Balancing Customer Interactions and Travelling Distance in Supermarket Design

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***Abstract*—Research showed that a higher in-store traveling distance resulted in an increase in sales. This economic perspective is logical, but with ever increasing interest into the risks of infectious diseases this design might prove to be flawed. In this research, an Agent Based Model is used to compare two different supermarket layouts on the distance travelled per customer and the number of interactions per agent. These parameters are expected to be an indicator of the likelihood of disease transmission.**

The results show significant differences between two supermarket layouts, called the *grid* and the *free form* layout, the former having less short-cuts than the latter. As expected, a supermarket with a higher number of short-cuts will result in a lower amount of distance travelled per customer and a lower number of interactions between customers. This shows an important trade-off for business owners, policy makers and other stakeholders, where taking into account social health would be disadvantageous from an economic perspective.

I. Introduction

Since the outbreak of COVID-19, Agent Based Modelling (ABM) has been extensively used to either advise political organs about potential lockdowns, or to understand behaviour of diseases like COVID-19 from a more detailed perspective (Cuevas, 2020; Blakely et al., 2021). Important decisions need to be made regarding the (restricted) opening of grocery shopping establishments, which need to stay open to provide food. This in turn induces conflicting interests between policy makers and business owners. Policy makers want to make shopping an efficient process, with a low level of interaction between customers to prevent the disease from spreading. Business owners will however want to optimize sale quantities. Through previous research there has been found that a positive relation exists between sales and in-store travelling distance (Boros et al., 2016; Dorismond, 2016; Kholod et al., 2010).

Targets of both parties mentioned above can be affected by supermarket design, but to the authors' knowledge, literature has merely focused on the economic impact that it has. This research will therefore focus on the comparison of frequently adopted supermarket designs and try to gain understanding in the important trade-off between customer interactions and in-store travelling distance, which ultimately relates to sales. Results are obtained by simulating shopping behavior in supermarkets with an ABM, as the problem contains a relatively large number of agents that interact and move in a certain space. Since we want to model, understand, analyse and tweak micro-scale behaviour and subsequently observe the emerging macro effects, an ABM might be an appropriate way of approaching and modelling such a concept (Heppenstall et al., 2011).

Specifically, this research wants to explore the trade-off between economic intents and social health components of designing a supermarket. As the COVID-19 pandemic is not expected to disappear overnight, and other epidemics are a constant risk, long term decisions on supermarket design could benefit from taking this trade-off into account. In upcoming years, results from our research could help grocery retailers when decisions are being made on newly built establishments.

This research will try to answer the following question: How does the number of shortcuts in a supermarket influence the number of human interactions and customer travel distance? The modelling approach is extensively described in section II-A, justifying decisions and clarifying the details of the performed simulations. The results of this work are presented in section III and are two-fold: a comparison between simulations with two supermarket designs are made and elaborate sensitivity analysis is done with multiple approaches. Lastly, section IV discusses our results and concludes this work.

II. Model Description

The following section will describe our model using the extended Overview, Design concepts, Details and human Decision-making (ODD+D) protocol, the most widely employed convention for reporting research with ABMs Müller et al. (2013). We initially outline the purpose of our model, with the major entities, their parameters and the scale of the model, a detailed overview of the simulation and scheduling follows. The important underlying design concepts and assumptions in our model and their effect on the output is portrayed afterwards. Lastly, implementation specifics are described in terms of model initialization, input and packages used.

A. Purpose

The main objective of this paper is to provide a framework which can be used to evaluate customer interaction and in-store travelling distance during the supermarket design process. The simulation framework can be used with various supermarket layouts and results may help make decisions on the trade-off between economic intents and novel social or health related ones under specific circumstances. Our method currently focuses on the two targets mentioned above, but could be extended to contain additional objectives. We focus on two designs that are frequently apparent in Dutch supermarkets, to show that our work could be practically used in designing an actual supermarket.

