An Agent-Based Model based on the Theory of Planned Behaviour with Long-Short Term Memory Modules—Case Study on Food Delivery and Its Implications

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Abstract. This work aims to develop a general, widely applicable Agent-Based Modelling (ABM) process for supporting public-health decision-making. To achieve these aims, we have developed a cohesive framework that utilises a robust cognitive model and enhanced memory capacities for the agents. This exploration is applied to a case study looking at an ABM exploring the impacts of food delivery choices on health, transport, and the environment. The model simulates a population of agents who make food delivery choices based on their financial, physical, socio-economic, and cognitive status and attitudes towards various food delivery methods. The agent's decision-making process is based on a cognitive model based on the Theory of Planned Behaviour and the needs model and utilises a long-short term memory framework. The core model, including the cognitive elements, is documented in a manner that is directly applicable to code while communicating the model to stakeholders as well, enhancing the transparency and replicability of models in public health. The model's outputs focus on health and environmental outcomes, including caloric input and incidental exercise, transport emissions, and environmental impact. To conclude, insights from this research will help policymakers and practitioners develop effective strategies to promote healthier and more sustainable food delivery choices, considering the complex interplay in the decision-making process around accessing food delivery services. We recommend the framework proposed in this work to be a useful instrument in modelling social phenomena. It has immense utility in examining how policy decisions can cause perturbations that have impacts on a larger scale.

Keywords: Agent-Based Modelling · Food Delivery · Cognitive Model

1 Introduction

ABMs have a high utility in population health research, especially when dealing with 'wicked' problems [1]. Food delivery services have experienced a rapid expansion over the past decade, propelled by technological advances [2]. With the emergence of new delivery methods, such as autonomous vehicles and drones, food delivery is expected to become even more widespread [3]. These new methods are being piloted in different parts of the world, with varying levels of success. The growing availability of food delivery services is expected to impact population health in two ways. Firstly, food delivered usually has a higher caloric value than home-cooked meals [4], potentially leading to unhealthy dietary habits. Secondly, the lack of incidental exercise associated with going out to buy or cook food may contribute to a more sedentary lifestyle [5]. In addition to the impact on health, food delivery services may have other environmental effects, including increased vehicle or road congestion, emissions, and other environmental impacts [6, 7]. Thus we can identify the complex issue of public health outcomes due to food delivery services as a 'wicked' issue where ABMs can be used to gain clarity around the policy-making process.

The aim of this paper is to investigate the implications of autonomous food delivery, including drone deliveries, on health, transport, and the environment using an agent-based model. Specifically, we seek to answer the following research questions in this study: How would the decision-making process around food delivery play out in a future world with various policy interventions? What would be the health implications of such decisions regarding increased caloric intake and decreased incidental exercise? And what would these decisions mean for road congestion, emissions, and other environmental impacts? We explore the preliminary findings around caloric intake and incidental exercise in this paper.

The ABM model used in this study consists of two main types of agents: consumers and food outlets. At this stage of the model, consumers are the only active agents, while the food outlets serve as passive agents. We define active agents as agents who initiate an interaction, while passive agents are the agents who respond to the interactions. Additionally, the model has two auxiliary agents: the environment and the policy-maker. The model simulates interactions between the agents, such as when a consumer agent places an order for a delivery meal, and the food outlet agent provides the delivery. The government is also simulated as an agent that can impose restrictions on deliveries and/or delivery methods. Finally, the environment agent tracks the resultant effects of the agents' actions, such as congestion, emissions, and other environmental impacts.

While various parameters describe the consumer and food outlet agents, this study focuses on monitoring the consumer agents' incidental exercise and caloric intake and the sales and expenditure of the food outlet agents. The policy-maker agent is not currently being monitored, but the model monitors the environment with respect to congestion, emissions and other environmental impacts. The model aims to provide insights into the complex dynamics of food delivery decision-making by monitoring these variables.

