obtain a thorough understanding of the system being analysed. Additionally, the insights could form a basis for a policy or intervention that could optimise the performance of human behaviour and the system.

Finally using the estimated DCM a realistic simulation based on the gameplay, including human behaviour, can be made. The ability of DCM to predict choices can be used to simulate human choice behaviour. Because a game is already a model of reality, a simplified structure of the system is given already. This makes it relatively easier to construct a simulation. Eventually, based on the structure of the game and the estimated DCM, a realistic simulation of the (future) real world can be created. This simulation then makes it possible to quickly test and evaluate interventions or policies in a simulation experiment. With this experiment, a clean (*ceteris paribus*) comparison in performance between different settings of the simulation can be made over much more rounds than in real gameplay.

4.2 Structure for conducting the GCBS methodology

In order to guide the conduction of the GCBS methodology on the application case (modelling study), structured guidance for conducting the methodology is defined. This guidance consists of phases that are considered essential for performing the methodology. As it is impossible to know how certain specific challenges can be handled before the methodology is conducted, some challenges have been left to be solved during the modelling study.

Before the methodology is conducted, it should be argued for why the research case fits with the GCBS methodology.

So, a convincing motivation for a case, where GCBS can help to analyse behaviour and evaluate a policy/intervention using the simulation, should be performed. The opportunities described in the previous section can help with this.

In the first phase of conducting the GCBS methodology, a profound understanding of the structure of the game needs to be obtained. The game steps and game dynamics need to be researched to create a comprehensive understanding and to be able to select important choice situations in the game. Eventually, a choice situation that is interesting to gain insight in and important for the system dynamics needs to be chosen. A clear definition of this choice situation and its alternatives needs to be created because a DCM is only applicable when a choice situation is considered at which a choice is made between two or more distinct alternatives.

In the second phase, a valid DCM should be created that captures the selected choice behaviour and produces quantitative and statistically rigorous insight into this behaviour. Conventionally, a researcher defines a certain choice or trade-off situation and attributes that could influence it before it is analysed using DCM. However, now a choice situation is given by the game design and a DCM should be created to capture this situation in a model. This reverse way of modelling brings some challenges with it; the choice situation needs to be captured in a way that it is possible to be analysed using DCM, the choice sets of players need to be defined and attributes that influence these choices need to be selected. Together this should lead to a valid DCM that imitates the choice situation as well as possible. So, the following questions needed to be answered by means of the modelling study:

- How can a choice situation be defined in order to be able to capture it using a DCM?
- How can the choice sets of players be created?
- How can attributes that influence the choice be selected?

Eventually, the required data needs to be collected, and DCM should be estimated. The DCM should be checked to verify if the choice situation is modelled in a valid way. A conventional method to assess the validity, especially when the aim is to predict choices, is an out-of-sample hit rate calculation (Boughanmi, Kohli, & Jedidi, 2016). If the DCM appears to be valid, conclusions about the behaviour of players can be drawn based on the estimated parameters of the choice model.

In the third phase, a realistic simulation that is based on the gameplay and uses the DCM to imitate human behaviour should be created. To create this game and choice-based simulation, the game steps should be simulated using mathematical rules (e.g. if, then, else) at which the earlier obtained structural insights of the game can be used. The player's behaviour can be simulated using the estimated DCM. So, for each choice situation, the simulation should generate

the corresponding choice set and calculate the utilities per alternative based on the estimated parameters and the utility function. Eventually, for each choice situation, the alternative with the highest total utility is chosen. When the GCBS is completed, experiments can be conducted with it to test policies or interventions. Using defined KPIs, the simulation results of the experiment can be interpreted.

5. Application case: the PI inspired Freight Transportation Game

5.1 Context and motive of the game

As mentioned in the introduction, the innovative future concept of a decentralised, Physical Internet inspired, transportation market has the potential to increase efficiency and sustainability within the transport and logistics sector (Ballot, Montreuil, & Meller, 2014). To investigate this future PI inspired market in real practice the "Freight Transportation Game" is developed at MINES ParisTech - PSL. It is a digital simulation game that allows analysing player decisions, behaviour and barriers to the best strategies (Lafkihi, Pan & Ballot, 2019).

The transportation market within the PI is decentralised, with independent carriers bidding for transportation requests. It roughly consists of hubs, carriers and a marketplace. The marketplace combines shipments to create the best composite offers, based on specific requirements, e.g. lead time, delivery date and costs. The offers are allocated by the marketplace, using an auction mechanism (Ballot, 2019). After auctioning the request is assigned to the carrier offering the lowest price and best service.

The game contains some crucial elements that relate to the Physical Internet transportation market. It has an open spot marked where players offer their own prices for requests. There is a central transit node and reallocation of requests is possible on that node.