B. Entities, State Variables and Scales

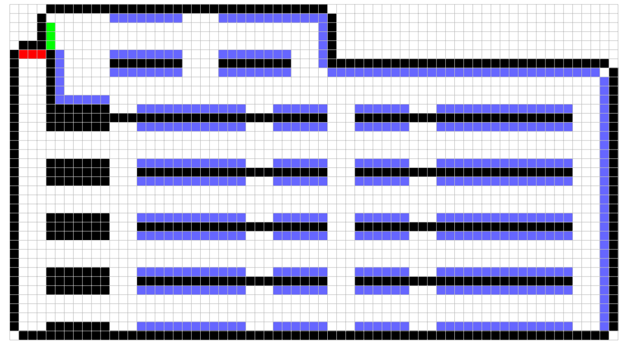
Our model consists of a heterogeneous population of customer agents that moves through a spatial grid. This is the layout of a supermarket and the first entity of our model. This supermarket contains different types of grid cells. The entry and exit of the supermarket are specific locations on the grid that the customer agents use to get in and out of the supermarket. A set of obstacle cells is placed on the grid as well. These cells represent walls or product shelves, that agents can not move through. Grocery products are placed along the supermarket shelves and are represented by a different cell type as well. Customers moving in the shop will have to move onto such a cell to collect the specific product. The remaining cells are pathways in the supermarket, where agents can freely move through.

The second entity of our model is the population of customer agents. It is a heterogeneous population and several characteristics distinguish the customers. All customers have a specific setting for: their walking speed (v), the level of familiarity with the store (f), the vision distance (ψ), their grocery list (G) and the arrival time at the supermarket (t_a). For the walking speed (v), familiarity (f) and vision (ψ) of a customer, two values and occurrence probabilities are specified. Each initialised customer gets one of the specified values with the corresponding occurrence probability. This way, a population of heterogeneous agents is created. Additionally, each customer is assigned a list of groceries that has to be collected on their trip. This list is a random selection of products from every available article that is in the store. Lastly, customers arrive to the store at a certain point in time. This arrival time is also part of a customer's state and is an exogenous variable of the model. The arrival time is homogeneously distributed through a Poisson distribution.

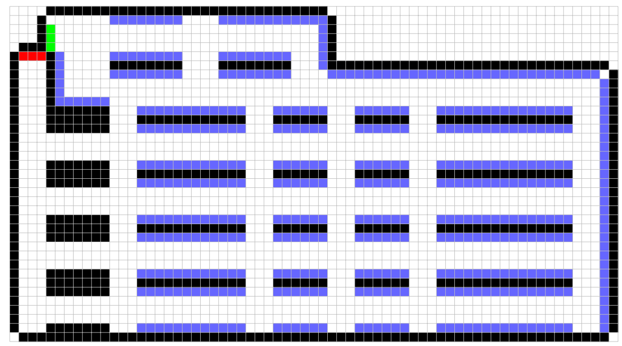
Symbol	Description
t_a	Arrival time (steps)
v	Speed (cells per step)
f	Familiarity with store
ψ	Vision distance (cells)
G	Grocery list (of length n)

TABLE I: Customer agent state variables, all variables are static except for the store familiarity.

The scale of our model is decided by balancing realistic spacial and temporal components with the computational costs of increased scale. Our model contains a spatial component that represents a supermarket with a 2-dimensional grid of



(a) Supermarket design representing a *grid layout*.



(b) Supermarket design representing a *freeform layout*.

Fig. 1: Supermarket design used in this research. The entry is green and the exit is red, unspecified product shelves are blue and wall tiles are black. Each tile represents a 50x50 centimeter square, the total grid then comprises 33.5x18.5 meters.

65x35 cells. Considering every cell as a square of 50x50 centimeters results in a supermarket of approximately 32.5 by 18.5 meters. Time-wise, each time step of the model represents approximately 2 seconds of real time and customers in the simulation were allowed to enter for 1800 time steps. This means that the shop will allow customers to enter the shop for approximately 3600 seconds or 1 hour of real time.

C. Process Overview and Scheduling

The model we use represents a period of time in which several customers enter a supermarket, do their shopping and leave the supermarket again. Starting with an empty supermarket, customers arrive at the supermarket entrance following a homogeneous Poisson distribution with the average arrival time (t_a). Each customer has a list of objective locations representing its grocery list (G). All objectives are selected randomly and sorted on distance from the exit. When all objectives are sorted, an exit objective is placed at the end to ensure the shopper leaves the shop after shopping.

Every time step, a customer enters the supermarket grid if sampled from the homogeneous Poisson distribution. Whenever customers are in the supermarket, they move a certain number of cells each step depending on their speed (v). The direction of these steps is determined by their familiarity (f)

with the store and their vision distance (ψ). Their familiarity determines the probability of the direction of these steps being a random walk or an aimed direction decided by an A*-algorithm. We furthermore make the assumption that over time, customers that are unknown with the store will learn the placements of products. Therefore, the familiarity is increased by 0.01 at every time step. The process of decision making and agent description further explained in section II-D2.

