Investigating factors influencing food choices in university catering through multi-agent simulations

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Abstract:
While seemingly very simple, the selection of dishes for composing a meal is a complex decision-making problem in which several factors come into play. The objective of this study was to determine the share of the diverse factors influencing the decisions made for composing a meal in a university restaurant setting. We combined an agent-based model together with *in situ* measures of guest's meal choices made in natural consumption situations. In the model, factors influencing the decision of each agent were individual preferences for the dishes presented, the social influence of other agents present in the simulated environment and the influence of environmental factors such as sensory perceptions when the agent came close to a dish or time to wait to obtain the desired item. In parallel, observations were made in 2 university restaurants during lunch time. They consisted in recording the meal choices made by 336 students. Anthropometric information as well as declared subjective decision criteria were collected by means of self-reported questionnaires. The composition of each guest's table was also recorded and used as a proxy of familiarity between individuals. Simulations of choices were conducted using the measured characteristics of the participants as initial parameters. Comparing the choices of these simulated agents with those of the real participants made it possible to retain sets of values for the importance of preferences, social influences and environmental factors in the guests' decisions. We found that, although the vast majority of respondents declared they were not influenced by others, models yielding the least errors gave an important share to the choices of others in the agents' decision. Also, when exploring the model, it was found that not all dishes are equal in face to social influences as the variation this parameter seemed to differentialy affect the various components of the meal. This study shows that an approach based on multi-agent simulation can help to better characterize the influencing factors at play in this complex decision making problem and can reveal fine mechanisms at work during the composition of meals in natural consumption situations.

Keywords: Food choice, Social simulation, Social influence, collective catering, meal composition problem, Agent based models.

Introduction

1.1 Current food practices are not sustainable and it is critical to reorient eating habits so as not to quickly jeopardize the natural resources, the environment and the health of populations (Willett et al. 2019). However, to act successfully on changing eating habits, it is necessary to have a good understanding of the factors that shape and determine eating choices. Food choices is a complex decision-making problem to tackle as it shaped by several intertwined factors. Food choices are indeed partly based on individual preferences but are also driven by contextual factors and social influences (Ruddock et al. 2019; Cruwys et al. 2015; Symmank et al. 2017).

1.2 Numerous studies in human eating behavior have focused on deciphering how either individual preferences, contextual factors or social influences can shape decisions, each factor is very often considered independently of the others. The reason for this is that if one considers possible interplays between these factors, understanding and predicting the choices made by eaters is equivalent to studying the evolution of a complex system. However, it is these complex situations that research must now succeed in deciphering if owe want to be effective in changing eating behaviors.

1.3 An illustrative example of the potential complexity of this decision making problem can be found in collective catering, such as in a university restaurants. Guests composing their meal from a buffet will select foods based upon their individual appeal for the served dishes (Deliens et al. 2014; Hebden et al. 2015; Roy et al. 2019) their availability (Tam et al. 2017), the choices made by others in the waiting line (Garcia et al. 2021; Christie & Chen 2018; Cruwys et al. 2015; Robinson et al. 2014) or the price and waiting time (Kabir et al. 2018).

1.4 Multi-agent systems, where a set of virtual autonomous agents interact according to certain simple rules in a defined environment, constitute an interesting possibility for studying human behaviors in such settings, which are often too complex to study with classical approaches because they are highly multi-factorial and based on too many interactions between individuals. More precisely, the use of multi-agent modeling methods could allow to better embrace the complexity of the phenomenon at work and to understand the share of each factor in the decision.

1.5 In this article we present the principles, validation and exploration of a multi-agent model to simulate the behavior of food choice in a collective restaurant. The paper is structured as follows: Section 2 proposes a state of the art of multi-agent models of eating behavior; Section 3 presents the model developed using the ODD protocol (Grimm et al. 2020); Section 4 presents the experiments conducted. We will detail in particular the calibration and the comparison with real data we carried out and the exploration of the model. Finally, Section 5 concludes this paper and presents the perspectives of this work.

Related Works

2.1 A number of works have already been proposed to use multi-agent models to simulation food consumption, in particular to study the impact of public health policies targeting overweight and obesity:

2.2 Zhang et al. (2015) developed a multi-agent model to better understand which network mechanisms are important or not in obesity prevention. Their model tested the impact of social influence on the prevalence of overweight and obesity over a year-long period. Their results suggested that peer influence may serve as a buffer to overweight and obesity rather than an amplifier. Zhang et al. (2014) examined how individuals' beliefs are influenced by interventions within the social network or consumption environment. To do so, they modeled individuals and food businesses (either businesses selling fruits and vegetables or fast food). Norm-based interventions were found to be more effective than tax-based interventions.

2.3 Beheshti et al. (2017) compared conventional methods of interventions to prevent the occurrence of obesity with a method that targets the network of individuals. This work argues that targeting individuals based on their position in the network leads to greater effectiveness in obesity interventions.

2.4 Blok et al. (2015) explored the impact of three hypothetical interventions to reduce income inequality in food consumption. They observed that eliminating residential segregation had the largest impact on reduction in inequality, but that in return, it implied a deterioration in healthy food consumption for higher-income households.

2.5 Wang et al. (2014) examined the effect of social norms on children's body mass index and fruit and vegetable consumption. The result was that a high prevalence of obesity leads to a continued increase in body mass index (BMI) which is explained by the increased social acceptability of the average BMI.

2.6 Other studies closer to our objective proposed to use agent-based modeling to explain dietary choices. Scalco et al. (2019) developed a multi-agent model to simulate British meat consumption by implementing the different types of concerns that drive people to adopt a vegetarian diet. In particular, they studied the changes in behavior (meat consumption) in response to different policy interventions: they showed that an increase in the price of meat had a greater effect than environmental and animal welfare campaigns, while a health campaign was more effective than all other campaigns.

2.7 On the same topic, Thomopoulos et al. (2021) proposed a multi-agent model to simulate meat consumption, built from a study of the arguments used to debate this topic. The model studies in particular the impact of communication campaigns and health crises on meat consumption. The simulation results showed that arguments in favor of meat reduction can be widely diffused in the population and that the ratio between the frequencies of crises and communication campaigns plays an important part on the meat consumption.

2.8 In line with this work, Taillandier et al. (2021) proposed an generic model to represent the processes of opinion diffusion via explicit argument exchanges between individuals. The model was applied to study the diffusion of vegetarian diet in the population. Unlike the model of Thomopoulos et al. (2021) where the arguments were just used to build the model but were not explicitly represented, this work explicitly integrates the arguments with the consideration of the existing attacks between them. The model shows a growing interest in vegetarian diets. It also shows the interest of targeted messages in terms of subject matter and who to send the message to in order to have a greater impact.

2.9 If these works are useful to understand the change of opinion on the long time, they do not allow to understand the food choices on the short time (at the time scale of a meal). To date, there is no model at this level that focuses on the time of the meal, although we know that this choice is not trivial and depends on many factors (personal, social, contextual). This is precisely this short meal time that we seek to model and simulate in this work.

Presentation of the model

Overview

Purpose and patterns

3.1 The objective of the model is to simulate eating behavior (choice of dishes) during a meal in a collective restaurant. We evaluate the model by its ability to reproduce two patterns. The first one concerns the impact of interpersonal relations on the choice of foods. Indeed, as stated by (Garcia et al. 2021; Christie & Chen 2018), the social interaction plays an important role in the choice of food. The second is the impact of factors such as price or contextual factors such as the sensory appeal of the dishes and the waiting time, which are known to play a role in food choice (Kabir et al. (2018)). Since in the university restaurants considered for this research, guests pay a fixed price, here only contextual factors were considered.