Section 2 presents a short literature review of the existing research on the cognitive models used in ABMs as well as on food delivery services and their impacts on health, transport, and the environment. In Section 3, we describe the agent-based modelling approach in detail, including the model's key components and its calibration. In Section 4, we present and analyse the outputs of the model in terms of health outcomes. In Section 5, we provide a brief interpretation of the results discussing the implications for policymakers and practitioners, as well as identifying the limitations of our research. Section 6 concludes the paper with a summary of the key findings and contributions and concluding remarks and suggestions for future research.

2 Literature Review

In order to better understand the context of our scenario, we will examine relevant cognitive models used in recent ABMs .

2.1 Cognitive Models in ABMs

A critical component for the success of an ABM is to have a cognitive model that represents the decision-making process of agents in a population. While some ABMs utilise mostly probabilistic models, incorporating additional cognitive components can be essential in capturing the heterogeneity of the thinking process of agents. We examine some recent works that used cognitive models that have influenced our cognitive model.

Theory of Planned Behaviour The Theory of Planned Behaviour (TPB) was first proposed by Ajzen [8] as a framework for understanding human behaviour. It is based on the idea that a person's intentions are the most important determinant of their behaviour. According to the TPB, intentions are influenced by three key factors: the person's attitudes towards the behaviour, their subjective norms, and their perceived behavioural control. The TPB has been widely used in various fields to understand and predict human behaviour, including health psychology, marketing, and environmental psychology [9]. This has been successfully used in modelling the cognitive behaviour of Agents in various studies [10–12]

Needs Model Dignum [13] introduces a needs-based cognitive model in his ABM related to covid-19. In this model, needs are represented as values and motives that deplete over time if left unfulfilled. The model prevents agents from focusing only on the need with the highest priority. By calibrating the size, threshold, and depletion rate of each need, the model can balance all the needs over a longer period and different contexts, allowing for the simulation of individual decision-making processes related to health, wealth, and social well-being.

Long Short-Term Memory Long Short-Term Memory (LSTM) network is a type of recurrent neural network (RNN) architecture that was first introduced by [14]. In the context of neural networks, LSTM solves the issue of vanishing gradients, which makes it difficult for the models to learn long-term dependencies while still allowing them to selectively prioritise long-term or short-term memory. We are interested in this, as the concept of LSTM could be very useful in modelling the cognitive behaviour of agents within an ABM.

3 Methodology

The ABM model comprises two primary agent types: consumers and food outlets. Additionally, there are two auxiliary agents, the policy-maker and the environment. Simple interactions between agents occur when a consumer agent places an order for a delivery meal, and the food outlet provides the delivery. Government policies may restrict certain delivery methods or practices, and the delivery methods affect the environment. Our main focus is on monitoring the caloric intake and incidental exercise of the consumer agents and the sales and expenditure of the food outlet agents. The policymaker agent is not monitored, but the environmental impact, in terms of congestion, emissions, and other environmental impacts, is monitored.

