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On Developing A More Comprehensive Decision-Making Architecture for Empirical Social Research: Lesson from Agent-Based Simulation of Mobility Demands in Switzerland

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Abstract. Agent-based simulation is an alternative approach to traditional analytical methods for understanding and capturing different types of complex, dynamic interactive processes. However, the application of these models is currently not common in the field of socio-economical science and many researchers still consider them as intransparent, unreliable and unsuitable for prediction. One of the main reasons is that these models are often built on architectures derived from computational concepts, and hence do not speak to the selected domain's ontologies. Using Triandis' Theory of Interpersonal Behaviour, we are developing a new agent architecture for choice model simulation that capable of combining a diverse number of determinants in human decision-making and being enhanced by empirical data. It also aims to promote communication between technical scientists and other disciplines in a collaborative environment. This paper illustrates an overview of this architecture and its implementation in creating an agent population for the simulation of mobility demand in Switzerland.

Keywords: Agent architecture · Multi-agent system · Agent-based modelling · Discrete choice analysis.

1 Introduction

The use of a specific architecture can facilitate the application of agent-based methodology in a particular domain. Traditionally, economists tend to give importance to the selfish and rational part (*homo economicus*), while sociologists focus on the social capabilities (*Aristotle's zoon politikon*) and psychologists tend to see humans as mainly irrational and emotional. Thus, explicitly or not, agent-based models often follow one or another of these perspectives (e.g [4, 9, 11]).

In recent years, we observe a trend of applying agent-based techniques to combine the views from different domains to provide more reliable descriptions for real-world phenomena [23] (e.g. self-organisation, the emergence of counter-intuitive behaviours [13]). This leads to the search for a generic computational platform that has a higher degree of abstract, while can also be adapted as an illustration of a specific theory or hypothesis [7]. There is still, however, a lack of decision-making architecture that is expressive and flexible enough to build arguments both micro-macro levels in the socio-economical context [3, 30].

This paper introduces an agent architecture for choice modelling simulation, which is inspired by Triandis' Theory of Interpersonal Behaviour (TIB) [34]. TIB states that behaviour is primarily a function of the intention to engage in the act, habit and facilitating conditions. It provides a meaningful set of determinants that contribute to decision-making in socio-psychology and can be used to produce statements about behaviours at society level as well as its individual members. In addition, the function given in TIB allows us to calculate the probability that a particular action will take place. By enhancing it with statistical data, this architecture can enable an agent-based model to have not only theoretical support from an established concept but also the capability to include empirical findings in scenario design. We demonstrate the implementation of this architecture in BedDeM (i.e. Behaviour-Driven Demand Model) - a simulation tool that aims to address both micro and macro perspectives of modal choice for mobility domain in Switzerland.

After considering some of the popular strategies for decision-making simulation in Section 2, a specification of the new architecture is presented (Section 3). Next, its contextualisation in the studied problem, Behavioural-driven Demand Model (BedDeM), is carried out in Section 4, especially focusing on the attribute definition, micro-behaviour and calibration. We then conclude our experience with the whole process and suggest further development in Section 5.

2 Related works

For models that aim to understand the aggregate consequences of real-world phenomena, it is important to specify an agent's behaviours in a way that is both theoretically and empirically defensible [12]. There are different approaches for this issue in choice modelling, ranging from as basic as a reactive mechanism to the level of a complex entity using a cognitive model.

A simple design involves agents follow some sets of behaviour rules (i.e. decision-tree or production-rule systems), which apply both in information-gathering stage and when making a final choice. It is typically used in conjunction with a set of assumed preferences for the agent to rank outcomes by desirability order. Examples include heuristics that update agent's behaviours according to the accumulated experience (e.g. [33]) or pick the next option that satisfies the qualities identified from empirical data analysis (e.g. [16]). In this setup, modellers have a straightforward job to trackback any changes in agents' behaviour but have to face a significant increase in computational complexity when a new rule is introduced [22].