D. Design Concepts

1) Theoretical and Empirical Background: As stated in section I, literature suggests that supermarket owners will try and optimize sale quantities. A relation is found between sales and in-store travelling distance of customers, leading to supermarket designs that attempt to increase this distance. This increase is expected to lead to more time spent in stores and subsequently a larger number of interactions between customers. As a result, in present times where highly infectious diseases such as COVID-19 are prevalent, policy makers might want to steer store design so that in-store travel distances and therefore the number of customer interactions are decreased. Focusing on in-store travelling distance and customer interactions, our model compares supermarket layouts and their effect on the mentioned outcomes.

The design of the model's spatial component is derived from literature (Vrechopoulos et al., 2004) and the two designs under consideration will be compared. In a more general context, store customers can be observed to be *recreational* or *purpose* shoppers (Van Rompay et al., 2012; Dorismond, 2016). This research assumes that supermarket customers are generally shopping with a purpose, coming into the store with a list of articles they want to purchase. The model initialises every customer agents with a personal shopping list.

Customer movement through the supermarket is assumed to be determined one item at a time. Research suggests that customers are individuals with bounded rationality that do not completely optimise their route beforehand (Dorismond, 2016). We implement this one-step approach with a mixture of a random walking algorithm and the A*-algorithm repeatedly determining the shortest path towards the next item on a customer's list (Hart et al., 1968). Since not all customers will only know the route to their desired objective, a familiarity parameter is used to determine which type of step to take. The A*-algorithm is based upon the evaluation function $f(n) = g(n) + h(n)$, where $g(n)$ is a cost function and $h(n)$ is an estimate of the cost. In this study, for $h(n)$ an euclidean distance function is used. In addition, when customers cross routes with other individuals, a random movement is made to avoid the other individual, which is a realistic assumption in actual supermarkets.

Research by Vrechopoulos et al. (2004) suggests that a specification of a *free form* supermarket results in more time spent in the supermarket than in a *grid layout*. As our specification of the *free form layout* is somewhat different from theirs, we expect our specification of the *grid layout* with less shortcuts to increase time or distance spent in the supermarket. This is because we expect that as customers move through the supermarket with a list of objective locations, streams of customers will develop. These emerging streams are expected to be more apparent in the *grid layout*, since customers are unable to use shortcuts and be limited to the customer flow. The most important parameters in terms of their effect on customer interaction and distance travelled are expected to be the average arrival time (t_a), the parameters related to speed (v) and the parameters related to vision (ψ).

2) Individual Decision Making: All agents have an individual grocery list (G) containing objective locations. This grocery list starts with the entry of the supermarket and ends with the exit as these are start and end locations of every customer. The list contains n objectives, which is a different value for every customer in the supermarket. The items on the list should be collected based on their order, as customers are expected to look forward one item at a time (Dorismond, 2016). Dependent on the familiarity (f) and a uniform pseudo-random number generator, the agent will decide to make an A*-algorithm move or a random move to the von Neumann neighbourhood grid cells. Impossible moves will be solved as explained in section II-D6 *Interaction*.

3) Learning: Agents will get to know the supermarket over time, since the familiarity (f) of each agent increases by a constant every time step. This increase of familiarity (f) results in a higher chance of customers performing A*-algorithm moves and increases the likelihood of customer agents proceeding to the correct location. This simulates the assumption that the longer someone is in the shop, the less time they will need to find an object that they may have previously passed.

4) Individual Sensing: The agents are able to sense their neighbourhood directly trough weighted edges between grid cells. After finding an optional route the agent senses whether it is busy on that specific route and adapts it routes accordingly. The radius of sense is constant over time per agent but varies between agents according to the vision parameter (ψ).

5) Individual Prediction: An agent follows a route calculated according to it's familiarity parameter (f) and vision parameter (ψ). When the agent is more familiar with the supermarket, the chances that it will make use of the A*-algorithm increases, minimizing the route distance. This route is then updated as explained in section II-D4 *Individual Sensing*. With these methods an agent is able to make an implicit prediction of the fastest route, that does not take into account movements of other agents.

6) Interaction: An agent can move to another empty grid cell in it's von Neumann neighbourhood. If the cell is not empty, agents will swap places if they are standing on each other's desired place, wait on the current position for 1 move or make a random move. These are the only interactions agents can have with each other. For an agent to interact with an objective (grocery item), the agent must position itself on the same grid cell as the objective to collect it. Once the agent has collected the objective, it will continue its route to the next objective.