Entities, state variables and scales

3.2 The main types of entities represented in the model is the individuals (`Individual agents`). An individual will have to choose the dishes she/he wants to take. She/he will choose a main course and can choose starters and desserts. An individual may not take a stater or dessert and may take up to 2 starters and 2 desserts. As is the practice in university restaurants in France, we consider that each dish represents a certain number of points and that an individual has a certain number of points for her/his meal. She/He can choose not to spend all her/his points or to exceed them by one or two points (and in this case pay more for the meal). Once inside the restaurant, the individual must first take a tray. Then she/he can choose the dishes she/he wants. Once the dishes have been chosen, she/he must go to one of the cashiers to pay for her/his meal. Concerning the main dishes, an individual must choose a protein intake (meat, fish, vegetable protein, etc.) and can add a side dish (vegetable, starch, etc.) if she/he wishes. Table 1 presents the state variables of the *Individual* entities.

3.3 The environment represents a restaurant. In the restaurant, in addition to places where trays can be retrieved, cash registers, entrances and exits, blocks offering different dishes are accessible. For each block, a queue is defined allowing individuals to wait their turn to get the desired dish. A dish is characterized by the number of points it costs. In addition, we characterized the attractiveness of a dish for a *Individual* agent according to her/his age, gender and BMI as presented below in Equation 1. Table 2 presents the state variables of the *Dish* entities.

$$A_i(d) = intercept_d + age_i \times f_d^{age} + gender_i \times f_d^{gender} + BMI_i \times f_d^{BMI} + age_i \times gender_i \times f_d^{BMI-gender} \quad (1)$$

3.4 In terms of temporal scale, a simulation step represents 1 second and the model aims to simulate the period of a meal (2-3 hours).

State variable	Data Type	Description
age_i	Integer - static	Age
$gender_i$	Integer - static	Gender (M = 0 /F = 1)
BMI_i	Float - static	Body mass index
$speed_i$	Float - static	walking speed
$dist\_p_i$	Float - static	Perception distance of dishes (in meters)
$is\_vegetarian_i$	Boolean - static	is vegetarian
$2\_starters_i$	Boolean - static	does she/he considers choosing 2 starters
$2\_desserts_i$	Boolean - static	does she/he considers choosing 2 desserts
1_points_i	Boolean - static	does she/he considers exceeding of one point
2_points_i	Boolean - static	does she/he considers exceeding of two points
$friends_i$	list of individuals - static	friends (= familiar guests) inside the restaurant
k_i^{social}	Float - static	importance of the social aspect in the food choice
$k_i^{personal}$	Float - static	importance of one's individual preferences in the food choice
$k_{environment}$	Float - static	importance one's external/contextual factors in the food choice
ks_i^{friend}	Float - static	importance of the choices made by familiar guests in one's choice
ks_{other}	Float - static	importance of the choices made by unfamiliar guests in one's choice
ke_i^{wait}	Float - static	importance of the waiting time in the food choice
$se_i^{perception}$	Float - static	strength of the perception of a dish in the food choice
$dishes_i$	List of dishes - dynamic	Dishes selected

Table 1: State variables of an *Individual* agent i

State variable	Data Type	Description
$type_d$	String - static	Type of the dish: starter, main course or dessert
$category_d$	String - static	Category of the dish: pizza, fish, dessert cream, fruit...
$intercept_d$	Float - static	Intercept for the choice of this dish
f_d^{age}	Float - static	Age factor for the choice of this dish
f_d^{gender}	Float - static	Gender factor for the choice of this dish
f_d^{BMI}	Float - static	BMI factor for the choice of this dish
$f_d^{BMI-gender}$	Float - static	BMI-Gender factor for the choice of this dish

Table 2: State variables of a *Dish* d

Process overview and scheduling

3.5 At each step of the simulation, *Individual* agents can arrive in the restaurant. They are then placed at one of the entrances (chosen randomly). *Individual* agents already in the restaurant start by moving to their objective: if they don't have a tray yet, this objective will be the nearest tray pick-up area. If they have already collected all the dishes that make up their meal, they first move to the nearest cashier and once they have paid for their meal, they move to the nearest exit. If they still have dishes to collect, they move to the next chosen dish. Once this dish is retrieved, they choose the next dish, then move towards it. Concerning the choice of dishes, this is done by first filtering the possibles dishes and then evaluating all these possible dishes, taking into account personal preferences, social and environmental influences (see 3.14). The choice of the dish is then probabilistic: its probability of being taken is equal to its score.

3.6 For the filtering of the dishes, foremost, if the *Individual* agent is vegetarian, She/he removes all the dishes not compatible with her/his diet. Then, if she/he has already taken a starter and she/he does not want to consider a second one, she/he will eliminate them. She/He will do the same for the desserts. Then, according to the sum of the points of the dishes already taken and her/his willingness to accept to exceed by one or two points the maximum of points granted, she/he will keep only dishes that do not exceed her/his maximum that she/he is ready to consent. The agent will then choose a dish from the list of those kept (see 3.14).

3.7 Once the objective selected, the *Individual* agent moves toward the chosen objective (a tray pick-area, a dish, a cashier or an exit). The movement action is based on the decomposition of the space using a grid. Each free cell (i.e. without wall, furniture, or obstacle) can be occupied by a single agent. The A* algorithm is used for shortest path computation. Once arrived at a dish, a tray collection area or a checkout, the *Individual* agent stands in line (in the queue) and waits for her/his turn. Each activity (taking a tray, taking a dish, paying) takes a given time. This time is considered the same for all the *Individual* agents.

Design concepts

Basic principles

3.8 The model draws on theories from the literature on the drivers of food choice. Existing works have shown the impact of social and environmental influence on this choice (see Introduction section).

Interaction

3.9 There are two types of interactions between *Individual* agents: direct influence (in the neighborhood) and indirect in link with the waiting time. There are also a spatial interaction between *Individual* agents and the dishes: when *Individual* agents are close to the dish, she/he will be influenced by its perception of the dishes.

Stochasticity

3.10 The first stochastic aspect of the model is its initialization, i.e. there can be stochasticity in the creation of agents (characteristics, friends, etc.). Also, the choice of dishes is probabilistic according to its score. Finally, the order of activation of the *Individual* agents at each simulation step can impact the simulation. To avoid order activation bias, at each simulation step, the *Individual* agents are activated in a random order.

Observation

3.11 The major observation for this model is the type of dish chosen by the individual agents. The goal is to know for each type of dish how many times it has been chosen.

Sensing

3.12 The *Individual* agents know all the dishes available in the restaurant. They can perceive the ones that are close to them, which can modify their opinion on these dishes. They also perceive the other *Individual* agents close to them, as well as those in the queues, which will influence their choice. They also all know the places where to take trays, the cashiers and the exits.

Details

Initialization

3.13 The model is initialized by using data on the restaurant: walls/obstacles, blocks offering dishes and the queue, dishes in the blocks with their characteristics, entrances, exits, cashiers, as well as tray pick-up areas. Once these data are loaded, the grid allowing the agents to move is updated in order to eliminate the cells on which there are obstacles. The Individual agents are generated from external data. These data must specify for each *Individual* agent her/his age, her/his gender, her/his BMI, her/his friends and her/his arrival time in the restaurant. Regarding the values of the attributes of dishes related to their attractiveness, we used a binary logistic regression based on consumption data from the INCA3 French food consumption database (Dubuisson et al. 2019). INCA3 is a study that dates back to 2014 on the food consumption of a representative sample of the French population that including 2,000 participants, aged 18 to 79 years. For the attributes defining the importance of the different factors in the choice of dishes, these are drawn randomly from a Gaussian distribution with a defined mean and standard deviation (Table 3). Considering the possibility of exceeding the predefined number of points by one or two points, choosing 2 starters or 2 desserts and being vegetarian, they are defined from the global probabilities (Table 3).