The game has been played multiple times with characteristics of the current market and of the PI market. From a conversation with developers and researchers of the game (E. Ballot, M. Lafkihi, April 2019) and as described in the working paper (Lafkihi, in press) it is known that the scenario with the PI setting outperforms the scenario of the current market. However, players still do not use the full potential of reallocation and are not able to reach the market performance of a centralised market. Therefore, it is important to gain insight into the behaviour of carriers and investigate possibilities to utilise the potential of a PI inspired decentralised transportation market better

5.2 Fit between GCBS methodology and the application case

Using the “Freight Transportation Game” dynamics of the future transportation market are investigated. However, it provides little quantitative and statistically rigorous insight into why players behave in a certain way. Played game sessions show that the current behaviour of players is not optimal, so there is a need to get more insight into that behaviour. DCM provides a way to analyse the behaviour by estimating parameters for attributes that influence choices people make. Estimating a DCM based on choice data of “Freight Transportation Game” (Player Preference data collection method) is a valid, reliable and efficient method in this case. This is because real-life observation using an RP method is not possible due to the future (not yet existing) concept of the PI inspired transport market. Additionally, the interaction between players (competing market) and interaction with their changing environment (reallocation of request to other players) likely influences the behaviour of players. So, using a “flat” survey SP method is unsuitable for this case as crucial information about the dynamic behaviour may be missed. Finally, the game provides an experimental setting, so choices are less likely to be influenced by all kinds of disturbing factors. The game model also provides a simplified structure of the system its representing, making it relatively straightforward to create a simulation based on the game. With implemented discrete choice modelling to simulate the player’s behaviour, this simulation can be used to test and evaluate policies in a realistic way and in addition more time-efficiently than testing the policy in the game. Playing a game session takes about two hours and simulating a game session is a matter of seconds or minutes.

The methodological choice to use the gaming data to analyse and simulate players behaviour is also motivated by recommendations given by researchers of the game, Lafkihi, Pan and Ballot (2019): “the developed game provides an efficient way to gather data for the future research work, for example, to test hypotheses in collaborative mechanism or to gather data to study carriers' behaviour empirically”.

6. Conducting the GCBS methodology

Using the defined phases of section 4.2, the GCBS methodology is applied to the case of the PI inspired “Freight Transportation Game”.

6.1 Phase 1; create an understanding of the structure of the game

In the game, each round starts with a pool of requests. This pool consists of the three randomly generated request per round and the reallocation requests. A request has an origin, destination, volume and lead time, telling from where to where the request with a volume of one or two units should be delivered and in how many rounds this should be completed. Players try to find a feasible combination of request or request

bundle and a route. The possibility of combining a request bundle and route is bounded by the capacity of four units and already set routing obligations of previously won bundles. The transportation cost and penalty cost of the bundle and route are calculated using a cost function. Eventually, the player can choose to bid on a composed feasible bundle by setting a price. At the end of a round when players have made their bids, the requests are allocated automatically to the winners, by minimising the total cost of transport.

For this modelling study, it is decided to focus on the bidding process of players, as this part requires a lot of information processing for players. They need to find feasible request bundles by combining a request (bundle) with a route that fulfils the requirements of that bundle and of the requests already being transported. It is interesting to get more insight into this complex “bidding behaviour”. Additionally, it has significant potential to be improved by a policy.

In the game, the bidding behaviour consists of two choices: selecting a bundle of one or more requests and selecting a route to transport these requests. Because a DCM is only applicable when a choice situation is considered at which a choice is made between two or more distinct alternatives, this bidding behaviour and its choices need to be redefined. Therefore, it is chosen to combine these choices and their alternatives. So, the alternatives used for capturing the bidding behaviour are considered as: all the unique possible combinations of requests and routes a player has in a certain round. For example, if a player in a certain round can select request “B” and transport this using six different routes (keeping in mind the requirements of the current load of the player), these are considered as six feasible alternatives. Because a player often can select multiple requests and combine them, the list of feasible alternatives per player (choice set) could be large.

6.2 Phase 2; create a DCM of the selected choice situation

6.2.1 Creating choice sets from the game data

To create a discrete choice model, a choice set should be collectively exhaustive, mutually exclusive, and the sets should contain a finite number of alternatives. At first, for this research, it is possible to collect all possible alternatives players have (collectively exhaustive), because the required information for this is digitally stored during game sessions. Secondly, players can choose multiple alternatives which does not meet the mutually exclusive requirement. However, by considering each alternative as a binary choice set, this requirement can still be met. Finally, the number of alternatives players can choose from is large but finite.

Because it is unknown which alternatives players considered while making a choice to bid or not, the considered choice sets had to be generated. Based on the insights of

Fiorenzo-Catalano (2007), it is defined that all relevant and chosen alternatives of all the possible alternatives should be selected to generate a considered choice set. So of all the feasible alternatives players have in a certain round, all unique ones (in terms of the combination of requests) with the shortest route are selected, together with all the chosen alternatives.