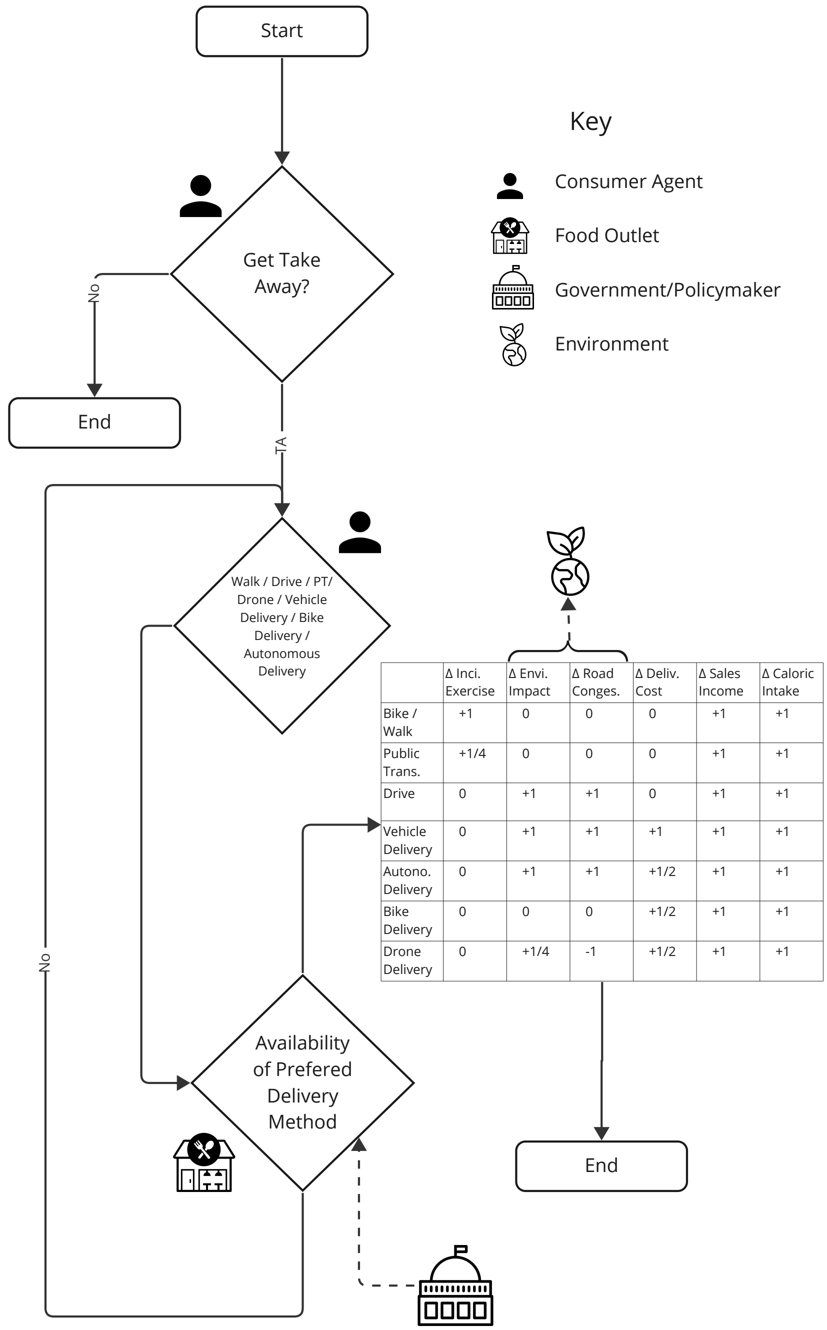
An overview of the main computational process is shown in the form of a flowchart in Figure 1.

3.1 Agent Descriptions, Behaviours, Decision-Making Process, etc.

This section will describe the model's different agents, behaviours, and decision-making processes. The model consists of four conceptual agents Consumer Agent, Food Outlet Agent, Environment Agent and the Policy Maker Agent.

Consumer Agent The consumer agent is the primary agent in the model and contains basic demographic characteristics, including age, gender, education, employment status, and income. Demographic variables were sampled according to the statistics published by the Australian Bureau of Statistics [15, 16]. Situational variables such as hunger, energy, and urgency are also considered in the decision-making process of the consumer agent. Identity variables, such as attitude towards exercise and attitude towards takeaway food, play a crucial role in the decision-making process of the consumer agent. The consumer agents are also monitored for their incidental exercise and caloric intake. Furthermore, the consumer agents are spatially located within a grid space.

Food Outlet Agent The food outlet agent is the second active agent in the model. It is activated when the consumer agent sends a request for takeaway and has the ability to provide a variety of delivery options with different delivery ranges and associated costs. The food outlet agent contains availability of delivery options, delivery range, and cost of a takeaway. The monitoring variables for the food outlet agent will be its sales and expenditure, which will provide insights into the performance of the outlet agent under different conditions. The food outlet agents are also located in the grid space. They will interact with the policymaker and consumer agents to facilitate behaviour based on policy restrictions and consumer preferences.