Input data

3.14 The model does not use any input data to represent time-varying processes.

Parameter	Type	Range	Description
k^{social}	float	[0,1]	Mean value for the importance of the social aspect in one's decision
σ^{social}	float	[0,1]	Standard deviation for the importance of the social aspect in one's decision
$k^{personal}$	float	[0,1]	Mean value for the importance of one's preferences in one's decision
$\sigma^{personal}$	float	[0,1]	Standard deviation for the importance of one's preferences in one's decision
$k^{environment}$	float	[0,1]	Mean value for the importance external/contextual factors in one's decision
$\sigma^{environment}$	float	[0,1]	Standard deviation for the importance of external/contextual factors in one's decision
ks^{friend}	float	[0,1]	Mean value for the importance of friend's choices in one's decision
σ^{friend}	float	[0.1]	Standard deviation for the importance of familiar guests' choices in one's decision
ks^{other}	float	[0,1]	Mean value for the importance of non-familiar guests' choices in one's decision
σ^{other}	float	[0,1]	Standard deviation for the importance of unfamiliar guests' choices in one's decision
ke^{wait}	float	[0,1]	Mean value for the importance of the waiting time in one's decision
σ^{wait}	float	[0,1]	Standard deviation for the importance of the waiting time in one's decision
$se^{perception}$	float	[0,∞]	Value of the strength of the perception of a dish in one's decision
P^{1_points}	float	[0,1]	Probability of considering exceeding of one point
P^{2_points}	float	[0,1]	Probability of considering exceeding of two points
$P^{2\_starters}$	float	[0,1]	Probability of considering taking 2 starters
$P^{2\_desserts}$	float	[0,1]	Probability of considering taking 2 desserts
$P^{is\_vegetarian}$	float	[0,1]	Probability of being vegetarian

Table 3: Parameters used for initialization

Submodels

3.15 The score $V_i(d)$ of a dish d by a *Individual* agent i is computed with Equation 2

$$V_i(d) = k_i^{personal} \times P_i(d) + k_i^{social} \times S_i(d) + k_i^{environment} \times E_i(d) \quad (2)$$

with $k_i^{personal}$, k_i^{social} and $k_i^{environment}$ the characteristics of *Individual* agent i.

3.16 $P_i(d)$ is the personal preference of the *Individual* agent i for a dish d, computed from the attractiveness of the dish considering the age, gender and BMI of the *Individual* agent (see Equation 1). $P_i(d)$ is computed as follow (Equation 3):

$$P_i(d) = \frac{A_i(d)}{1 + A_i(d)} \quad (3)$$

3.17 $E_i(d)$ is the external/contextual influence towards the *Individual* agent i for a dish d. It is based on two distinct factors: the expected waiting time to get the dish and the perception of the dish - our hypothesis here is that if an individual perceives a dish, it can make her/him want to choose it (visual, olfactory perception, etc.). $E_i(d)$ is computed as follow (Equation 4):

$$E_i(d) = W_i(d) - ke_i^{wait}(d) \times IQ(d) \quad (4)$$

with $ke_i^{wait}(d)$ the number of *Individual* agents in the queue for the dish d and $W_i(d)$ equal to $se_i^{perception}$ if the dish is within the distance $dist\_p_i$ to i.

3.18 $S_i(d)$ is the social influence towards the *Individual* agent i for a dish d computed as follows (Equation 5):

$$S_i(d) = ks_i^{friend} \times F_i(d) + ks_i^{other} \times O_i(d) \quad (5)$$

with $F_i(d)$ and $O_i(d)$ the number of *Individual* agents in the perception distance who have already taken the dish d and who are respectively in the friend list ($friends_i$) or not in the friend list of i. Making this distinction between friends and non-friends allows to give more importance to friends in social influence.

Experiments

Data collection

Ethics approval

4.1 Approval for the study was obtained from the ethics committee of Université Paris-Saclay (registration number CER-Paris-Saclay-2021-094)

Observation settings

4.2 Data collection was conducted in two university restaurants serving students of a university of the Paris region. The "Kantine" of Ecole Normale Supérieure Paris Saclay and the "Lieu de Vie" of Université Paris-Saclay. These restaurants are run by the public operator "Regional Center for University and Academic Affairs" (Centre régional des œuvres universitaires et scolaires - CROUS). These restaurants are organized as a "scramble" buffet configuration such as guests can decide to select dishes with no pre-defined order. Such a configuration is interesting because it allows to generate a more important mixing of the crowd of guests and possibly to increase the level of social interaction. Figure 1 presents the plan of one the two university restaurants ("Lieu de Vie"). The configuration of the second restaurant is similar to this one.

Timing and periods of measurements

4.3 Data collection were conducted over 2 weeks in October 2021, on 2 consecutive days in each of the restaurants (Thursdays and Fridays,) yielding a total of 4 days of observations (October 21st and 22nd for "Lieu de vie" restaurant and October 28th and 29th for the "Kantine" restaurant). Observations were conducted on guests having their lunch at the university restaurant between 11:30 and 12:30.

Proposed dishes

4.4 Several options for each meal component were available daily. The menus were different on the 4 days of measurements, especially for the main courses, as the starters and desserts could sometimes be similar. The proposed dishes, although different from one day to another, could always be categorized as follows: starters {cold cuts, raw vegetables, fish, starch salads}; main dishes {meat, fish, vegetarian dishes}; dairy {fresh dairy products, dairy creams, cheese}; desserts {fresh fruits, gourmet desserts}. This categorization was used to record consumption data and was used for the analyzing the simulation results.

Measured parameters

4.5 Paper questionnaires were given to guests upon their arrival in the restaurant. These questionnaires aimed at collecting information on participants' age, sex, height, weight, special diets or food exclusions. This questionnaire also included questions concerning the frequency of visit to the restaurant, and importance granted to choice criteria: influence of the choice of others, influence of the visual aspect of the dishes, whether the waiting time to be served mattered for them, their level of hunger when entering the restaurant.

4.6 Questionnaires were anonymous and only identified with a registration number. Guests were prompted to indicate on the questionnaire the registration number of the other guests with whom they had shared their meal (the composition of each guest's table was used as a proxy of familiarity). This questionnaire was filled out during the meal and then given to the experimenters by the guests at the exit of the restaurant.

4.7 Participants' food choices were recorded by investigators using a form containing the day's menu. At the check-out, the experimenters noted the food chosen and the number of each guest. Table 4 gives the number of students surveyed for each restaurant and each date. Of the students surveyed, 75% were male and 25% were female, with a mean age of $21.16\ y$ and a mean BMI of $21.5\ kg.m^{-2}$. There were more observations on Thursday (21st and 28th) than on Friday (22nd and 29th) because some of the students who were already surveyed on Thursday did not accept to fill in the form for a second consecutive day.