Alternatively, researchers can choose to assign agents with beliefs, values or world views that correspond to observation from ethnographic data or stakeholder's assessment. A range of cognitive inspired agent architectures has been developed in recent years for this purpose. Mostly supported by process-based theories [30] and a bounded rationality approach [27], they aim for providing a framework for a psychological mechanism through specifying essential structures, divisions of modules and their relations while always embodying fundamental theoretical assumptions [29]. One of the most well-known architecture is Belief-Desires-Intentions (BDI) [20]. It provides a robust standard framework for any agent-based simulation that wants to take into account human's decision-making process. However, these methods are often criticised for the lack of experimental grounding [6] and the agent choice of being homogeneous, completely rational and selfish [20].

Taking into account the dual nature of social processes, working on individual and societal levels requires the consideration of both and the interaction dynamics among them [8]. Thus, other cognitive models that add complexity to the classical rational agent, have emerged. Representatives for this category are CLARION [28], ACT-R [32], SOAR [17] etc. They usually take into account social theories and focus on different issues that were ignored in the rational agent. For example, Conte et al. [5] empower the social learning capabilities or Sun et al. [31] focus on organisational theories and the agent roles while others stress on the importance of beliefs in cognition [25]. There have been attempts in finding a global unifying principles for cognitive architecture (e.g. [6]), but it still remains an open debate [29,30]. Balke et al. [3] make a comparison between their features, which reveals none of the mentioned models is currently cover all socio-psychological aspects of decision-making (i.e. cognitive, affective, social, norm and learning).

Another popular approach is to enhance the agent's preferences, strategies and likelihood of making a particular decision with discrete choice models (e.g. [14]). Giving some defined set of possible options, it specifies a ranking order of these choice outcomes, which can then be converted into predicted probabilities. To produce an actual choice, a random component (representing human-error) can be introduced by sampling from a multinomial distribution with these probabilities. Alternatively, one can assume the computed value reflect the underlying desire of the agent and specify it to always pick the option with the highest utility value. By incorporating empirical data (such as observed choices, survey responses to hypothetical scenarios or administrative records), the discrete choice model provides one flexible framework for estimating the parameter of choice behaviour, especially when there is a lack of information on which determinants affecting individual choice decisions. Despite that, without comprehensive support from a socio-psychological theory, current discrete choice models are often difficult for non-experts to understand the underlying implications of different modelling scenarios and associated behavioural assumptions [15].

3 New architecture design

As an effort to produce a more comprehensive agent architecture for empirical researches, we decide to implement Triandis' Theory of Interpersonal Behaviour (TIB) [34] (Fig 1). The first level is concerned with the way personal characteristics and prior experiences shape personal attitudes, beliefs and social determinants related to the behaviour. The second level explains how cognition, affect and social determinants and personal normative beliefs influence the formation of intentions with regards to a specific behaviour. Finally, the third level states that intentions regarding the behaviour, prior experience and situational conditions predict whether or not the person will perform the behaviour in question.

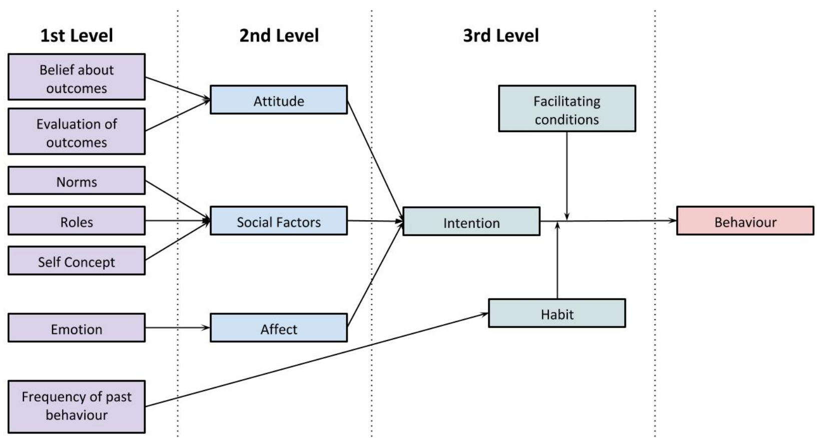

Fig. 1: Triandis' tri-level model [34]

A full decision-making cycle with an example of a mobility application is illustrated in Fig. 2. An agent first selects an isolated decision-making task from the list that is sequentially executed. Its personal desire/goal is then combined with means provided by the external environment to generate a set of possible options. For all determinants (d), each option (opt) is given a referenced value which comes from comparing its property with other's ($R_d(opt)$). In the first level, this can be done using either a real numerical system (for determinants such as price or time) or ranking function (for determinants such as emotion). Both can be derived from empirical data (e.g. census/survey) or calibrated with expert's knowledge/stakeholder's assessment.