	Δ Inci. Exercise	Δ Envi. Impact	Δ Road Conges.	Δ Deliv. Cost	Δ Sales Income	Δ Caloric Intake
Bike / Walk	+1	0	0	0	+1	+1
Public Trans.	+1/4	0	0	0	+1	+1
Drive	0	+1	+1	0	+1	+1
Vehicle Delivery	0	+1	+1	+1	+1	+1
Autono. Delivery	0	+1	+1	+1/2	+1	+1
Bike Delivery	0	0	0	+1/2	+1	+1
Drone Delivery	0	+1/4	-1	+1/2	+1	+1

Fig. 1. Multiple agent types provide instances to the ABM that inhere independently in different dimensions

The Policymaker The policymaker is omniscient and monitors and sets policies for the active agents in the model. This agent is not physically located in the grid space and is considered omniscient. The policymaker enacts policy by enforcing restrictions on the delivery methods through taxation, caps on delivery methods, and licensing limitations, specifically for autonomous and drone deliveries. Its decisions and policies directly impact the consumer and food outlet agents and the resulting effects on the environment.

The Environment The environment agent is responsible for monitoring the aggregate effects of the activity of the other agents in the model. Its primary function is to track the emissions, congestion, and other environmental impacts resulting from the interactions of the consumer, food outlet, and policy-maker agents. As the agents make decisions about food delivery methods and other related factors, the environment agent records the environmental effects of these decisions. The environment agent does not exist in the physical space but serves as a monitoring agent, recording and analysing the environmental impacts of the interactions among the other agents.

Behaviour The overall behaviour of the agents in the model is presented in Figure 1. At each time step, a consumer agent is presented with a choice of whether to obtain a takeaway meal or not. This decision-making process is based on the agent's demographics, situational, identity, and monitoring variables.

If the consumer agent decides to obtain a takeaway meal, they will then make a decision on whether to go to the food outlet themselves or to request a delivery. Multiple transit options are available for both options, including autonomous vehicles, drones, and other delivery methods, listed in Figure 1. The consumer agent's decision on the mode of transit is based on a combination of factors, including cost and convenience.

Once the consumer agent has finalised the decision, the workflow is handed over to an outlet agent within a pre-defined radius of the consumer. The outlet agent will then compute the availability of the preferred delivery method based on the policymaker's input by taking into account any restrictions or limitations imposed by the policymaker.

After this process is finalised, the effect on the monitoring variables of the environment, consumer agent, and food outlet agent is calculated. This concludes one iteration of the model for one consumer agent. The same process is repeated for all consumer agents in the model, with each iteration considering the effects of the previous iteration.

Cognitive Decision-Making Process In order to model the decision-making process of the agents, we introduce a cognitive process based on the Theory of Planned Behaviour [8] and inspired by the needs model [13]. The cognitive process is represented in a functional manner in Figure 2.