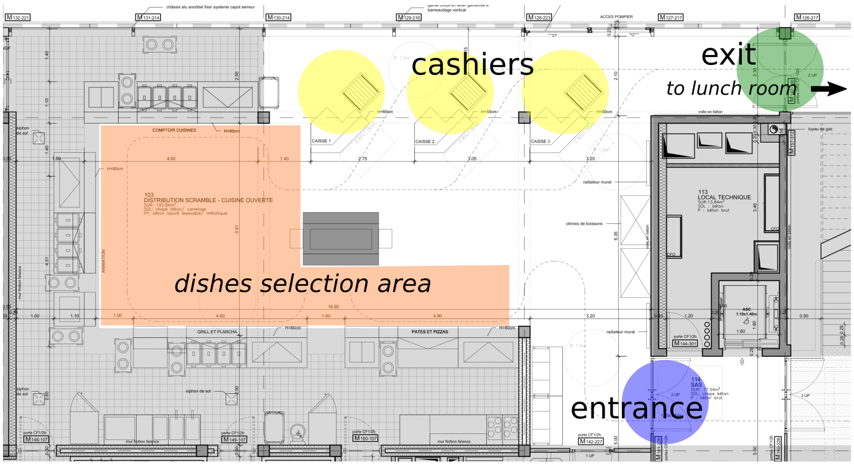

Figure 1: Architect's plan of the "Lieu de Vie" restaurant; the blue circle represent the entrance, orange area corresponds to the dishes selection area, the yellow circles the cashiers and the green circle the exits toward the lunch room. Both restaurants are organized on the same basis

Restaurant	Date	Number of students
Lieu de vie	October 21st	101
Lieu de vie	October 22nd	56
Kantine	October 28th	122
Kantine	October 29th	49

Table 4: Number of students who completed surveys by restaurant and date

Stochasticity analysis

4.8 In a first experiment, we analyze the impact of the stochasticity of the simulations on the results and in particular on the chosen dishes. The main objective is to find a threshold value of replications beyond which an increase in the number of replications would not imply a significant marginal decrease of the difference between the results. To do this, we compare the number of times each type of dishes has been chosen between different number of replications of the simulation. We undertake this exploration using parameter values such as to maximize the stochasticity. As such, as reference scenario, we used the "Kantine" restaurant on Thursday because it is the scenario with the largest number of students. Table 5 presents the parameter used.

4.9 Figure 2 shows the standard error of the number of times each dish type has been chosen obtained with different number of replicates. Figure 3 shows the impact of the number of replicates: the black lines is the median, the box shows the second and third quartiles (IQR), the whisker shows the minimum and maximum excluding outliers (simulation results that differ from the median by more than 1.5 times the IQR). The results suggest that increasing the number of replications beyond 100 does not have a great impact on the aggregate trend of the simulation.

Calibration and validation

4.10 In order to obtain credible parameter values, we calibrated the model on one of the available datasets. Specifically, we used a genetic algorithm to find the set of parameters that minimizes the fitness function, which in this model is the difference between the categories of dishes chosen in the observed data and in the simulation. The fitness function (to be minimized) for a simulation s is thus given by the following equation:

$$fitness(s) = \frac{\sum_{cinC} |Num_c^{obs} - Num_c^s|}{N} \quad (6)$$

with C the set of dish categories, Num_c^{obs}, the number of times a dish from category c has been chosen in the observed data, and Num_c^s, the number of times a dish from category c has been chosen in simulation s.

Parameter	Value
k^{social}	0.5
σ^{social}	0.5
$k^{personal}$	0.5
$\sigma^{personal}$	0.5
$k^{environment}$	0.5
$\sigma^{environment}$	0.5
ks^{friend}	0.5
σ^{friend}	0.5
ks^{other}	0.5
σ^{other}	0.5
ke^{wait}	0.5
σ^{wait}	0.5
$se^{perception}$	2.0
P^{1_points}	0.5
P^{2_points}	0.5
$P^{2\_starters}$	0.5
$P^{2\_desserts}$	0.5
$P^{is\_vegetarian}$	0.05

Table 5: Value of parameters for the stochasticity analysis

4.11 The dataset used for the calibration is the "Kantine" restaurant on Thursday October 28th. Table 6 presents the value obtained for the parameter after calibration. The table 6 shows the value obtained for the parameters after calibration. Note that the probability of being vegetarian was not defined by calibration, but was directly taken from the questionnaires and set to 0.05.

Parameter	Value
k^{social}	0.8
σ^{social}	0.1
$k^{personal}$	0.1
$\sigma^{personal}$	0.1
$k^{environment}$	0.7
$\sigma^{environment}$	0.1
ks^{friend}	0.7
σ^{friend}	0.5
ks^{other}	0.2
σ^{other}	0.2
ke^{wait}	1.0
σ^{wait}	0.6
$se^{perception}$	2.3
P^{1_points}	0.6
P^{2_points}	0.2
$P^{2\_starters}$	0.1
$P^{2\_desserts}$	0.1

Table 6: Value of parameters obtained by calibration

4.12 Comparing declared choice criteria (presented in figure 4) and parameters inferred by the model's calibration highlighted several divergences between shares of declared and inferred choices criteria. While guests mostly stated that they were not influenced by waiting time as $32.4 \pm 8.7\%$ of respondents declared to be *"Not at all"* and $32.4 \pm 8.7\%$ *"very little" influenced by waiting time"*, the models displaying the best fitness were those that gave significant weight to this parameter.

4.13 Similarly, in real life, guests declared *"No or little influence of the influence of other's choices"* $(62.3 \pm 7.0\%$ of respondents declared to be *"not at all"* influenced and $26.7 \pm 2.6\%$ of respondents declared to be *"very little"* influenced), the parameter corresponding to the influence of choice of others was high in the calibrated model.