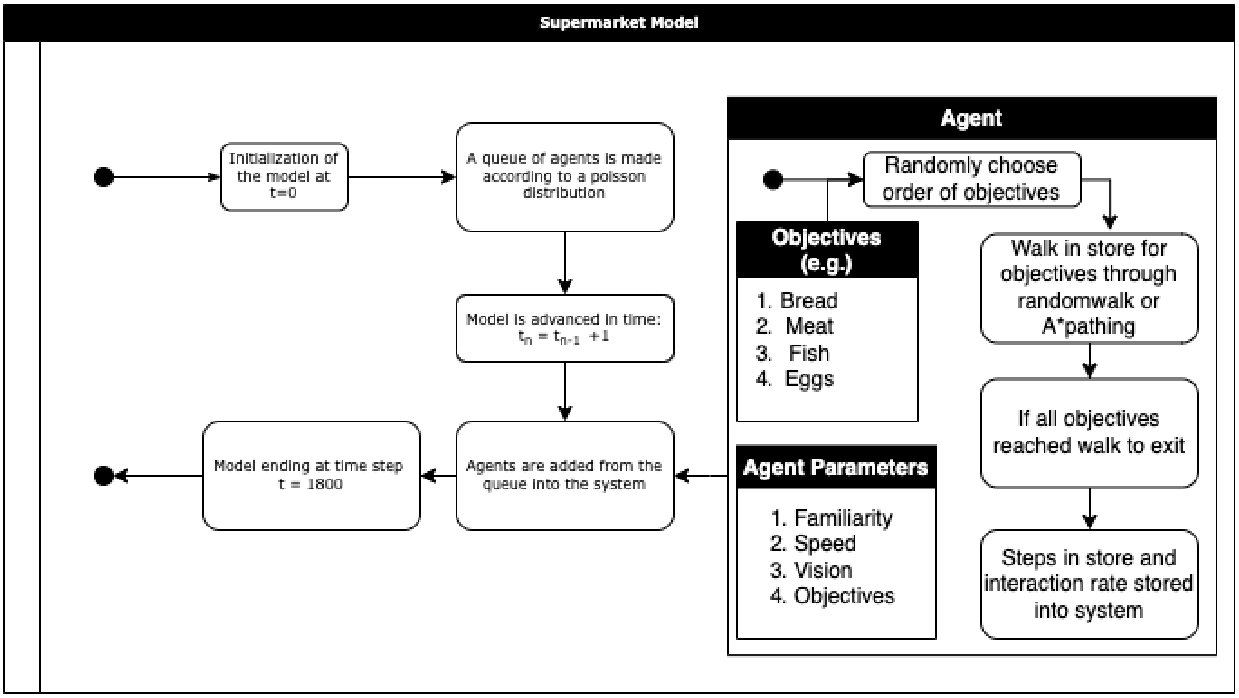


Fig. 2: A schematic overview of the modelling steps.

7) Collectives: The model does not include collectives (aggregations of agents) that affect the state or behaviour of the agents in the model.

8) Heterogeneity: Agents are heterogeneous. They differ in the list of objectives to complete (G) and individual parameters: familiarity (f), vision (ψ) and speed (v).

9) Stochasticity: Stochasticity is implemented in several levels of this model. Firstly, a homogeneous Poisson distribution with a given expected arrival rate λ_a is used to determine the arrival time of each agent. Secondly, stochasticity is implemented trough assigning random objectives to each agent. Thirdly, random moves are decided for agents when their desired next position is occupied by another agent. Fourthly, stochasticity is implemented through decision making. When the agent is partly familiar with the supermarket, a uniform pseudo-random number generator is used to determine whether the agent makes a random step or an A*-algorithm calculated step.

10) Observation: Two specific data points are collected from the simulations: the mean number of interactions per customer agent N_i and the mean number of steps taken in the store N_s. A total interaction value is augmented with a value of the number of direct Moore agent neighbours at their stationary position and positions while moving. The calculations exclude duplicates. The total interaction value at the end of the simulation is divided by the amount of agents, resulting in N_i. For each agent the total amount of moves taken is calculated by augmenting a variable each time it has moved. These are summed for all agents and then divided by the number of agents, resulting in N_s. The outcomes emerge from individual variables or from interaction between agents through the routes they walk, which in turn is dependent on the lay-out of the supermarket.