The results for these determinants are then normalised and multiplied with an associated weight (called w_d); the sum of which becomes the referenced value for the option in the next level (see Eq.1). The weight, in this case, represents the importance of a decision-making determinant compare to others at the same level and emphasises on the heterogeneity of individuals. It also allows the modeller to express a certain theory by cutting of determinants (by setting their values to

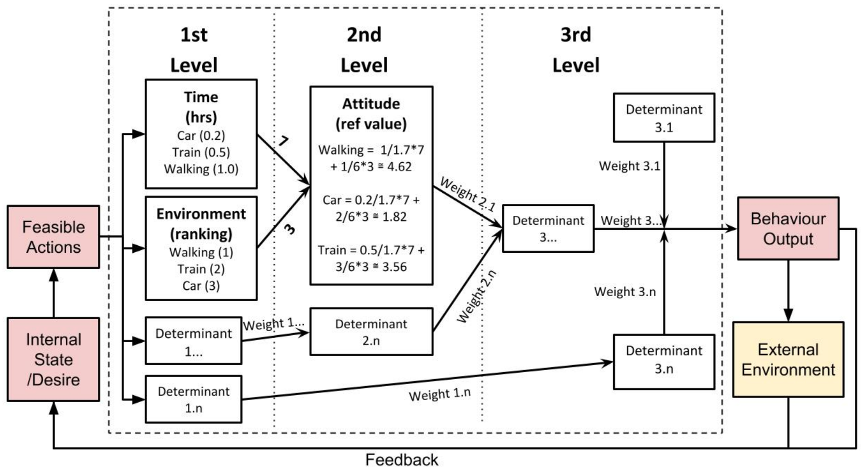

Fig. 2: Agent's decision-making procedure

0) that are not relevant to a case study. The combination process then continues until it reaches the behaviour output list; the referenced value of which can be interpreted as the probabilities that an agent will perform that option. If the agent is assumed to be deterministic, it can pick the option that is correlated to best-evaluated value.

$$R_d(opt) = \sum_{c=1}^{C}(R_c(opt)/(\sum_{o=1}^{O} R_c(o)) * w_c)$$

where
- $R_d(opt)$ is the reference value of an option (opt) at determinant d.
- C is the set of the children of d (i.e. determinants connects with d in the previous level).
- O is the set of all available options.
- w_c is the weight of child determinant c.

(1)

In our mobility example (see Fig. 2), the agent has access to 3 options: *walking*, using *car* or taking *train*. For a working trip of around 10 kilometres distance, according to *time*, their referenced values are: R_{time} =car(0.2), train(0.5), walking(1.0) (measured in hours); which combine to 1.7. According to *environmental friendly* determinant, they can be ranked as $R_{environment}$ = walking(1), train(2), car(3) (from best to worst); the sum of which is 6. If w_{time} and $w_{environment}$ are 7 and 3 respectively, the new referenced value in next level list($R_{attitude}$) of *walking* would be 1/1.7*7 + 1/6*3 $\approx$ 4.62, *car* would be 0.2/1.7*7+2/6*3 $\approx$ 1.82 and *train* would be 0.5/1.7*7+3/6*3 $\approx$ 3.56. Hence, according to *attitude*, *car* would have the highest chance to be picked for this individual agent, followed by *train* and *walking*.

4 A case study - BedDeM [1]

BedDeM is being developed in Java using Repast library for agent-based modelling [21], aiming to generate yearly mobility data at the individual household level that can be interpreted at the granularity of a historical *evolution of transportation* for Switzerland. In this section, we describe technical details of the agent population design starting with mapping data sources with their attributes, followed by an overview of the simulation process and the calibration procedure.