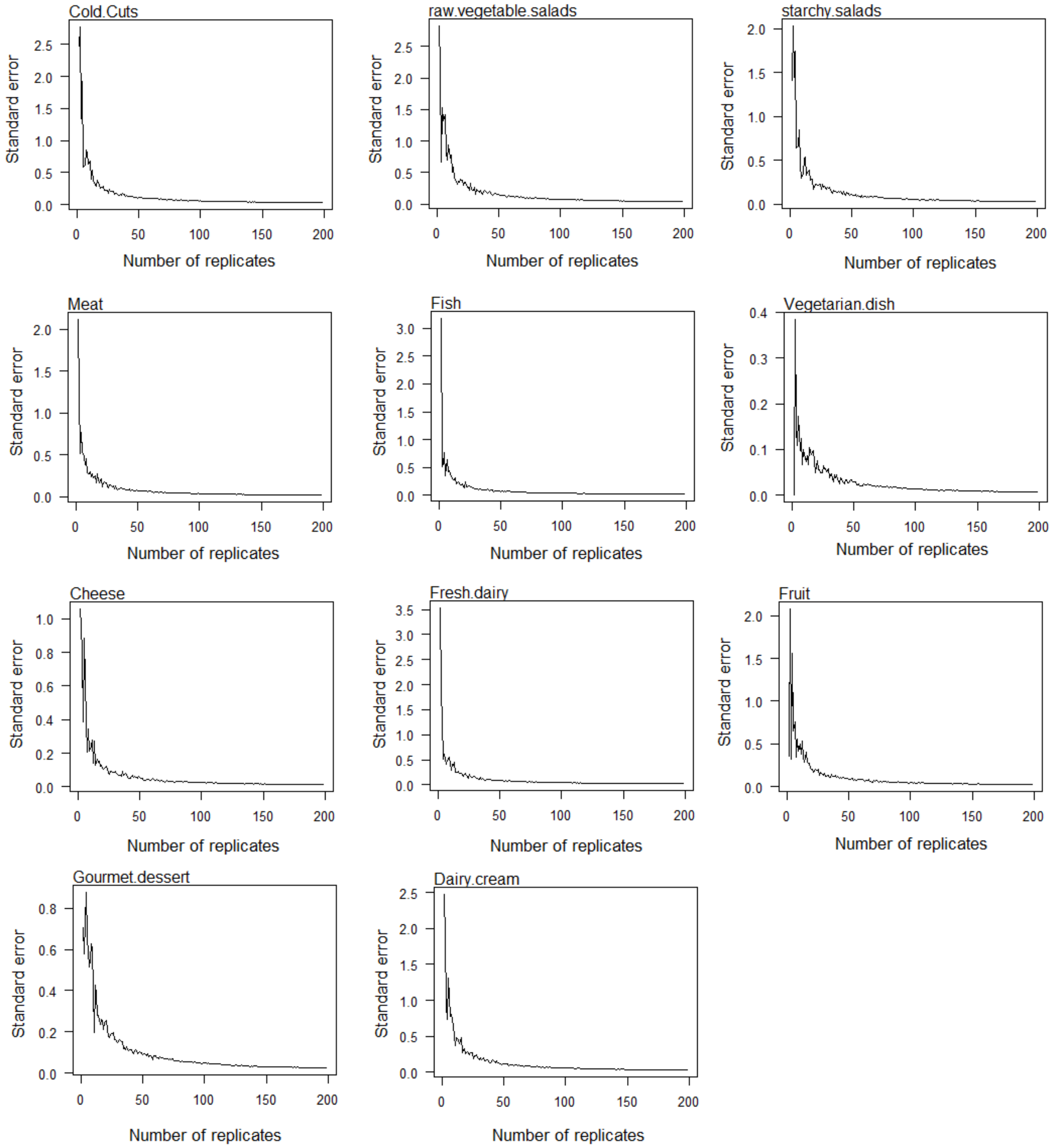

Figure 2: Comparison of the standard error of the number of times each dish type has been chosen for the different number of replicates.

4.14 Regarding the influences of sensory perceptions, which include the visual and olfactory appeal of the dishes, the distribution of responses is much more uniform and consistent with the parameters inferred from the model.

4.15 Figure 6 shows the results obtained with the model using the parameter values after calibration for 100 replications. The mean fitness for 100 repetition is 1.843. For starters, the results obtained by the simulation are close to the observed results, for some other types of dishes, the difference is higher (example: gourmet desserts, creme desserts, vegetarian dishes). One explanation comes from the method used to define the preferences for the dishes. Indeed the preferences are estimated according to their relative frequency of consumption from the INCA 3 (Dubuisson et al. 2019) database. These frequencies include all meals, and not only meals eaten in collective restaurants at lunchtime. In addition, they are estimated from a population with much larger age range (INCA3 compiles the consumption of 2,000 adults aged from 18 to 79 years) than the population (young adults with a mean age of $21.16\ y$) followed in the two university restaurants considered. These values are

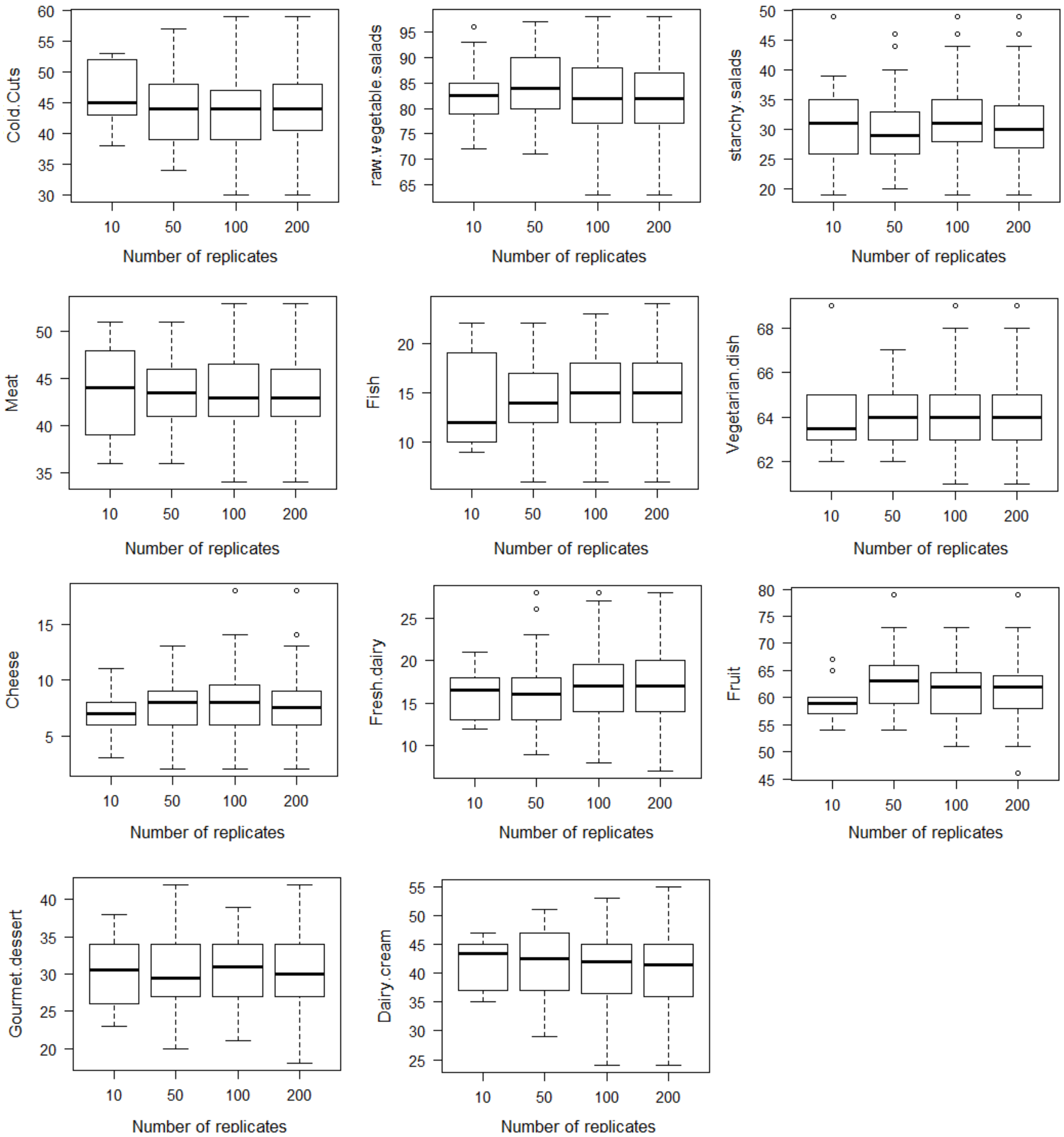

Figure 3: Whiskers plots of the number of times each dish type has been chosen for the different number of replicates. The black lines represent the median values; the boxes represent the interquartile range (IQR), the whiskers represent the minimum/maximum excluding 1.5 IQR outliers. Points are outliers beyond that distance.

therefore, not surprisingly, a very rough estimator of the preferences for the dishes offered.

