Alma Mater Studiorum Università di Bologna
Archivio istituzionale della ricerca

Shopping with(out) distancing: modeling the personal space to limit the spread of contagious disease among consumers in retail stores

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Abstract.

This research aims at providing a new model of consumers' personal space to limit the spread of contagious disease while shopping in person. To this end, it adopts an agents-based simulation

approach to model consumers' movements in the store during COVID-19 pandemic. Findings show the extent to which consumers' contacts with others increase the risk of contagion, due to the occurrence of social gatherings in certain areas. Specifically, there is a linear correlation between the number of consumers in the store and the number of consumers susceptible to contract the disease. Thus, the personal space from a psychological perception becomes an individual and compulsory boundary to protect consumers from contagious disease. Finally, our results extend the concept of social distance and personal space while shopping, and support retailers to provide safer shopping experiences.

Statement of contribution: Our findings model consumers' personal space to limit the spread of contagious disease, due to occurrence of social gatherings while shopping in person. Specifically, they show a linear correlation between the number of consumers in the store and the number of consumers susceptible to contract the disease, extending the concept of social distance and personal space while shopping. Our results also contribute to the definition of retail physical distance to limit the spread of the virus and ensure a safer shopping experience.

Keywords: physical distancing; retailing; agents-based simulations; personal space; COVID-19; contagion

1. Introduction

The COVID-19 pandemic has generated a relevant set of consequences for business and consumers globally, whose impact on society will be likely not relegated to the short-term (Donthu & Gustafsson, 2020). Such an unprecedented situation has stimulated the interest of scholars from many disciplines, contributing at assessing the impact of the risk of contagious disease on the various facets of societal life with potential solutions, including retailing and consumer behaviour (Pantano et al., 2021a; Omar et al., 2021; Eger et al., 2021). Among the different research domains, literature has

well documented the considerable impact that COVID19 pandemic has exerted on retailing and consumer behavior (Roggeveen & Sethuraman, 2020; Malter et al., 2020), and the strategies put into place by retailers to cope with such an emergency situation (Pantano et al., 2020). Accordingly, retailers and managers were forced to adopt physical distancing to prevent excessive density of customers crowding across the areas of different premises (Prentice et al., 2020; Wang et al., 2021). In this vein, literature has widely discussed that consumer crowding is not an objective property of a (store space), but rather an individual perception shaped by the extent to which individuals feel constrained by the presence of other customers within the same store space (Pons et al., 2014). However, such a subjective perception is influenced by the objective density of shoppers' movements throughout the same store space (Blut & Iyer, 2020). Specifically, literature has documented that crowding can exert significant effects on shoppers' behaviors, not just in terms of time spent in the store (Li et al., 2009), but also with respect to the basket composition (Aydinli et al., 2020). Studies conducted prior to the COVID-19 pandemic also identified an inverted-u-shape relationship between perceived crowding and consumers' reactions (e.g., Pan & Siemens, 2011; Knoeferle et al., 2017; Mehta et al., 2013). While studies conducted during the COVID-19 pandemic documented that human crowding in retail stores negatively affects purchase intentions due to the higher perceived contamination concerns (Gupta & Coskun 2021).

Providing a safe shopping environment in light of the potential contagion of the COVID-19 virus should be a key objective for retail managers during a pandemic in order to protect both customers' and employees' well-being (Tuzovic & Kabadayi, 2020). Given the recommended distance of at least **1m** between customers to protect from contagion imposed by Government in several Countries, retailers were accordingly forced to restrict the number of customers allowed to enter the store simultaneously. However, when it comes to the understanding of the levels of social density which might allow a safe, yet rewarding, shopping experience to customers, there is still lack of empirical evidence in the extant literature (Pantano et al., 2021b). Indeed, there is a recent call for new solutions able to minimize human contact and maintenance of social distance while shopping, which further

pushes retailers to have a flexible approach to incorporate new guidelines or measures to improve consumers' safety during and after pandemics (Shankar et al., 2021). Although preliminary studies made some attempts to pre-determine the number of customers which can safely access the store in compliance with physical distancing measures (Luck & Benkenstein, 2015; Ntounis et al., 2020), these studies are not definitive.