E. Implementation details

The base architectures of our model are implemented using *Mesa* (Kazil et al., 2020), agent route planning with the A*-algorithm is specified using the *networkx* package (Hagberg et al., 2008). The complete model can be found on https://github.com/tjerkok/AgentBasedModelling and is freely accessible.

The simulations in this research start with an empty supermarket, sampling arrival times for the maximum number of customers and letting them entry according to their arrival time. This represents the opening moment of a supermarket, where the store also starts out empty. Customers are initialised at the moment that their arrival time is reached. When these customers enter the supermarket, a list of objective locations is initialised along with the customer's speed (v), familiarity (f) with the supermarket and vision (ψ).

Input for the model is a separate file that specifies the layout of the supermarket, this research uses two different variations.

III. RESULTS

Having described the specifics of our model using the ODD+D protocol (Grimm et al. (2010)), we have provided an overview of the purpose and theoretical background of our work as well as modelling decisions and implementation steps. The specified model is used to compare two supermarket layouts as depicted in Figure 1 and results are provided in the following section. Afterwards, we perform local and global sensitivity analysis to observe the effect of our parameters on

Symbol	Description	Min	Max	Step
λ_a	Mean arrival time of homogeneous Poisson distribution	4.5	6	0.25
v	Speed of fast customers	1.0	4.0	1.0
p_v	Probability of customer being fast	0.0	1.0	0.1
f	Familiarity of less familiar customers	0.5	1.1	0.1
p_f	Probability of less familiar customer	0.0	1.0	0.1
ψ	Vision of customer with low vision	2.0	10.0	1.0
p_ψ	Probability of customer with low vision	0.0	1.0	0.1

TABLE II: Description of parameters used in local sensitivity analysis, as well as their value range. A more detailed description of the parameters and their use can be found in section II-D.

the outcomes. We do these analyses with the *grid layout* and expect similar results for the *free form layout*.

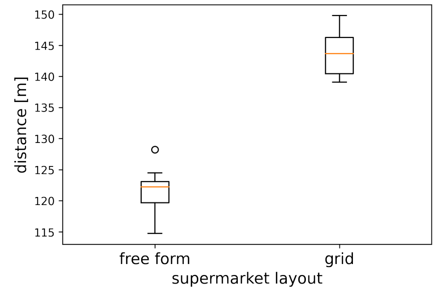
A. Supermarket Layout Comparisons

The results for the distance and interactions are shown in Figure 3. As seen in Figure 3a, the average distance a customer walked through the store is significantly lower for the free form supermarket layout than the grid layout (Welch T(17.9) = -13.26, p < 0.05). The average distance a customer walked in the store, shown in Figure 3b, is also lower for the free form supermarket layout than the grid layout (Welch T(14.5) = -6.51, p < 0.05). The free form grid has for both the distance and interactions an outlier which means this value lies higher than the rest of the data.

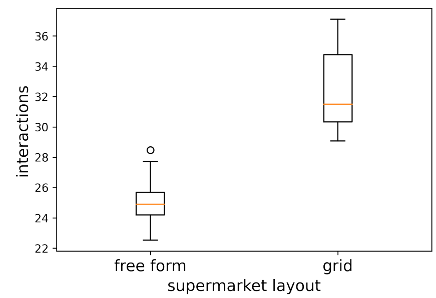
B. OFAT Local Sensitivity Analysis

Local sensitivity analysis is performed using the One Factor At a Time (OFAT) approach. Each parameter under consideration is given a default value, and during the OFAT method every parameter is varied over a specified range while the rest of the parameters is kept at the default value. This research considers 7 distinct parameters that are experimented with during the OFAT analysis, these parameters are specified in Table II.

Figure 4 provides an overview of the parameters that have an actual significant effect on our output measures. It portrays the effect of three different parameters on the average number of interactions between customers, that are varied as specified in II. Increasing the average arrival rate of customers in the store significantly decreases the number of interactions between customers, for almost every increase of a single time unit (Figure 4a). A similar effect can be observed for the speed of fast individuals, but this is only significant when increasing the speed from 1 to 4 (Figure 4b). For the probability of an individual being fast, no effects were found for a probability between 0 and 0.4. However, significant effects were found for a probability between 0.4 and 1 (Figure 4c). The remaining parameters under investigation show to have no effect on the number of interactions between customers or average distance travelled, as can be seen in Figure 7 in the Appendix.



(a) The average distance a customer walks in the two supermarket layouts.



(b) The average number of interactions that a customer has in the two supermarket layouts.