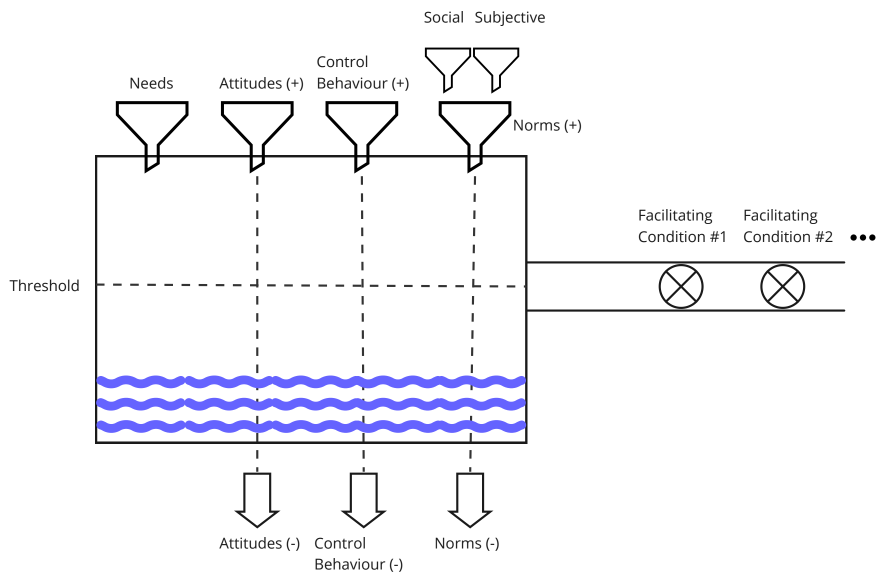


Fig. 2. Multiple agent types provide instances to the ABM that inhere independently in different dimensions

Each agent in the model has a tank-based representation of the drive to act on a behaviour. This tank is filled by various factors such as needs, positive attitudes, positive control behaviour, and social and subjective norms. The tank can also leak through negative attitudes, negative control behaviour, and negative norms. Once the threshold for actioning a behaviour is met, there are further facilitating conditions that may either allow or veto the behaviour.

We can apply this cognitive model to the food delivery model we are building. For example, let us consider the decision point where a consumer agent decides whether to get a takeaway. The needs, in this case, would be hunger, energy levels, and urgency. The attitudes would be the agent's attitude towards takeaway food, with a positive attitude being a preference for a certain type of food and a negative attitude being an awareness about the healthiness of takeaway. Positive control behaviour is represented by the identity of the agent with respect to getting a takeaway, for example, whether they consider themselves to be a "takeaway person". Negative control behaviour is identified as behaviour in the recent past that may prevent an agent from taking a certain action. Social norms would be the general population's tendencies towards getting takeaway, while subjective norms would be the tendencies for take-away in the agent's social network or neighbours (proximity in the grid space). Finally, some facilitating conditions would include the income or financial situation of the agent, as well as the availability of the desired takeaway food.

By modelling the decision-making process in this way, we can ensure that the process is dynamic and that agents adjust to new circumstances, particularly in response to the decisions made by other agents in the vicinity. This will allow for emergent behaviour to occur naturally in the model.

LSTM Memory Function Within the agent's cognitive model, three aspects combine to inform the decision-making—The long-term memory from the preceding timestep (L_{t-1}), short-term memory from the preceding timestep (S_{t-1}), and the perception from the current timestep (P_t). An abstraction of this is shown in Figure 3. The long-term memory incorporates the current perceptions (P_t) into itself and carries forward the collated information (L_t). Short-term memory is only pertinent to the current decision-making process. When the decision is taken, it is expressed as the current action (A_t) and copied onto the current short-term memory (S_t).

In our model, the positive control behaviour ($CB+$) represents the identity-forming and is thus utilised as long-term memory. It is collated across timesteps according to Equation 1.

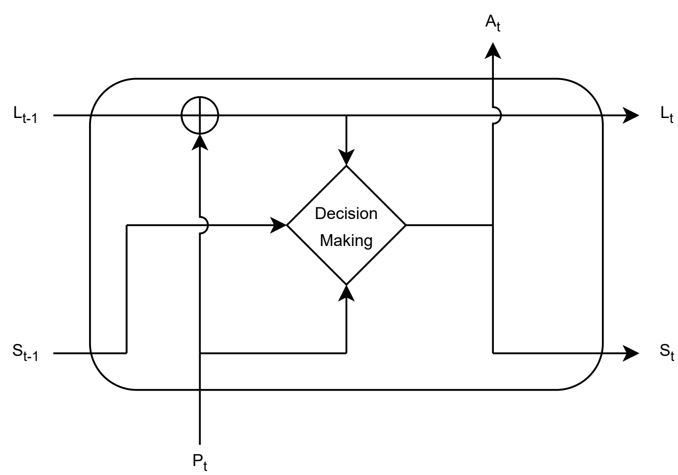


Fig. 3. The consumer agents keep a long-term memory as well as a short-term memory. This diagram shows an abstraction of the memory configuration within an agent. L and S represent Long-term and Short-term memories, respectively. P and A represent Perception and Action. Subscripts represent the temporal aspect with t indicating the current time and $t-1$ indicating the immediately preceding time.