4.1 Agent specification

As mentioned in Section 3, the decision-making architecture requires 2 elements to calculate the probabilities for a set of options: (1) how to specify a ranking order of the option according to a determinant ($R_d(opt)$) and (2) the weight of the determinant (w_d). For this purpose, we utilise the Swiss Household Energy Demand Survey (SHEDS) [26]. There are several questions that compared the criteria for mobility mode choices, which answer can be interpreted as the weights(w_i) for different psychological determinants in TIB. A typical example is "Please rate how important the following aspects are for choosing this mode of transportation (from 1 to 5) - •Choosing the cheapest option; •Travelling as fast as possible, etc.". A large number of similar questions can be categories into TIB determinants. However, as the first step into this experimental design, we decided on a mapping of a smaller set (see Table 1), which is based on some of the past researches [2] and what properties can be measured or ranked objectively (using common sense). Note that in this case, the determinant *belief* is omitted since the system assumes that the knowledge/perception of agents is always correct.

Having the decision-making components figured, the next step is parametrising the profiles to build a synthetic population. This is accomplished by utilising another data source - the Mobility and Transport Microcensus [18], which includes the attributes listed in Table 2. Its entries (N = 57,091) are placed in a latent space (socio-matrix) that is represented by a symmetric Gower distance matrix [10]. All pairwise distances/dissimilarities are created based on the common features of the two data sources (e.g. age group, gender, region, household size, income level, number of personal vehicles). This matrix also provides a way to calculate the recommendation for agents from the same network (i.e. R_{role} - see Table 1). We then find the most similar peers that have the lowest distance towards each other and join them with entries from SHEDS (N=5,515). A random number of representatives for each geographical region in Switzerland are selected to become our agent population (N=3,080).

Along with the attributes in Table 2, a weekly schedule is also derived for each agent from microcensus to provide a way to calculate all relative costs for a trip (including purpose, distance, execution time). The agent's main purpose

[1] Behaviour-Driven Demand Model

Determinant	**Layer**	**Measuring/Ranking property ($R(opt)$)**	**Matching question(s) in SHEDS** (w, with scale 1-5)
Evaluation - *Price*	1st	R_{price} = Cost of travelling	w_{price} = •Choosing the cheapest option
Evaluation - *Time*	1st	R_{time} = Duration of the trip (including the journey to station)	w_{time} = •Travelling as fast as possible
Norm - *Environment Friendly*	1st	R_{norm} = Motor type of the vehicle (Gas/Electric/No motor)	w_{norm} = •In the Swiss society, it is usually expected that one behaves in an environmentally friendly manner
Role - *Environment Friendly*	1st	R_{role} = Recommend from other agents in its network	w_{role} = •Most of my acquaintances expect that I behave in an environmentally friendly manner
Self-concept - *Environment Friendly*	1st	$R_{self-concept}$ = No data available - **to be calibrated** (see Section 4.3)	$w_{self-concept}$ = •I feel personally obliged to behave in an environmentally friendly manner as much as possible
Emotion - *Enjoyment*	1st	$R_{emotion}$ = Vehicle's comfortableness/luxury	$w_{emotion}$ = •I enjoy this way of travelling
Frequency of past behaviours	1st	R_{freq} = The number of usage over a certain period	w_{freq} = •I am used to taking this means of transport
Attitude	2nd	$R_{attitude} = R_{price}/\sum_{price} * w_{price} + R_{time}/\sum_{time} * w_{time}$	$w_{attitude}$ = •Wealth(material possessions,money)
Social factors	2nd	$R_{soc} = R_{norm}/\sum_{norm} * w_{norm} + R_{role}/\sum_{role} * w_{role} + R_{self}/\sum_{self} * w_{self}$	w_{soc} = Avg(•Equality •Social power •Authority •Protect the environment •Influential •Helpful •Prevent pollution)
Affect	2nd	$R_{affect} = R_{emotion} * w_{emotion}$	w_{soc} = Avg(•Pleasure •Enjoying life •Self-indulgent)
Facilitating conditions	3rd	R_{cond} = Does the trip pass all constrains? (e.g. time, budget, vehicle's availability) (0/1)	Agent filters the options that are possible to be performed that the time of decision-making
Habit	3rd	$R_{habit} = R_{freq} * w_{freq}$	w_{habit} = •Habit and Routine: I do without thinking
Intention	3rd	$R_{intent} = R_{attitude}/\sum_{attitude} * w_{attitude} + R_{soc}/\sum_{soc} * w_{soc} + R_{affect}/\sum_{affect} * w_{affect}$	w_{intent} = MAX_SCALE - •I do without thinking
Decision	Output	$R_{decision} = (R_{intent}/\sum_{intent} * w_{intent} + R_{habit}/\sum_{habit} * w_{habit}) * R_{cond}$	

