Poster Abstract: Architecture of perception for Behaviour-driven Demand Modelling

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CCS Concepts: • **Computing methodologies** → *Multi-agent systems.*

Additional Key Words and Phrases: agent-based modelling, consumer perception, behaviour-driven demand modelling

Availability of Data and Material:
Available datasets are multiple waves of the Swiss Household Energy Demand Survey (SHEDS) [23] and Swiss Microcensus (MTMC) [21].

1 INTRODUCTION AND MOTIVATION

Agent-based model simulations (ABMs) are increasingly used across disciplines to study individual behaviours, such as the adoption of sustainable technologies or consumer decision-making[9]. These simulations offer a more dynamic and accurate representation of how individual actions and interactions shape broader systems. One of these applications of ABMs is behaviour-driven demand modelling [13]. This entails developing software agents that either replicate real-world behaviours or utilize existing data to estimate the missing information allowing modelling of complex system dynamics such as energy demand.It requires modelling of individual decision-making and interactions of the individuals as agents. Agents in models can represent individual consumers or entities characterized by specific behaviours and attributes. In general, an agent perceives its environment and acts based on these perceptions. The agent's behaviour is guided by an agent function that maps perceptions to actions [16]. Agents encounter cognitive constraints in both knowledge and computational capacity [18], as well as limitations in their ability to process information [10]. Hence the agent functions must be thoughtfully designed.

In previous work the Behaviour-driven Demand Model framework (BedDeM)[13] was developed incorporating *Triandis' theory of Interpersonal behaviour* (TIB) [22] as a decision making function. The current framework has a simplified and limited model of perception, which this research aims to improve. In this context perception refers to how an agent (consumer) observes and interprets its environment, including other agents, social influences, and its own internal state. This perceived information, which may differ from reality, shapes the agent's beliefs, preferences, and its behaviour.

The goal of this research is to enhance the current BedDeM framework by incorporating more coherent cognitive architecture of perception. This would involve interdisciplinary exploration of theories drawn from various fields such as psychology or neuroscience. As demonstrated in previous work [14], perception plays a key role in how demand patterns emerge and evolve over time. A better model of perception could allow for more realistic results, which could be used to create better recommendations how the individual decisions are influenced. This enhanced understanding could help policymakers and businesses design more effective strategies to encourage sustainable consumer choices.

1.1 Research questions

- RQ1 Which theories of perception are most suitable for enhancing the plausibility and behavioural realism?
- RQ2 What are the methods for evaluating and validating the integration of perception theories?

2 RELATED WORK

The perception component was already enhanced in the BedDeM framework to investigate the trust and reputation consequences of the rail service on the mobility behaviour[14]. This demonstrated that the consumer perceptions have quite an impact in daily decisions such as mode-choice as investigated by other disciplines before [8]. Recent advancements in the perception of sustainable technologies highlight the importance of persuasive interventions and innovative solutions to encourage more sustainable choices [12]. Several theories of perception from different disciplines could be used:

- *Society of Mind*[11] describes the mind as a collection of interacting agents, each responsible for different aspects of perception and cognition.
- *Architecture-Based Conceptions of Mind*[19] describes that the mind's architecture, including its various subsystems and their interactions, plays a crucial role in shaping perception.
- *ACT-R Cognitive Architecture*[15] models human cognition, including perception, as a set of modules interacting to produce behaviour.
- *Interface Theory of Perception* [7] suggesting that the perceptions of reality are shaped by evolutionary processes to enhance survival.
- Reinforcement learning methods [17, 20]

All these theories and methods or their fusion could be used to model consumers perception. This could lead to better understanding of the underlying mechanisms and help to create more efficient strategies to shape behaviour into sustainable directions.

3 METHODOLOGY

As previously mentioned, this research aims to enhance the BedDeM framework by incorporating a more comprehensive cognitive architecture of perception. The BedDeM framework [13] is composed of agents and an environment, where agents interact with the environment and execute actions. An agent consists of five components: *Memory*, *Perception*, *Trigger*, *Decision-making* and *Communication*, as shown in Figure 1. The *Perception* observes current state of the environment, other agent preferences and combines them with the

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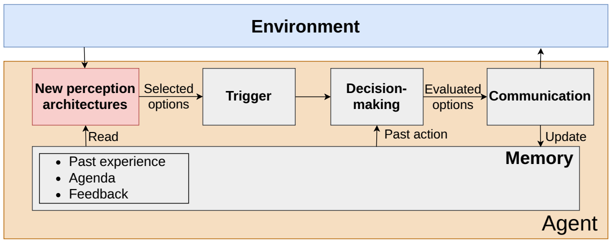

Fig. 1. Agent component architecture BedDeM.