$$CB_t^+ = \frac{CB_{t-1}^+ \times (t-1) + P_t}{t} \tag{1}$$

3.2 Calibration of the model

The results presented in this paper are from a calibration that achieves equilibrium conditions on the takeaways and deliveries that can be perturbed by policy decisions. The final model will be calibrated to three hypothetical future scenarios based on a survey provided to 1209 participants on autonomous vehicles, drone deliveries and food choices.

3.3 Assumptions

Agent-based models rely on a set of assumptions that are necessary to establish a logical framework for the simulation. In the context of our food delivery model, several assumptions were made to create a realistic simulation.

Firstly, the decision-making process for the consumer agent was based on the model described in the theory of planned behaviour, which assumes that individuals make decisions based on their attitudes, subjective norms, and perceived behavioural control. It was also assumed that the decision to obtain a takeaway meal was based solely on the information available within the model, without considering any external or internal factors.

Additionally, it was assumed that the caloric content of takeaway food was higher than that of other food options available to the consumer, which is a common observation. It was also assumed that the monitoring variables, including incidental exercise, environmental impact, road congestion, and delivery cost, varied according to the parameters described in Figure 1.

The model also assumes that the restrictions set by the policymaker are respected by the agents and that they accurately reflect real-world policies. Finally, a simplified model of environmental impacts by various delivery services was assumed to maintain the computational tractability of the model.

In addition to these specific assumptions, the model also incorporates general assumptions that are commonly made in Agent-Based Models. These include assumptions around agent autonomy, heterogeneity, interactions, and adaptation. Specifically, the model assumes that agents are autonomous and have the ability to make independent decisions based on their individual circumstances and preferences. The model also assumes that agents are heterogeneous, meaning they have different characteristics, preferences, and constraints.

Interactions between agents are assumed to occur in a decentralised manner, with each agent having limited knowledge about the state of the system as a whole. Finally, the model assumes that agents are able to adapt their behaviour over time based on feedback from their environment and other agents. These assumptions collectively provide a foundation for understanding the emergent behaviour of the system as a whole and enable us to explore how changes to individual agents or policies may impact the system as a whole.

4 Results

We present preliminary results from the Agent-Based Modelling exercise, focusing on the two main binary decision-making components of the Agent-Based

Model, namely the decision to order takeaway and the decision to get the takeaway as a delivery.

4.1 State of Equilibrium

Figure 4 shows the equilibrium status achieved in the number of takeaway orders and the delivery orders after the initial model calibration for an ABM with 1000 agents. The timeline is indicative of 50 days (odd timesteps represent daytime while even timesteps represent nighttime). The system takes around 5 days to achieve the equilibrium status and retains the status for the duration of the study. An additional simulation with 500 days duration was also indicative of the equilibrium status being maintained. We observe a correspondence between the number of takeaway orders and the number of deliveries. This is expected as the first decision leads to the latter.

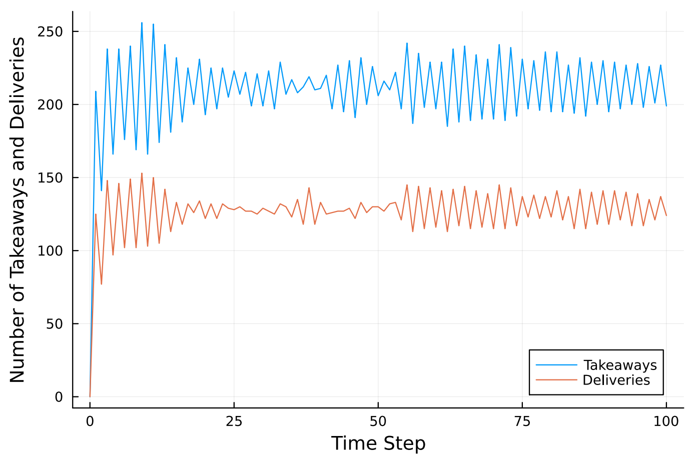


Fig. 4. Under the cognitive model that incorporates the theory of planned behaviour and long-short-term memory components, takeaway orders reach an equilibrium.