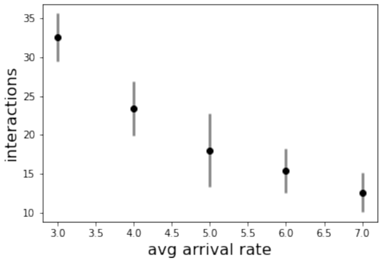
Fig. 3: The effect of different supermarket layouts on output measures. The median of the output values is shown with orange lines, circles represent outliers.

None of the parameters show to have a significant effect on the distance travelled by customers. As none of the parameter changes result in significant differences between outcome values, graphs are not shown here and can be found in Figures 8 and 9 in the Appendix.

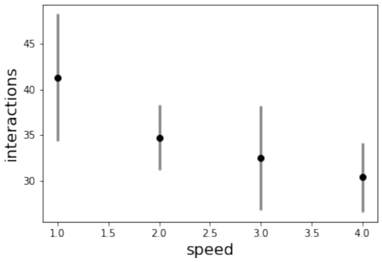
C. Sobol Global Sensitivity Analysis

A total of 16384 simulations were evaluated for the Sobol global sensitivity analysis. These were set up with 512 distinct samples and 10 replicates per run. Due to time constraints only the three most sensitive parameters from the local sensitivity analysis were varied, being the average arrival time, speed and speed probability distribution. For all three parameters, the main effect (S_i) on the distance each agent travelled is relatively low: for the average arrival time $S_i = -0.025, SD\pm 0.047$, for the speed $S_i = 0.030, SD \pm 0.062$, and the speed probability $S_i = 0.070, SD\pm 0.055$, which can also be seen in Figure 5a. The main effect (S_i) on the average number of total interactions is also relatively low: for the average arrival time $S_i = 0.064, SD \pm 0.057$, for the speed $S_i = 0.056, SD \pm 0.054$, and the speed probability $S_i = 0.033, SD \pm 0.059$, which can also be seen in Figure 6a.

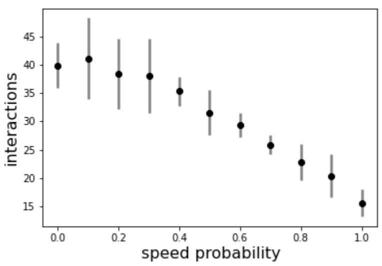
However, the total sensitivity indexes for each parameter on both the distance travelled and the number of interactions were much higher. The total sensitivity S_{Ti} for the distance traveled was: for the average arrival $S_{Ti} = 1.007, SD \pm 0.161$, for the speed $S_{Ti} = 1.023, SD \pm 0.096$, and for the speed probability



(a) The individual effect of average arrival time on customer interactions.

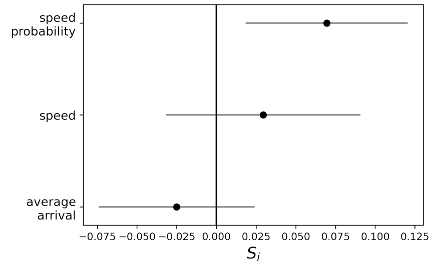


(b) The individual effect of fast customer speed on customer interactions.

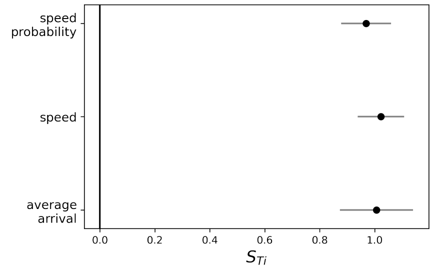


(c) The individual effect of fast customer probability on customer interactions.

Fig. 4: Influence of various parameters on the average number of customer interactions during OFAT analysis. All the parameters shown here have a significant effect on the outcome at some point.

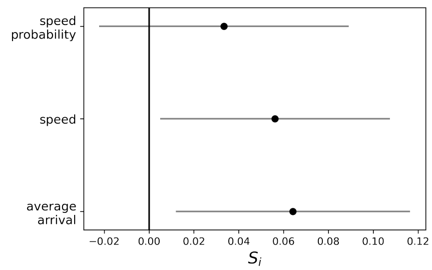


(a) First order sensitivities.