4.16 In order to assess the generality of the parameter values found, we evaluated the ability of the model to simulate the situation of the other days and the other restaurant. Figure 5, Figure 7 and Figure 8 show respectively the results obtained for 100 simulations for the "Kantine" restaurant on October 29th, and the "Lieu de vie" restaurant on October 21st and 22nd. The mean fitness obtained are respectively 1.654, 1.942 and 2.592. A first observation for the day of the 29th is that the model obtains as for the 28th convincing results for the starters. For the main courses, we observe the same bias as for the 28th with an over-choice in the simulations of the vegetarian dishes at the expense of the other dishes. For the deserts, an important element in the observed data is that the gourmet desserts were chosen a lot on the 28th and not at all on the 29th. This can be explained by the fact that the gourmet desserts, which are very popular with students, are available in limited numbers and

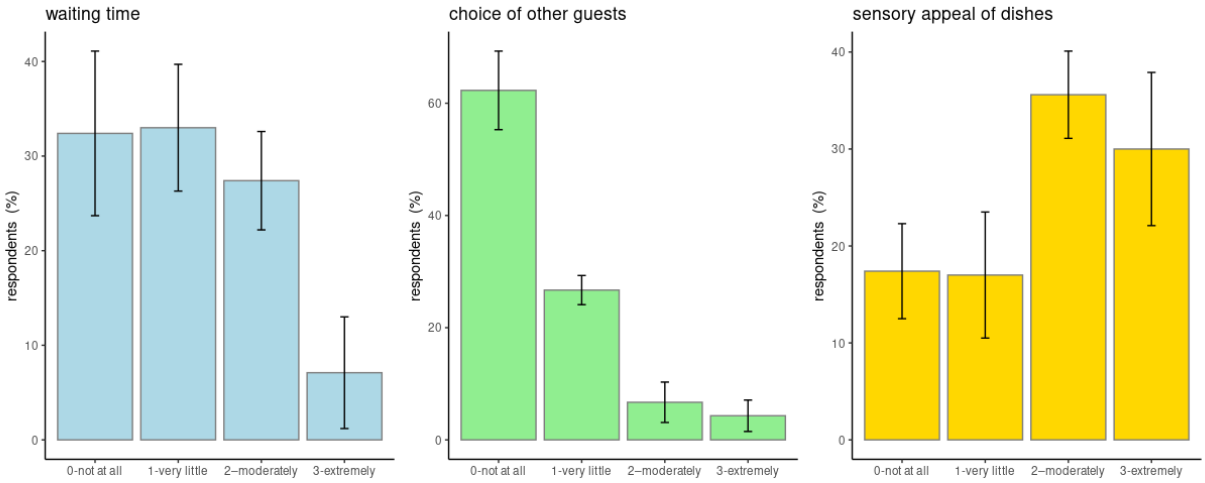

Figure 4: Importance of three choice criteria declared by guests of the University restaurants. Values are represented are means $\pm$ standard deviation of percentage of answers over the 4 days of data collection. Left Panel corresponds to the answers to the question *"do you think the waiting time to get your dish influenced your choice today?"*, center panel corresponds to the answers to the question *"do you think that the choice of the other guests influenced your choice of dish today?"*, right panel corresponds to the answers to the question *"do you think that the visual and olfactory appeal of the dishes presented has influenced your choice today?"*

were not available on the 29th, so students switched to the other desserts. This aspect of stock was not taken into account in the simulation, which explains why students in the simulation continued to choose gourmet desserts and therefore less other desserts. Another bias in the observed data that makes the results different from one day to another and that is not taken into account in the model is the fact that they are mostly the same students between the 28th and the 29th and that they may have a tendency, especially for the main course, not to take the same dish as the day before.

4.17 For the day of the 21st and the "Lieu de Vie" restaurant we can see more difference in the results. If for some of the starters, the results obtained by simulation are close to the observed data, it is not the case for the starch salads very overestimated by the simulation and the cold cuts which is underestimated by the simulation. The results are closer for the main dishes, with still an overestimation of the number of students choosing the vegetarian dish in the simulation, even if less than for the "Kantine" restaurant. For the desserts, like for the "Kantine" restaurant on October 29th, we are in a case where there was no gourmet dessert available, hence the lack of choice of this type of dessert in the data observed, which bias the choice of desserts.

4.18 Finally, the day of October 22nd at the restaurant "Lieu de vie", obtains the most distant results between the simulation and the observed data. The difference is particularly important for the appetizers with in the observed data an overrepresentation of raw vegetables for starters while the simulation proposes a more balanced choice of starters. It is not to be excluded that on certain days a particular dish will attract a large number of guests and that on this particular day the predictions will be particularly distorted.

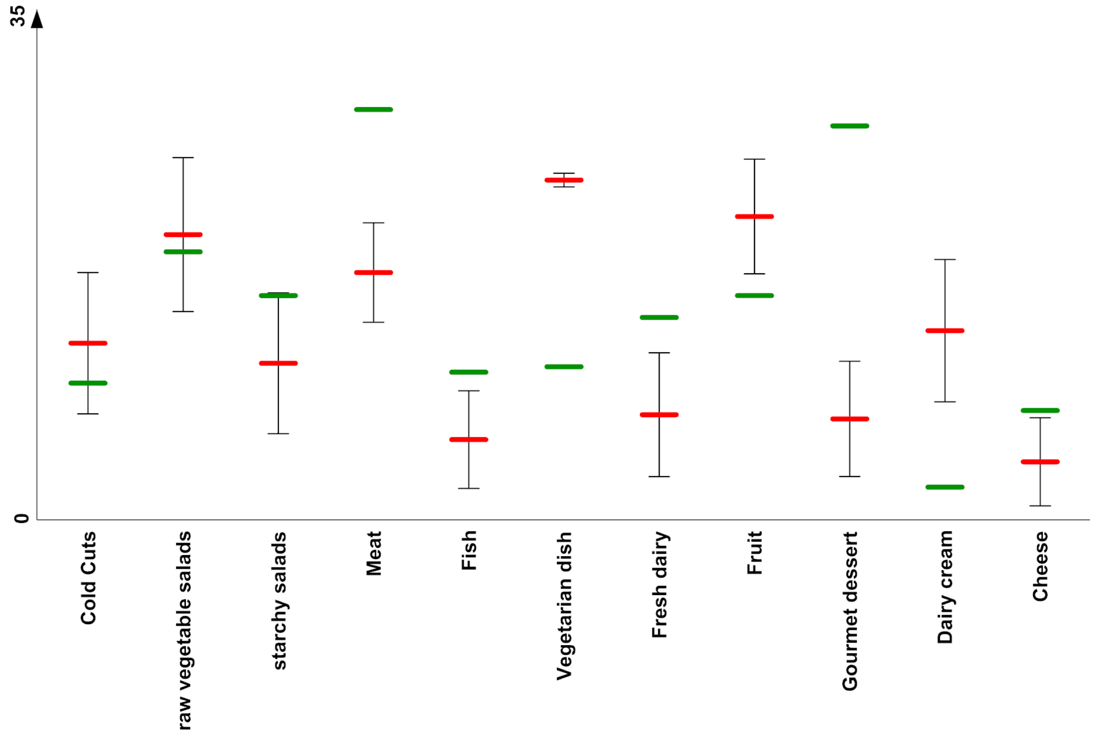

Figure 5: Number of dishes of each category chosen with the calibrated model for the "Kantine" restaurant on October 28th. In green, the observed data; in red, the mean simulation results (100 simulations) with the standard deviation