6.2.2 Attribute selection for DCM

Because this generated considered choice set is still quite large and players do not really consider all these alternatives during the gameplay, extra attributes that could explain the creation of the considered choice set (in this case the complexity to find a feasible alternative) are defined. Together with attributes that could explain the consideration players make when choosing an alternative, these form the selected attributes for the DCM estimation.

Based on literature and experience of playing the game, the attributes to capture the “complexity to find a feasible alternative” behaviour, have been selected. At first, “Game Round” is selected, as it is possible that players learn to play the game while playing it (Ryu, 2013) making it less complex to find feasible bundles as the game progresses. Additionally, “Total/Bundle of Request” and “Route Length” are selected as the more requests need to be considered and connected, the longer the feasible route is and the more difficult it is to find that bundle. Attributes to capture “choice to bid or not bid for a feasible bundle” behaviour have been selected as follows. The effect of the possibility to set competitive prices, make a profit and the profit already won as described by Van Duin, Tavasszy and Taniguchi (2007) are taken into account by selecting a constant for “Bidding” (the effect of potentially making profit), “Total/Penalty Costs” (the extent to which a competitive price can be set), “Current load” (the effect of profit already won) and “Player Ranking” (the relative effect of profit already won).

A visual presentation of the theoretical framework for imitating choice behaviour is shown in Appendix B.

6.2.3 DCM estimation

Based on a data-set of 485 observations, several possible MNL models are estimated to check whether evidence can be found if the attributes really do have their effect on the bidding behaviour. Herewith the: rho squared value of the model, significance of parameter value, the purpose of the model and the interpretability of the utility function composition, have been used as criteria for selecting the attributes and model.

Therefrom, the following attributes remained: Bundle Number of Requests, Penalty Costs and the constant for Bidding. More sophisticated ML models for capturing panel effects, nesting effects and beta heterogeneity have been tested as well. Eventually, a model is chosen with the following utility function:

$$U_{bid} = \beta_{BNR} * BNR + \beta_{PC} * PC + ASC_{Bid} + \varepsilon$$

$$U_{NotBid} = 0 + \varepsilon$$

This MNL model is chosen because it performs equally as good as the ML models (in terms of Rho-square value), it is well explainable and relatively straight forward to simulate. The estimated parameters are presented in Table 1.

Attribute	Notation	Value	Std err.	p-value
Beta Bundle Number of Requests	β_{BNR}	- 1,22	0,196	0,00
Beta Penalty Costs	β_{PC}	- 0,0242	0,0118	0,04
Constant for Bidding	ASC_{Bid}	1,37	0,313	0,00

Table 1, Estimated parameter values

The Rho squared value of the model is 0,256

6.2.4 Validation of the DCM

To check how reliable this model is considering its ability to predict the right choices, a validation of the model is carried out. Herewith, it is calculated what percentage of choices is predicted right by the model (hit rate). This validation consists of calculating the hit rate using out-of-sample testing. For this, the data-set of 485 observations is split into two parts. The first $\frac{2}{3}$ of the observations is selected randomly to estimate the model on. Then this model is applied to the remaining $\frac{1}{3}$ of the observations. The percentage of correctly predicted choices is the hit rate. To reach robust results, the hit rate is calculated ten times, each time with another randomly selected estimation- /data-set.

The hit-rate of the model was found to be quite stable over the ten validations, and on average, 73%. This is considered to be a good validation-score for the model. As herewith, the bidding behaviour can be realistically imitated.

6.2.5 Conclusions about players' behaviour based on the DCM

Based on the estimated parameters of the final chosen model, some careful conclusions could be drawn about the bidding behaviour of players. It can be stated that players prefer making a bid (the positive constant Bid). However, when a player wants to bid on a request, this effect is almost entirely abolished due to the negative effect of the parameter; number of requests (BNR). Because evidence is found that the number of requests (within a feasible bundle) negatively affects the likeliness of making a bid. Players presumably find it difficult to deal with the complexity of combining a bundle and feasible route when more requests need to be considered. This attribute of complexity has relatively the most substantial influence on the systematic bidding behaviour found by estimating the DCM. The other attribute of which evidence is found that it influences player bidding behaviour is penalty cost. The higher the penalty cost a player should pay when bidding on the corresponding request bundle, the less likely

he/she will bid on it. However, this influence is logical, and it only really affects the bidding behaviour with hefty penalties. Although, even then this effect is relatively small compared to the previously mentioned complexity effect.