4.2 Changes in Caloric Intake and Incidental Exercise

Figure 5 shows the changes to the monitoring variables Caloric Intake and Incidental Exercice throughout the simulation described earlier. The observations are inconsistent with the expectations due to the equilibrium discussed earlier.

5 Discussion

This discussion mainly focuses on the methodologies employed during the development of the Agent-Based Model, with a minor focus on the interpretation of the results, as it represents a work in progress.

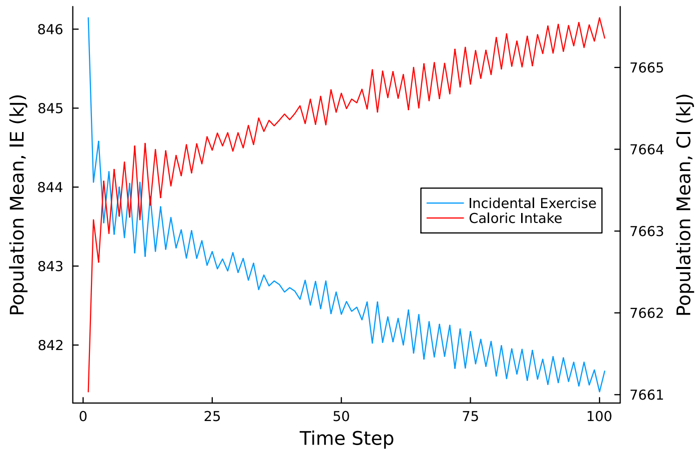


Fig. 5. The population means for caloric intake and incidental exercise is shown here, as it changes with time. It is observed that the caloric intake slowly rises while the incidental exercise slowly declines.

5.1 Critique of the Methods

The central cognitive framework is based on the TPB. However, it is not without its faults [17]. One of the main criticisms is that TPB only takes into account the rational processes, discounting the irrational part of the decision-making process. Some other criticisms are the inability to take into account the dynamic nature of the decision-making process, where intentions change over time and the cultural contexts in which the TPB may be of limited use. These faults are inherently acquired by our cognitive model as well. We also assume the thresholds for actioning a decision remain sufficiently static over time, which can result in inaccurate simulations. The long short-term memory components are quite simplified as of the current implementation, and a more nuanced representation of memory within agents would be beneficial as well.

5.2 Interpretation of the results

The preliminary results shown above are mostly expected. in Figure 4, the equilibrium state is a result of the calibration. However, it is interesting to see the slow decline of incidental exercise and the corresponding increase in caloric intake. It would be interesting to examine further whether this is due to identity-forming features. Although the negative control behaviours come into restricting decisions around actually getting a takeaway or choosing delivery for a takeaway, the positive control behaviour associated with takeaways will result in a minor increase in the caloric intake; similarly, the positive control behaviour associated with delivery results in the minor increase in incidental exercise.

6 Conclusion

This study presents a promising Agent-Based Model that incorporates a needs model [13] inspired implementation of the Theory of Planned Behaviour [8] to investigate agents' decision-making processes regarding takeaway meals and their pickup or delivery options. The results of the preliminary analysis demonstrate the potential of this model to capture the complex interactions between cognitive processes and environmental factors. This work is still in progress, but the promising results indicate the potential of the model to be applied in policy-based perturbations. While the cognitive model is currently simplified, it lays a robust foundation for future improvement and refinement. Overall, this study presents an innovative approach that has the potential to inform policy interventions that could improve decision-making related to public health outcomes.

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