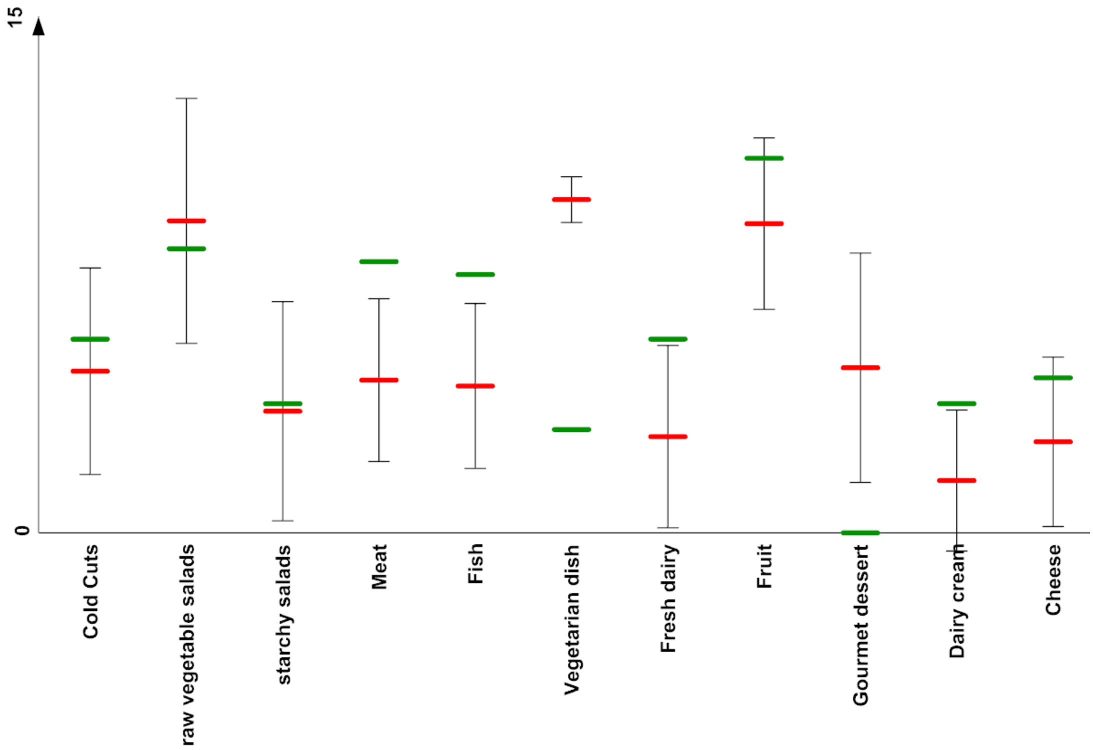

Figure 6: Number of dishes of each category chosen with the calibrated model for the "Kantine" restaurant on October 29th. In green, the observed data; in red, the mean simulation results (100 simulations) with the standard deviation

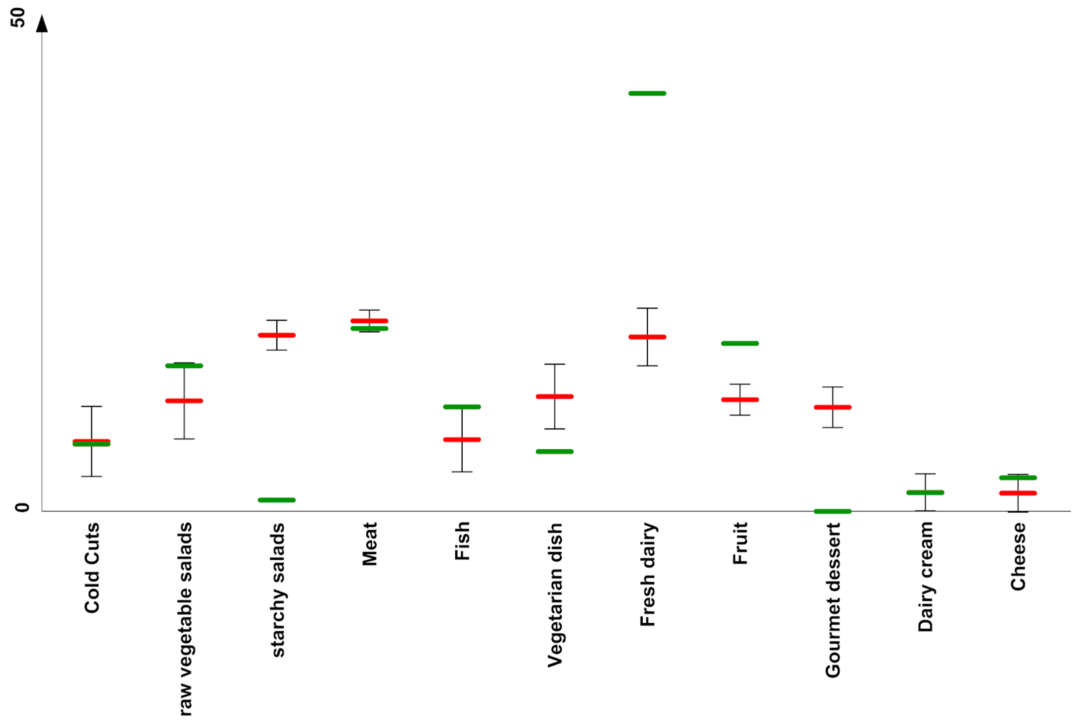

Figure 7: Number of dishes of each category chosen with the calibrated model for the "Lieu de Vie" restaurant on October 21st. In green, the observed data; in red, the mean simulation results (100 simulations) with the standard deviation

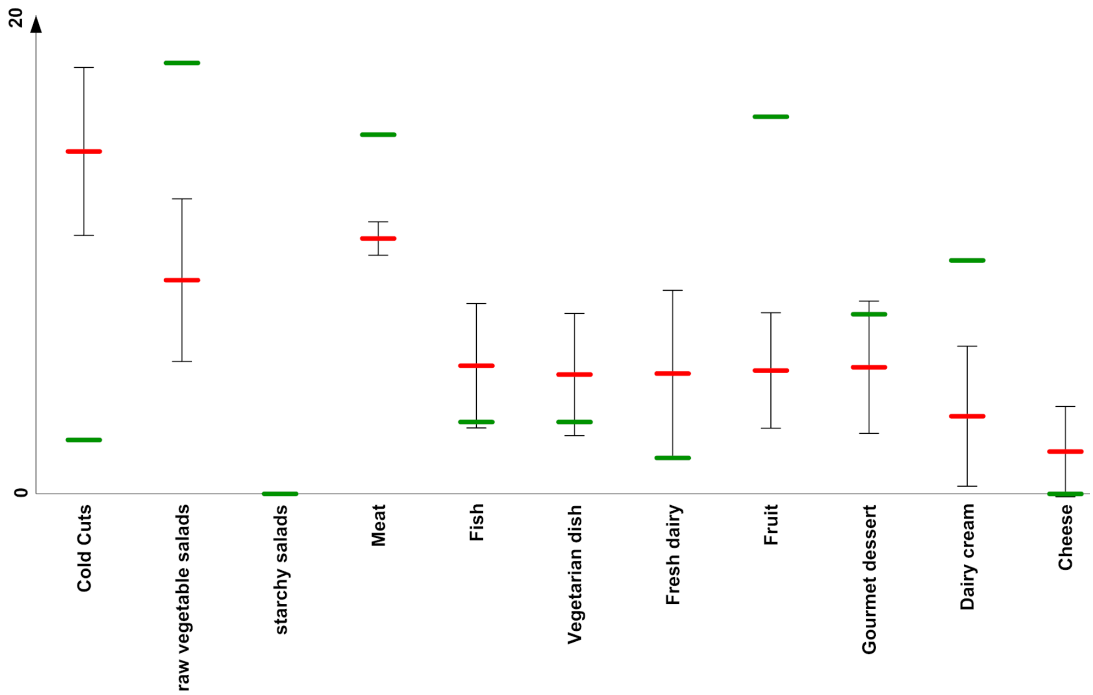

Figure 8: Number of dishes of each category chosen with the calibrated model for the "Lieu de Vie" restaurant on October 22nd. In green, the observed data; in red, the mean simulation results (100 simulations) with the standard deviation

Exploration of the model

4.19 Figure 9 represents the explorations of the the model by navigating the `social_influence` parameters through its amplitude ranges. Increasing the share of social influences in the decisions of the simulated agents hare differential effects for the various dishes. We have chosen to present here only the dishes with a relatively high frequency of choice because the poorly selected foods give, even with a large number of simulations, results that are difficult to interpret.