So, it can be stated that the main factor influencing the bidding behaviour for carriers in this PI inspired transportation market environment (that could become a reality in the future) is the complexity of having to deal with combining a bundle and feasible routes. Other than in the game, carriers in real life could, however, have other incentives than only making a profit as well. They may also care about the region in which they conduct their transport or the length of the route. These extra requirements could make it even more complex for carriers to find their optimal bids. This complexity, as a result of bounded rationality, creates a sub-optimal market performance as bids are not made on the most efficient alternatives. Additionally, it generates a weak position for the independent carrier, as he/she is not able to compose the most attractive bid based on his/her requirements.

6.3 Phase 3; create a game and choice-based simulation to test a policy

6.3.1 Create the game and choice-based simulation

To create a simulation based on the gameplay, all game steps of one game round, as described in section 6.1, are simulated in MatLab using mathematical rules. The bidding behaviour of players is imitated using the estimated DCM. Therefore, first, the considered choice set is selected by the simulation using the selection rules of 6.2.1. Hereafter the systematic utilities per alternative are calculated using the utility formula and estimated parameters of section 6.2.3. Eventually, a random parameter ε is added to represent the (general independent) unobserved utility. It is distributed i.i.d. Extreme Value type I, $\text{var} = \pi^2/6$. Therefore, it is drawn from a Standard Gumbel ($\mu = 0$ and $\beta = 1$) distribution each time separately for each utility calculation. Eventually, when the total utility to Bid on an alternative is bigger than the total utility Not Bid on that alternative, a bid is placed and vice versa. The prices are set using pricing functions based on costs. Herewith, a game round (or bidding round) is imitated, and as many rounds as needed can be simulated.

6.3.2 Policy definition

Based on the DCM conclusions drawn in section 6.2.5, it can be stated that the players have difficulties with the complexity of combining requests with a feasible route in order to make a bid. Additionally, game data shows that it could be plausible that players experience too many options to find and oversee them all, or too little options to be able to catch them. This phenomenon of bounded rationality of carriers could decrease the effectiveness and efficiency of the transport market and weakens the position of an independent

carrier. A solution can be found in the concept of a decision support system. All the information regarding routing, load size, start and end time, reallocation, and so on, can logically not be processed by a human. Therefore a system that helps carriers to process all that information to improve their decision making, without them losing control, could make the transport market more efficient and effective. Decision support systems are used a lot in the world of transport and logistics for all kinds of challenges. However, to the best of the authors' knowledge, it has not been tested what the effect of such a system could be on the PI inspired decentralised market place with reallocation possibilities.

In the PI inspired decentralised transportation market, two aspects are essential for an optimised transport system. At first, carriers want to bid on bundles with the lowest cost; in this way, they can set competitive prices. Additionally, carriers want to utilise the reallocation more as it provides them with a win-win situation. To capture the two aspects in one policy, a decision support tool for carriers is proposed that processes all the transportation information for each individual carrier and calculates their optimal bid compositions. These optimal bids per carrier consist of request bundles that have the lowest total cost and pass by the reallocation point. By this way, carriers can set more competitive prices and utilise the reallocation opportunity of the PI concept more.

6.3.3 Experiment to test the policy

To test the effect of the policy, the created game and choice-based simulation is used. This simulation represents the current PI inspired transportation market behaviour. Additionally, two other simulation settings are used. One simulation setting with implemented policy, where carriers bid on bundles that have the lowest total cost and pass by the reallocation point, and one simulation setting representing a centralised market situation. Because this market type performs well in terms of efficiency and effectiveness, it is used as a benchmark situation. So eventually, the three different simulation settings have been run *ceteris paribus* and the results are compared using the following effectiveness and efficiency KPIs: number of unallocated requests, number of total delays, the total price of all allocated requests, the price per allocated request, the mean filling rate and the total number of reallocations. This indicates whether the policy produces the desired effect and in what aspects it performs better or worse in comparison to the current situation and a central market situation.

The experiment settings are summarised in Table 2.

Simulation settings per experiment	Current situation - Future situation - Centralised situation
Price function per setting	Current & Future situation: use the same pricing functions that set different margins per carrier Centralised situation: uses a different pricing function that sets the same margin for each carrier
Generated requests by simulation within one experiment session	The same for each round for each simulation setting
Length of an experiment session	33 bidding rounds
Number of experiment sessions	9

Table 2, Simulation settings

6.3.4 Experiment results

A table with the results of the conducted experiment is presented in Appendix C. It shows the mean and the standard deviation value of the nine conducted sessions.

The results show that the filling rate of trucks in the simulation of the current situation is low. This is presumably because carriers likely do not bid on bundles with multiple requests (because it becomes too complicated). The proposed policy was partly aimed at solving this complex issue for carriers. The simulations show that the policy works in this respect, as the filling rate is much higher and even about as high as in the centralised market situation. The other aim of the policy was to create more reallocations, which it did well. So, the policy creates a much more efficient market situation. Additionally, almost all requests are allocated in the future situation, which is definitely not the case in the current situation. Therefore, the policy also creates a more effective market. In general, it can be stated that the policy of providing the player with decision-support about their most “attractive” potential bids, causes as much more efficient and effective game performance, which is close to the results of a central market situation.