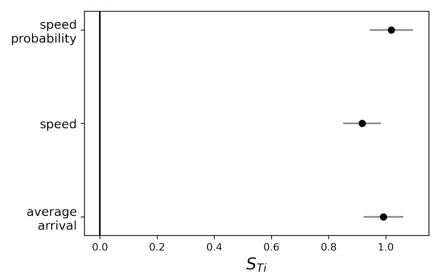


(b) Total order sensitivities.

Fig. 5: Results of global sensitivity analysis for the average distance walked by an agent.



(a) First order sensitivities.



(b) Total order sensitivities.

Fig. 6: Results of global sensitivity analysis for the average distance walked by an agent.

$S_{Ti} = 0.969, SD{\pm}0.082$, which can also be seen in Figure 5b. The total sensitivity S_{Ti} for the average number of iterations was: for the average arrival $S_{Ti} = 0.992, SD{\pm}0.0.059$, for the speed $S_{Ti} = 0.917, SD \pm 0.056$, and for the speed probability $S_{Ti} = 1.019, SD \pm 0.071$, which can also be seen in 6b.

IV. Discussion

This section first discusses the results comparing two supermarket layouts as portrayed in section III-A. The results of the two different sensitivity analyses are subsequently discussed, and we provide some suggestions for future work afterwards.

A. Supermarket Layout Comparisons

The results show that the free form layout ends up with a significantly lower average number of interactions and distance travelled per agent, compared to the grid layout. This was expected, since a free form layout includes more shortcuts to the exit and agents should generally be able to find a route without making large detours. Having more shortcuts also generates a higher total of possible routes, leading to less agents per route, in turn leading to the expectation of a decrease in agent interactions.

These findings indicate that choosing a specific layout could reduce the number of interactions which in turn might result in a safer shopping environment during health-crises. Since this model still has a number of simplifications compared to reality, some future work is advised in section IV-C. Extensions of our model, such as implementation of impulsive shopping behaviour or different grid shapes, might help retailers and political organs to make decisions during public health crises.

B. Sensitivity Analysis

Sensitivity analysis was performed using the OFAT and Sobol approach to determine the influence of parameters on the model outputs, the average number of interactions and average distance travelled per agent. The OFAT analysis reveals that the average arrival time, setting for high speed and probability of high speed have the biggest influence on the average number of interactions for each agent. This was intuitively expected, since a higher average arrival rate, higher speed and higher speed probability on average all result in more empty cells between agents. However, it was also expected that the vision and vision probability would show a significant influence in the OFAT analysis, since the agent uses its vision to find a route without bumping into others. The lack of this influence could be due to the fact that the agent most likely will re-calculate the route so that it will pass the agent within a 2 cells distance (resulting in an interaction), since this will result in the fastest route to the next objective. The vision parameter could be extended with implementing a minimum distance between agents when passing.

Based on the results of the OFAT analysis, only the parameters having a significant effect (average arrival time, speed for fast individuals and probability for fast individuals) were further explored using Sobol sensitivity analysis.

As observed in Figure 5b and Figure 6b, all three parameters tested in the Sobol sensitivity analysis had significant influence on the model. Therefore, the most important factors to tune this model to reality are the three parameters average arrival rate, speed and speed probability.

C. Suggested Future Work

Besides the suggested adaptations as described in sections IV-B and IV-A, some other advice for future work is described below.

Firstly, as the average number of interactions is a direct measure for the transmission of infectious diseases, one could extend this research by combining our model with some version of a SIR model (e.g. the model of Barrett et al. (2008)). This way, a more direct measure for the spread of diseases could be used to make conclusions, stating differences between the influence of supermarket layouts.

Secondly, it is advised to implement a non-homogeneous Poisson process for the arrival time of agents. In reality, the number of customers entering a supermarket is higher during lunch hours and after working hours.

Thirdly, one would optimally want to validate this model with real supermarket lay-outs and real travelling data. Validation of this model has not yet been executed due to time and resource constraints, thus should be done in further work.

Lastly, to fully quantify the trade-off between sales as a result of in-store travelling distance and the number of interactions it is advised to further specify product demand and product placement. For this extension it is also needed to implement a characteristic of agents to assign impulsive buys, since an increase in in-store travelling distance results in an increase of impulsive buys.

V. Conclusion

The two supermarket layouts have a different impact on the distance a customer travels in the store and the amount of interactions they have with other customers. The grid layout, with less shortcuts, results in a higher distance travelled and more interactions per customer than the free form layout. In the model used, the only parameters being sensitive to these outputs were the average arrival time between customers arriving at the store, the speed for the fast individuals and the probability an individual is fast. For the future, more parameters can be added into the model, such as impulsive shopping behaviour, to ensure that supermarket owners can create a profitable yet safe supermarket experience.