Table 1: Mapping of TIB's determinants and SHEDS to initiate decision-making weights

Attribute	Brief description
Location	Region (or *Cantons* in Switzerland) in which the agent is living
Budget	Weekly travelling budget
Accessibility set	List of available transportation services for the agent, which can be used to calculate all relative costs from a trip
Owned vehicles and Discounts	List of vehicles that the agent own
Weight to universe	The proportion of population that the agent represents

Table 2: An agent's state attributes

is to select a mode of transportation (including rail, car, bus, tram, biking, walking, others) to perform a task on its schedule. There is also an option of not performing the scheduled activity due to the constraints from the agent's states or environment (e.g. exhaustion of budget or exceeded travelling time on all available modes). Agents perform this filtering procedure before any decision-making activities (see determinant *Facilitating conditions* in Table.1).

4.2 Simulation procedure

The simulation process starts with a central controller creating all the agents with all their attributes and assigned them to their respective regions. Initial values for these attributes are coming from the mapping process above. The agent then looks at its individual schedule and creates decision-making events to be activated. At the time of simulation, the controller triggers these events simultaneously, waits for them to finish, then skips to the next scheduled point (i.e. event-driven). At this developing stage, no learning technique is applied for feedback loop inside the agent's decision-making process. Agents simply keep track of the number of times its used a vehicle for trips of the same purpose, which is used for determinant *habit* (see Table 1). After all the task finished, a reporter component in the region collects the final results.

4.3 Calibration

The purpose of calibration is to improve the compatibility of the current population with the target system. We are focusing on figuring out the most fitted ranking patterns of $R_{self-concept}$. Since the mapping question in SHEDS for this determinant is related to environmental friendly aspect of the option, we divided the agent population into 4 main profiles, depending on their daily main transportations: (1) soft-mobility modes (walking/biking), (2) public vehicles (tram/bus/train) (3) private vehicles (car/motorbike) and (4) others. $R_{self-concept}$ for each of them can then be calibrated by permuting the ranking order of all the modal choices.

Objective function: Our main objective is to minimise the error calculated the Eq.2. It is measured from the total differences between the final sum of kilometres in each mobility mode at the end of a period (i.e. a year in this case) and historical data. From microcensus [18], the total kilometres result for one year of all mobility profiles mentioned above can be obtained (i.e. walking/biking, bus/tram/train, car/motorbike, others). Assuming that no two modes can be ranked in the same position, calibration involves using the permutation of these four sets of modes as configurations for the $R_{self-concept}$. We repeat this procedure for all agent's profiles set at either deterministic (choose the best option) or stochastic (choose from a random function with probabilities provided by sampling distribution of final referenced values) to find the smallest error.

$$\underset{conf}{\text{minimise}} \quad err(conf) = \sum_{i=1}^{M} \mid census_i - sim_i(conf) \mid$$

where
- $M = \{$walking/biking, bus/tram/train, car/motorbike, other$\}$.
- $conf = S(M) \oplus S(M) \oplus S(M) \oplus S(M)$, an instance of the concatenation of two permutation sequences of M.
- $census_i$ is census data for mode i (in kilometres).
- $sim_i(conf)$ is the simutation result for mode i (in kilometres).