As mentioned before, other than in the game, carriers in real life could have other incentives than only making a profit. In this case, the decision support system should be adjustable to a variety of carrier’s preferences. For example, it should advise the carrier with the optimal bids based on his preference for low cost, service region, route length etc. Herewith, the carrier is in control, and the inefficient and ineffective effects of the complex market and bounded rationality are taken away. So, a decision support tool for carriers in the complex PI inspired decentralised transportation market seems to be an essential tool to reach an optimal market performance with a firm and “in control” position of the independent carrier.

7. Final Methodological GCBS framework

The final methodological GCBS framework is designed by evaluating and improving the first design of chapter 3, using the insights of the conducted modelling study.

7.1 Evaluation of the first framework design and insight from the modelling study

The opportunities, as described in section 3.1, proved to help motivate why the research case of the “Freight Transportation Game” suited the GCBS methodology. Eventually, the opportunities stated in the framework turned out to be a good match with the modelling study. In addition, these options appeared to not only be theoretically promising, but have also proved to be valuable in practice. Therefore, the designed framework for the opportunities of the GCBS methodology of section 4.1 is considered to meet requirement 1; provide insight into the opportunities of the methodology.

Phase 1 of conducting the GCBS methodology is considered to be an essential phase. This phase is crucial for the rest of the phases as creating a thorough understanding of the game provides the basis for the rest of the modelling phases. Additionally, creating a clear definition of the choice situation and alternatives of that situation is considered useful and essential. In conclusion, this phase created enough guidance to be able to perform the rest of the methodology.

Phase 2 did not prove to be sufficient enough to conduct the methodology. However, this was expected, as some methodological challenges needed to be handled during the modelling study. The first question that needed to be answered by conducting the modelling study was: How can a choice situation be defined in order to be able to capture it using a DCM? It turned out that, in addition to the choice definition created in phase one, it is important that the choice together with its alternatives (the choice set) needs to be collectively exhaustive, mutually exclusive, and the sets should contain a finite number of alternatives. Otherwise, it is not possible to create a DCM with it. The second, to be answered question, was: how can the choice sets be created? It was found that, just as with RP data, it is hard (or impossible) for a researcher to know the considered choice sets of players when using a “player preference” data collection method. Therefore, based on theoretical insights of Fiorenzo-Catalano (2007), the following guideline to be able to generate considered choice sets are formulated: include all relevant and chosen alternatives. It is up to the users of the GCBS methodology to define what the “relevant” alternatives of a particular choice situation are. Because these generated considered choice sets were still not representative for the real considered choice sets it was chosen to select two categories of attributes; attributes that could explain the creation of the considered choices and attributes that could explain the consideration players make when choosing an alternative. This leads to the final question

that needed to be clarified: how can attributes that influence the choice be selected? Because no literature or experience about the specific choice situation of modelling case was available, more general literature and experience with the gameplay was used to define multiple attributes that could influence the choices behaviour. Eventually, by iteratively estimating multiple models with different compositions of the utility function and attributes a final model was chosen. This selection process was based on: the Rho Squared value of the models, the significance of estimated parameters, the purpose of the model and the explicability of the model. Eventually, this innovate created methodology of capturing a given choice situation into a DCM appeared to be successful as the validation of the final model turned out to be satisfaction. Additionally, the final DCM provided insight into the behaviour of players.

Phase 3 was sufficient enough for guiding the creation of the game and choice-based simulation. It turned out to be straight forward as the structure of the game, unravelled in phase one, already provides a structure for the simulation, and the DCM is already created in Phase two. However, for creating the simulation based on the game and for implementing the DCM to imitate the selected choice behaviour correctly, still modelling skills and own insight of the user of the GCBS methodology are needed. The same applies to the process of defining an experiment and conducting it using the GCBS. Eventually, this phase helped to create a realistic simulation based on the gameplay, including human behaviour.

7.2 The improved methodological GCBS framework design

As mentioned in the previous section, the opportunities of the GCBS methodology are considered to be helpful, sufficient and in line with the design requirement 1. Therefore, it is decided that no adjustments need to be made to this part.

Because Phase 1 created enough guidance to be able to perform the rest of the methodology, it is decided that it needed no adjustment as well.

In order to create better-structured guidance of Phase 2, it is chosen to split this phase into a data collection/preparation phase and a DCM estimation phase. In the data collection phase, a flowchart is created, telling the user what to do in order to generate considered choice sets, when and how to select what kind of attributes and how to deal with choice sets that do not contain a finite number of alternatives, and how to deal with the collectively exhaustive and mutually exclusive requirements. After following this flowchart thoroughly, the user is able to collect the right data and proceed to the next phase of the GCBS methodology. In the next phase, the user is presented with information about how to iteratively create and select a discrete choice model and validate it.