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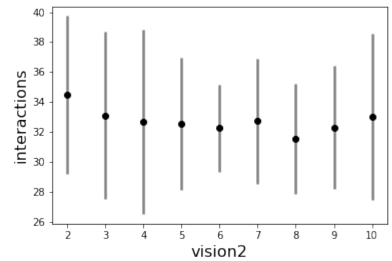
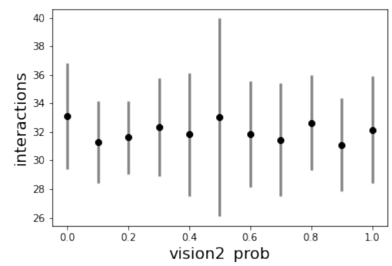
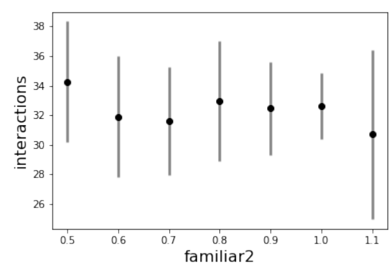
Appendix A
Local Sensitivity Analysis



(a) The individual effect of average arrival time on customer interactions.

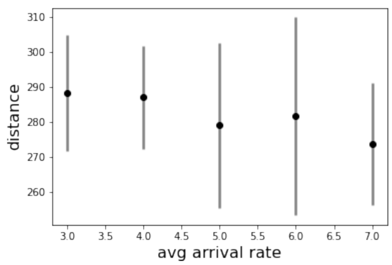


(b) The individual effect of fast customer speed on customer interactions.

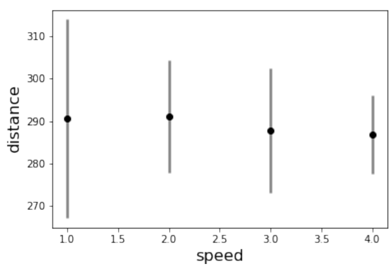


(c) The individual effect of fast customer probability on customer interactions.

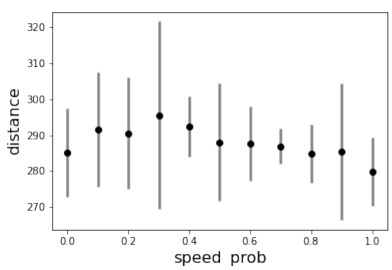
Fig. 7: Influence of various parameters on the average number of customer interactions during OFAT analysis. None of these parameters have a significant effect on outcome measures within this range.



(a) The individual effect of average arrival time on customer travel distance.

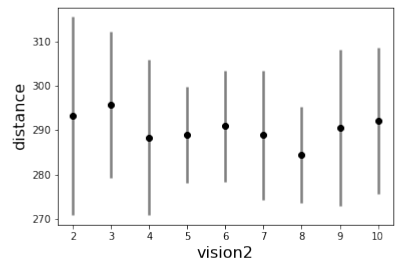


(b) The individual effect of fast customer speed on customer travel distance.

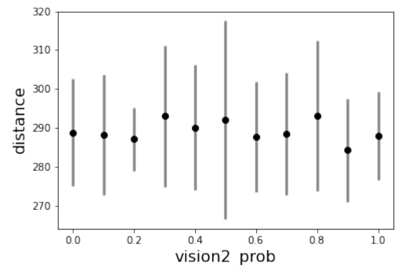


(c) The individual effect of fast customer probability on customer travel distance.

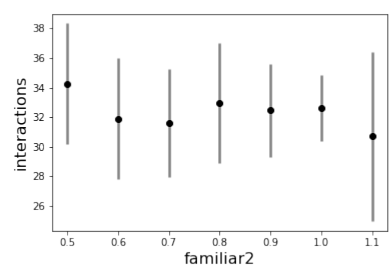
Fig. 8: Influence of various parameters on the average distance travelled per customer during OFAT analysis. None of these parameters have a significant effect on outcome measures within this range, although they did have an effect on the number of interactions.



(a) The individual effect of average arrival time on customer travel distance.



(b) The individual effect of fast customer speed on customer travel distance.



(c) The individual effect of fast customer probability on customer travel distance.

Fig. 9: Influence of various parameters on the average distance travelled per customer during OFAT analysis. None of these parameters have a significant effect on outcome measures within this range.