(2)

Type	**conf**	**CM**	**BTT**	**WB**	**O**	**err(conf)**
Census		72.7	27.5	8.6	3.7	n/a
Deterministic	R_{CM} = (1)CM, (2)BTT, (3)WB, (4)O R_{BTT} = (3)CM, (1)BTT, (4)WB, (2)O R_{WB} = (4)CM, (2)BTT, (1)WB, (3)O R_O = (2)CM, (4)BTT, (3)WB, (1)O	73.1	26.7	3.3	4.4	7.3
Stochastic	R_{CM} = (1)CM, (2)BTT, (4)WB, (3)O R_{BTT} = (3)CM, (1)BTT, (4)WB, (2)O R_{WB} = (4)CM, (3)BTT, (1)WB, (2)O R_O = (4)CM, (2)BTT, (3)WB, (1)O	46.7	6.0	5.0	4.6	51.9

Table 3: Calibration results[2 3]

Result: We list the kilometres in census data and the top results of two types of agents in Table.3. The best configuration is in the deterministic model with an error around 7.3x10^9 kilometres, which accounts for 6.5% of the total scheduled kilometres. The main differences are in the *public* (i.e. walking/biking) numbers. We also observe that the stochastic error are much larger - above 51.8x10^9

[2] All units are in 10^9 kilometres
[3] Abbreviation - CM: Car/ Motobike, BTT: Bus/Tram/Train, WB: Walking/Biking, O:Others

kilometres, which is only 46% accuracy. This is expected since agents in stochastic mode choose options based on a random function of probabilities derived from the referenced values. Currently, there is no pattern shown in the ranking function $R_{self-concept}$ of the results of *stochastic* mode, and hence additional runs with different distribution functions are needed in order to have a broader picture for this setting.

5 Conclusion and future direction

The tree-like and layered structure of TIB has inspired us to develop a new agent architecture that can combine many different determinants in human decision-making; each of which can also be enhanced by empirical data. This is potentially a useful tool to facilitate the engagement of socio-psychologists, economists and the general public with research projects. We aim to demonstrate its practicality by creating a fully-working model to predict trends in the mobility domain for Switzerland - BedDeM. An agent population has been created and calibrated with the data of Mobility and Transport Microcensus and SHEDS.

There is some small margin error from the calibration process (around 6.5% of the total scheduled kilometres). To address this, we are planning to focus on learning in the upcoming developing stage. As mentioned in Section 4.2, agents are currently keeping track of the number of times they used a mode on trips with the same purpose, which accounts for *habit* in decision-making. We also aim to capture the influence of past experience to the ranking function of elements such as *enjoyment*, and/or enable self-reflection by changing the weights of determinants. Reinforcement Learning techniques (e.g. [19]) can be utilised for these updates.

The next important step is assessing the model's uncertainty, variability and sensitivity. This can be done by selecting different representatives for the population when joining the two data sources. Although we have acquired the help of an economist specialised in environmental substantiality, it is also necessary to receive inputs from sociologist to derive alternative mappings of empirical data to TIB determinants (see Table 1) for more agent profiles. Another potential research direction is comparing the efficiency of Triandis' Theory with other similar behavioural theories (e.g. Theory of Planned Behaviour [1]) by also changing the mapping of determinants. The next wave of microcensus (available in 2020) is a potential source for this test.

In term of validation, one of the good direction for our model is determining whether the key relationship or mechanisms highlighted in the agent-based model seem to be plausible explanations of real-world phenomena, which often involves analysis of empirical data that is separate from the agent-based model. A good data source is SCCER-CEST [24], which can be used to indicate the pattern in demand for the transportation sector. Another way to do this is to design an experimental scenario aimed at capturing mechanisms of interest. It can be done with the support of an expert in sociology.

We close with a few words about software and documentation. As mentioned above, the core agent framework and BedDeM are developed in Java using an agent-based platform called RePast [21]. Although facing some problem with documentation, it is easy to understand and has reduced the learning curve for the development process. RePast is also actively updated for newer Java version and functionalities. We are using the R language to take care of handling and analysis to empirical input data. We also plan to publish the core architecture along with BedDeM's agent implementation to gather peer review. This will allows us to have feedback from multiple perspectives to improve the platform so that it can be employed for researches across different domains.

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