The final phase, of creating a game and choice-based simulation to test policies or interventions, is not adjusted as it met the design requirement 5 of helping to create a realistic simulation based on the gameplay, including human behaviour. The final designed framework applying the GCBS methodology is shown in Appendix D.

7.3 Validation of the final framework design

In order to determine whether the final methodological GCBS framework design is successful, a qualitative validation on the basis of the design requirements is shown in table 3. This shows how the requirements are met using the deliverables of the designed methodological GCBS framework.

Design requirement	Corresponding deliverable
1. Provide insight into the opportunities of the methodology	Sub-framework showing the opportunities of the GCBS methodology
2. Help to provide insight into the behaviour of players.	Phase 1 + Phase 2 + Phase 3
3. Provide structured guidance on how to conduct the methodology.	Sub-framework showing how to conduct the GCBS methodology
4. Contribute to the creation of a valid game based discrete choice model.	Phase 1 + Phase 2 + Phase 3
5. Help to create a realistic simulation based on the gameplay, including human behaviour.	Phase 4
6. Use a combination of serious gaming, DCM and simulation	For conducting the GCBS serious gaming, DCM and simulation are needed

Table 3, Design requirements and corresponding deliverables

The methodology and the framework proved its potential for the case of application of this research, as they helped to gain insight into the behaviour and test a policy using the created game and choice-based simulation. However, it is not possible to know how useful, reliable and robust the framework is when it is applied to other research projects that fit with the GCBS methodology.

8. Conclusion and Recommendations

The conducted research, described in this paper, has provided some valuable insights and contributions to the

existing literature. At first, an innovative Player Preference data collection method for DCM is been explored and defined. This method proved to be a valuable alternative for the conventional RP and SP methods, and opportunities of this Player Preference method proved to be promising.

Additionally, an innovative methodology of creating a game and choice-based simulation is been defined and tested. This methodology proved to be successful in gaining quantitative and statistically rigorous insight into the behaviour of people and creating a realistic simulation. By applying the methodology on the case of the PI inspired "Freight transportation game" it has been discovered that the bidding behaviour of players is affected mainly by the complexity of having to deal with combining a bundle and feasible routes. Additionally, using the GCBS methodology, it has been found out that a decision support tool for independent carriers in the PI inspired freight transportation market creates not only an efficient and effective market performance (comparable to the performance of a centralised market) but also creates a more firm and "in control" position of the independent carrier.

To facilitate future research that suits the GCBS methodology, a methodological framework has been designed. This provides insight into the opportunities of the methodology and guidelines to systematically conduct it.

Eventually, more research needs to be done to test the (external) validity of the decision support tool as it would be interesting to see if such a tool is technically feasible and viable in the real world. Additionally, it would be valuable to test and extend the designed methodological GCBS framework in order to increase its robustness. Finally, it would be interesting to create a serious game with the objective of applying the GCBS methodology with it. Currently, the methodological framework is designed for ex-post creation of the DCM, based on an existing game. If a game is created for a GCBS purpose, the choice situations of players in the game could be designed with a DCM perspective. Herewith the game could, for example, be designed in a way that considered choice sets of player are traceable, a limited correlation of attributes occurs, and a game with multiple goals so that trade-offs (e.g. time vs money) can be measured.

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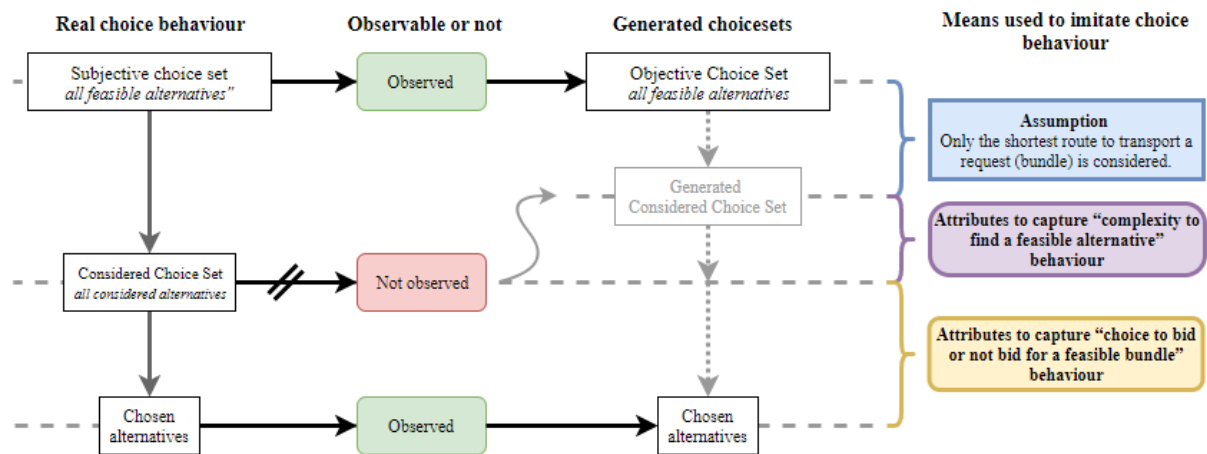
Appendix A