4.20 Interestingly, the proposed dishes seem to be driven by the `social_influence` parameter in different ways. Some are not significantly influenced, such as the main course containing fish, the dairy cream or the gourmet desserts. Other dishes were significantly influenced but to a very small extent, such as cold cuts (estimated regression coefficient $= -0.63 \pm 0.07, p < 10^{-12}$), raw vegetables salads (est. coef. $= -0.31 \pm 0.07, p < 10^{-12}$), starters with starchy foods (est. coef. $= 0.06 \pm 0.04$, $p < 10^{-12}$), main courses containing meat (est. coef. $= 0.16 \pm 0.02, p < 10^{-12}$) and vegetarian main courses (est. coef. $= 0.11 \pm 0.05, p < 10^{-12}$). Finally, some dishes were more strongly driven by the `social_influence` parameter, namely fresh dairy (est. coef. $= -2.8 \pm 0.8$, $p < 10^{-12}$) and fruits (est. coef. $= 1.26 \pm 0.06, p < 10^{-12}$). It is interesting to note that the case of gourmet desserts is interesting because only very low values of the `social_influence` parameter seem to have a depressing effect on the number of desserts chosen (one can imagine that as soon as few virtual agents have made this choice then its probability of choosing increases significantly).

4.21 We found that not all dishes were affected similarly by social influences. Indeed, variation of the importance of the `social_influence` parameter in the model's decision function seemed to affect dairy products and desserts in a greater fashion than main dishes (meat or vegetarian dishes). This result is in agreement with previous studies of our group (Garcia et al. 2021).

Conclusion

5.1 In this article, we have presented a new model designed to simulate eating behaviors in a catering context. The model was calibrated from data collected for a reference day in a university restaurant in France and we then evaluated by testing it for other days as well as a different restaurant. The results are promising, even if some aspects, like individual preferences, could be better represented in the model.

5.2 Although there is still much to be made to improve the model and simulations, it is interesting to note that such a model, based on the consideration of a relatively limited number of influencing factors (individual preferences, social influences and contextual elements), makes it possible to simulate behaviors that are fairly close to those observed in reality. Also, we were able to reproduce quite accurately the effects already observed in other studies of social influences on only some components of the meals (starters and desserts). These effects probably result from a competition between decision criteria, (here social influences versus personal preferences) (Garcia et al. 2021). This work has also revealed a certain number of factors that sometimes act in an unconscious manner or that are often difficult to identify with work based on declarative data, as we have observed by comparing the declared weight of social influences or context effects and the values inferred from calibrated models. In the future, this work could provide an interesting tool to study and understand the decision criteria in natural consumption situations and to evaluate the criteria that promote the acceptability of behavioral change towards healthier and more sustainable behaviors.

5.3 Model's decision function could integrate even more realistic mechanics of interactions between individuals taking into account, for example, emotions or familiarity, dominance or empathy (Jager 2017; Bourgais et al. 2018) or social contagion mechanisms (Hatfield et al. 1993). Such complex decision function could also take into account the criterion of nutritional quality of the food, which is another important determinant of food decisions. Importance granted to nutritional quality is interestingly subject to social influence (Robinson & Higgs 2013; Robinson et al. 2013a,b) but also drives meal composition by inducing trade-off mechanisms in an individual's meal choices (Abou Jaoudé et al. 2022). In addition to the development of more complete models, efforts will be necessary to collect larger sets of observations in real situations to train such improved models.

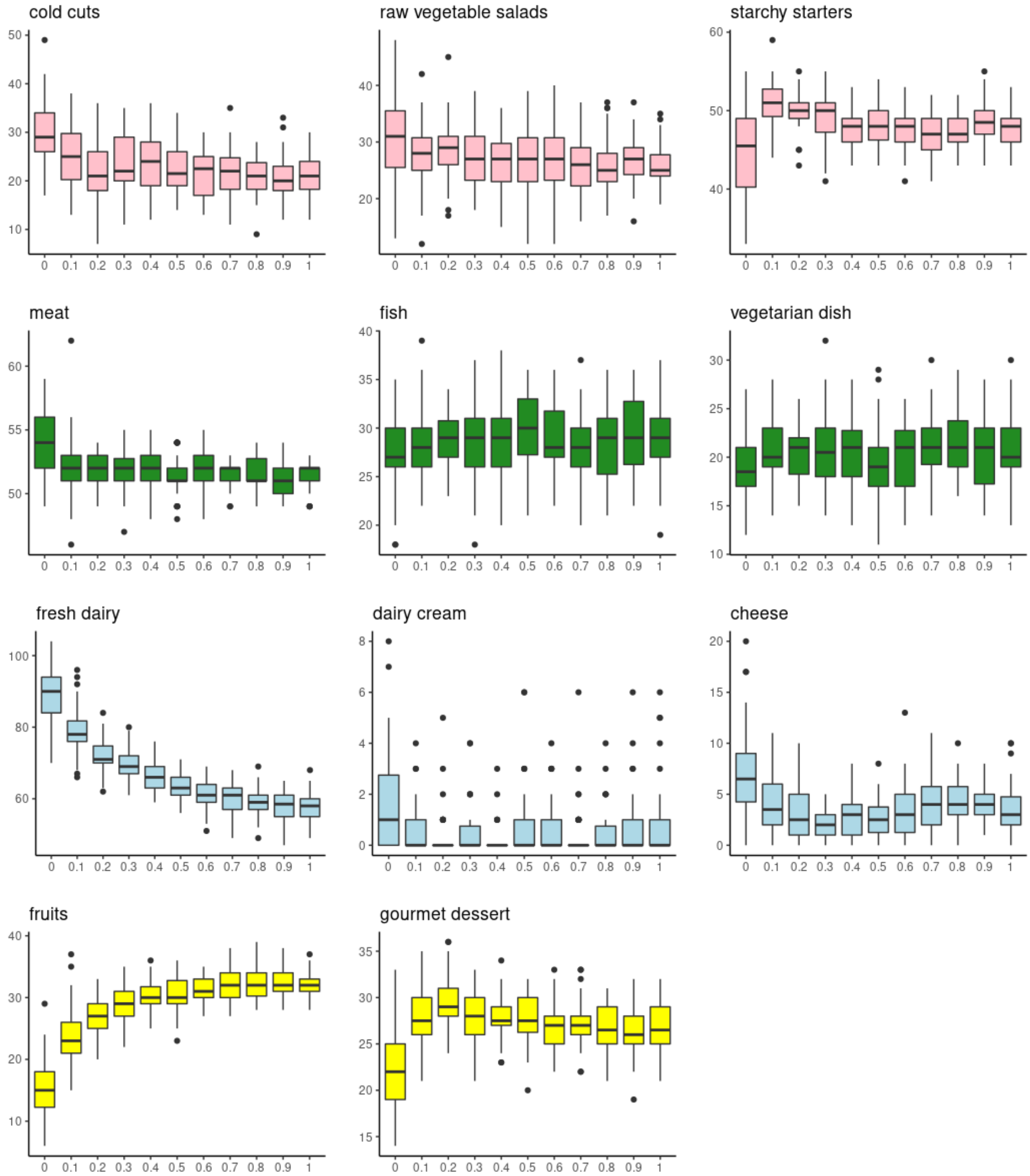

Figure 9: Effect of the importance of the parameter "social influences" in the simulated choices of different components of the meal: Representation of the number of choices made for each dish resulting from the simulation of each set of parameters (y axis) according to the importance given to the "social influence" parameter (average values over 50 simulations $\pm$ standard deviation). All the parameters used are from the calibrated models except for the "social influence" parameter which varies over its entire range (x axis). The "social influence" parameter is composed of two sub-components: the parameters of the familiar people and the parameters of the people met in the food selection area. The top panel represents the results obtained for starters, the middle-top panel for main courses, the middle-bottom panel for dairy products and the bottom panel for desserts.

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