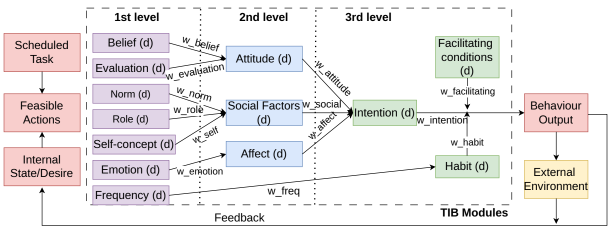

Fig. 2. Decision making component based on TIB in BedDeM agent.

agent internal state stored in the *Memory*. The list of available options is produced and passed to the *Trigger*. When certain criteria is met the *Decision-making* component is triggered and the inputs are passed to the TIB graph in Figure 2. Each option *opt* is assigned an expected utility $EU_d(opt)$ at determinant d, by aggregating weighted, normalized scores from ancestor determinants $a \in A$. These scores, derived from quantitative or qualitative data (e.g., MTMC, SHEDS), are combined as shown in Equation 1 [13].

$$EU_d(opt) = \sum_{a=1}^{A} \frac{EU_a(opt)}{\sum_{o=1}^{O} EU_a(o)} \cdot w_a \tag{1}$$

where:

- $EU_a(opt)$ is the utility value of an option (opt) at determinant d.
- A is the set of the ancestors of d (i.e., determinants connected with d at the previous level).
- O is the set of all available options.
- w_a is the weight of ancestor determinant a.

The final decision is communicated back to the *Memory* and to the *Environment*. The agent values are configured based on the mobility profiles generated by cluster analysis of the MTMC dataset and SHEDS. There are in total 3080 agents representing of different geographical regions in Switzerland. Each agent is assigned a *weight to universe* value from the MTMC dataset, reflecting its proportional representation within the Swiss population. This value is then used to scale up the final outputs to the national level.

The *Perception* component illustrated in Figure 1 is going to be extended by implementing several selected theories or methods of perception to identify the best plausible theory trying to explain changes in attributes and behaviour. For each of these methods the computational architecture of the component would be created and integrated into the agent decision pipeline. The integration workflow pipeline can be seen in the Figure 3. Firstly, the automation of the workflow pipeline would be developed for the baseline case with already existing simplified theory of perception. This includes calibration and validation of the model and prepares for the implementation of the new theories. Consequently, each perception theory is integrated into this pipeline and evaluated using the established metrics.

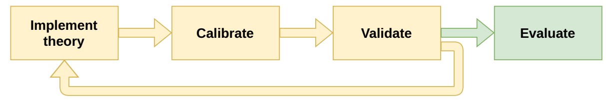

Fig. 3. Workflow diagram.

In order to compare different types of architecture, it is essential to develop appropriate metrics and validation methods[3, 6]. Following methods were identified:

(1) A meso-level empirical method shown in Figure 4 was previously used to validate BedDeM model comparing synthetic and real-world mobility profiles. By clustering individuals and measuring distribution differences via the L1 norm, the model's behavioural realism was assessed, ensuring alignment between artificial and real populations [1, 2].
(2) The overall validation strategy at macro-level using annual mode share data from the MTMC dataset [21] collected in a year distinct from the model's calibration year.
(3) New validation metrics, grounded in tailored psychological experiments to assess their impact on agent behaviour, still need to be developed.

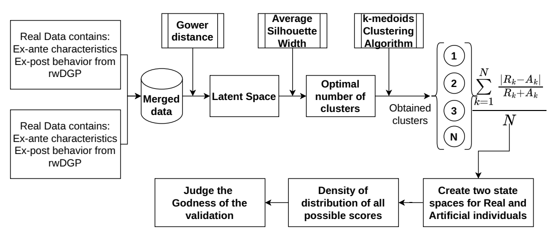

Fig. 4. Meso-level validation [1].

The overall average deviation can be quantified using the Root Mean Squared Error (RMSE) to estimate overall score. Ideally, the model should accurately reproduce both the aggregate mode shares and the behavioural patterns observed in the real-world agent population validated by meso-level validation. For each validation method evaluation scores can be created. These scores can be separately used to evaluate, which of the implementations performs the best across all available metrics assessing the plausibility of different perception architectures.

4 BASELINE RESULTS

To compare different perception architectures we establish the baseline results. We run the current model and compare the outcomes against the 2021 Microcensus [5, 21] for the mobility mode choice use case [13]. Two baseline results:

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Table 1. Comparison of Transport Mode Shares by Daily Distance (in Billion km)

Transport mode	Microcensus 2021	BedDeM 2021
Passenger cars	69.0%	59.2%
Public transport	20.0%	28.5%
Others	11.0%	12.3%

(1) Transport mode shares by annual passenger shown in Table 1 estimated by Equation 2. There is significant discrepancy between the simulated and real data regarding public transport usage. This could be attributed to the impact of COVID-19 measures [4] indicating that public transport had not fully recovered to pre-COVID levels.
(2) Annual and daily mobility per person in kilometres can be compared as shown in the Table 2.

$$A_p = \frac{\sum(P_k \cdot W_u) \cdot 4 \cdot 12}{N_p} \quad (2)$$

where:

- A_p - Annual mobility distance per person in km,
- P_k - Passenger kilometres in billion km,
- W_u - Weight to universe of the corresponding agent,
- N_p - Population size in 2021 (8 738 800) [21].

Table 2. Comparison of Annual and Daily Mobility per Person in 2021: BedDeM vs. Microcensus

Distance per person	Microcensus	BedDeM
Total Annual Mobility (km)	14,926	14,560
Daily Mobility in Switzerland (km)	30.0	29.66

5 CONCLUSION AND OUTLOOK

This paper presents a research proposal aiming at exploring a plausible perception architecture for Behaviour-driven demand modelling. The goal is to enhance the existing BedDeM framework by incorporating a more comprehensive and cognitively plausible computational model of consumer perception. The next steps involve identifying feasible theories of perception and integrating them into the BedDeM model. The validation method and evaluation scores need to be designed to compare these theories against the baseline scenario in order to identify most plausible theory.

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