Compared data collection methods, based on Louviere et al. (2000)

Revealed Preference	Player Preference	Stated Preference
Portrays the world as it is	Portrays decision within the boundaries of the gameplay	Described hypothetical and virtual decisions context
Consist of inherent relationship between attributes	Consist of relationships between attributes	Control relationships between attributes
Only existing alternatives as observables	Including existing and/or proposed and/or generic alternatives	Including existing and/or proposed and/or generic alternatives
Represent market & personal limitations on decision-maker	Represent in-game market & player limitations	Does not represent changes in market & personal limitations effectively
High reliability & face validity	Assumed to be reliable when game is well designed, players understand the game and feel committed to the gameplay	Appears reliable when respondents understand, commit to and respond to tasks
Yield one observation per respondent	Yield multiple observations per respondent	Yield multiple observations per respondent
Valid & Reliable		Accurate & Efficient

Appendix B

The theoretical framework for imitating choice behaviour



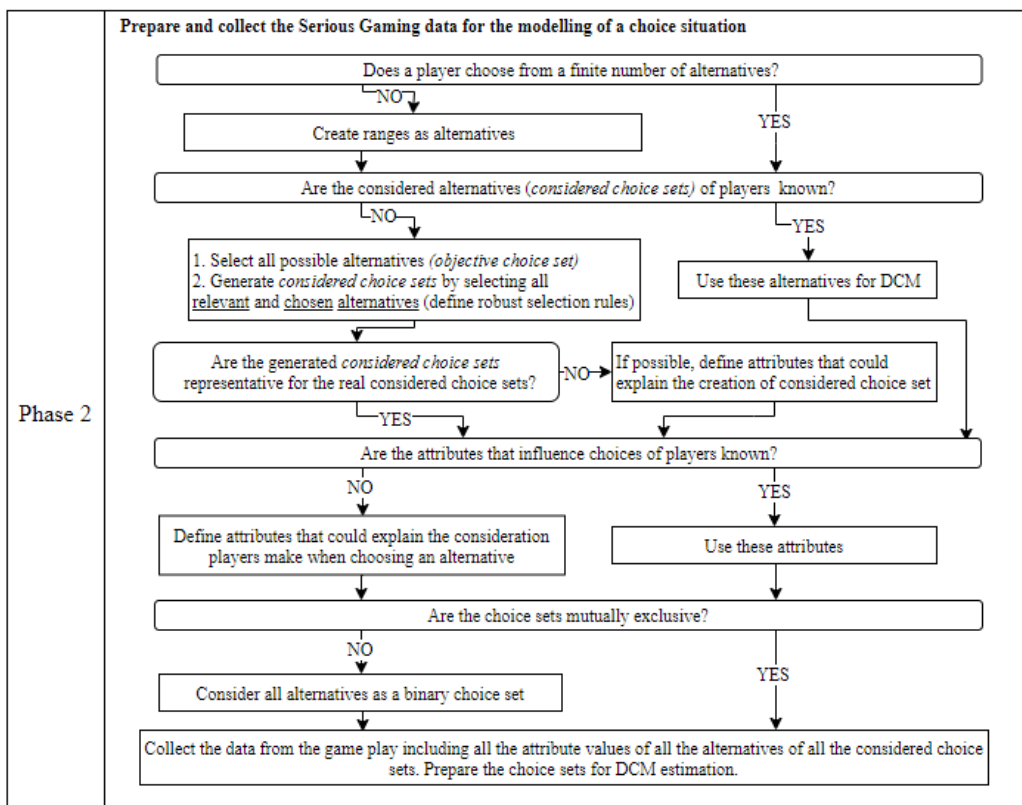
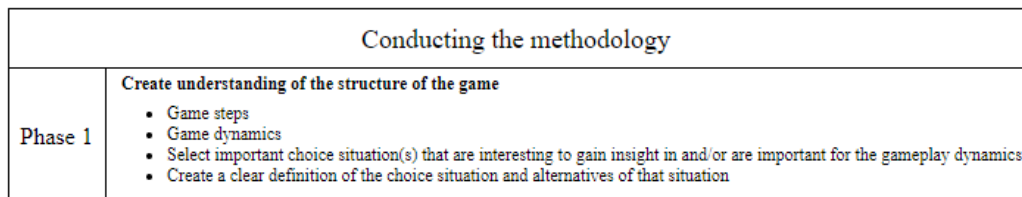
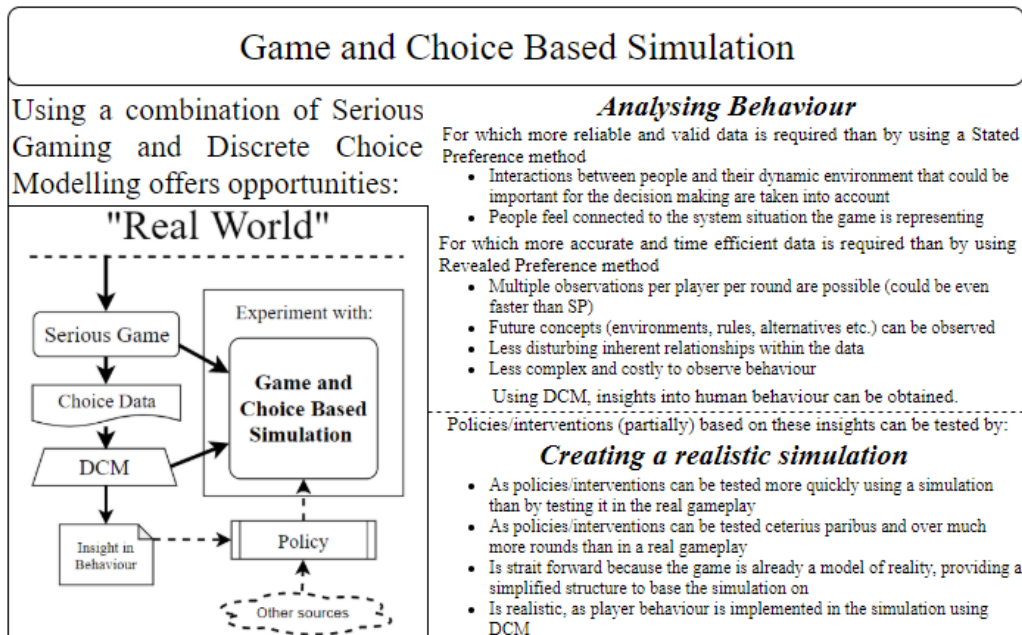
Appendix C

Simulation Results

KPI		Simulation of the current Situation		Simulation with Policy		Simulation of a Centralised Market Situation	
		Mean	Std	Mean	Std	Mean	Std
Effectiveness	Unallocated requests	35,22	1,55	1,00	0,94	0,56	0,68
	Total delays	0	0	0	0	0	0
Efficiency	Total price	€ 287,43	€ 10,49	€ 335,57	€ 53,04	€ 317,35*	€ 39,34*
	Price/allocated request	€ 4,51	€ 0,21	€ 3,42	€ 0,53	€ 3,23*	€ 0,42*
	Mean filling rate	10,15 %	0,89 %p	53,06 %	3,64 %p	50,89 %	2,71 %p
	Number of reallocations	0,00	0,00	4,00	2,79	3,11	1,52

Appendix D

Game and Choice Based Simulation (GCBS) Methodological Framework



Phase 3	<p>Estimate a Discrete Choice Model using the collected and prepared Serious Gaming data</p> <p>If the choice model is not unambiguously clear; iteratively estimate models with different:</p> <ul style="list-style-type: none"> • Attributes • Utility functions • Random variables (to capture nesting effects, taste heterogeneity, panel effects) • Models (MNL, ML) <p>Select the model based on:</p> <ul style="list-style-type: none"> • Rho Squared value • Significance of parameter value • Purpose of the model (insight in behaviour, simulating choices, predicting choices, VOT estimation, etc.) • A well explainable composition of the utility function <p>Validate the model e.g. using out-of-sample hit-rate computation</p> <p>Interpreted the final estimated model and use the explained choice behaviour to gain insights</p>
Phase 4	<p>Create a Game and Choice Based Simulation to test policies/interventions</p> <p>Create a simulation experiment to test the policy/intervention</p> <p>Define KPIs to measure the results of the simulation performance</p> <p>Create a simulation of the gameplay</p> <ol style="list-style-type: none"> 1. Simulate the game steps using mathematical rules (e.g. if, then, else), based on Phase 1 2. Simulate the (important) player behaviour using DCM <p>For each choice situation let the simulation:</p> <ul style="list-style-type: none"> • Create the considered choice set using the defined selection rules of Phase 2 (if needed) • Calculate the total utility for each alternative in the choice set based on the specifications of the selected model of Phase 3. Define choices between alternatives based on their utilities (inc. random utility). <p>Create other simulations needed for the experiment (simulation with intervention or implemented policy)</p> <p>Conduct the experiment and interpreted the results</p>