Merely dividing the floorspace area by the area of the circles centered on customers with a half-meter radius would yield a poorly accurate estimation of the safe number of customers allowed to enter a store at time, since consumers do not typically stand while shopping, nor they follow linear and regular paths (Luck & Benkenstein, 2015; Kim & Runyan, 2011; Pantano et al., 2021b). To this end, Ntounis and colleagues (2020) proposed a model based on hexagons rather than circles around consumers as an initial attempt to incorporate the dynamic nature of customers' shopping paths. Nevertheless, these prior models are built on the underlying assumption that customers can be equally distributed along the store floorspace. This is not generally the case for retail stores, since consumers display different ways of navigating the store with some areas being more crowded, and other areas displaying lower levels of density (Larson et al., 2005; Pantano et al., 2021b).

For these reasons, the present study aims at proposing a new method to model customers' movements within a store, which better reflects the dynamic nature of their behavior, and at accounting for an exogenous, rather than endogenous, definition of their personal space under the pathogen threat of COVID-19. Specifically, this research adopts agent-based simulation to describe the consumer spatial behavior within a store, assuming that consumers are not equally distributed, and move irregularly within the area. In this way, the model is able to simulate the spread of the virus among consumers, and to model the consequence of no physical distance between customers. Accordingly, our results contribute to enriching the concept of distancing and personal space during risk of contagious disease. More specifically, the present research aims at addressing the following research questions:

RQ1: To what extent can the pathogen threat spread among consumers be predicted in a certain retail setting given the store space?

RQ2: How can consumers' personal space against the risk of contagious disease among consumers be modelled?

In the following sections, after reviewing the pertinent literature on physical distancing and personal space in retailing, the present research presents and discusses the results of our study. In particular, our research is based on agents simulation to model consumers' movements within a store given the risk of COVID-19 contagion and store layout constraints (in a hypothetical and real scenario). Implications for scholars and practitioners are finally discussed.

2. Theoretical Background

2.1. Physical distancing and personal space

Physical distancing among consumers in retailing has been at the core of a wide stream of studies which roots its origins before the COVID-19 outbreak, dealing with consumers' perceptions of and reactions to violations of their personal space (Argo et al., 2005). Specifically, the Theory of Personal Space (Hall, 1966; Sommer, 1969) posits that individuals tend to display discomfort and to adopt coping strategies when they perceive other persons to invade their personal space. Accordingly, consumers have been found to change their shopping behavior and deviate from their paths inside the store when they perceive that their personal space is infringed by the presence of other shoppers (Pons et al., 2014). According to the Theory of Personal Space (Hall, 1966; Sommer, 1969), personal space can be conceived as a sphere or a bubble whose radius defines the minimum threshold of physical distance that individuals require to perceive the presence of others in the same space without eliciting negative reactions. The size of such personal space has been found to be shaped by several factors such as culture, perceived familiarity and/or affinity with others, and situational factors (Evans & Howard, 1973). When people perceive that other individuals are passing beyond this psychological

barrier, they start feeling discomfort as it happens when other shoppers are accidentally touched by others in front of a shelf (Martin, 2012). When such discomfort is experienced, consumers adopt coping strategies to escape from the annoying situation which might even lead them to leave the place where they are (Manzo, 2005). Accordingly, previous studies found that shoppers are comfortable within a distance of approximately two feet from other customers within a store (Argo et al., 2005), and that the violation of such distance might be detrimental to several factors such as satisfaction, purchase intention, and number of product alternatives taken into consideration in the decision-making process (Luck & Benkenstein, 2015). However, retailers might provide some music to alleviate this sense of discomfort (Oakes & North, 2008).

Interestingly, the conceptualization of personal space as an individual-centered bubble posited by the Theory of Personal Space displays a partial overlap with the physical distancing measures required by Government to be adopted during a pandemic to prevent any virus contagion. Thus, the Theory of Personal Space assumes an endogenous size of the individual's bubble defined by the individuals' reaction to the entrance of another individual within his/her personal space (Luck & Benkenstein, 2015). Nevertheless, the size of individuals' personal space can be exogenously imposed due to the regulation to contain the contagion.

Although one of the most immediate leverages which can be used to exogenously affect the levels of social density in a space would consist of limiting the number of individuals allowed to enter a place per time unit, the dynamics of individuals' crowding might be much more complex (Still et al. 2020). Restrictions to physical distancing might require a decrease either in social or spatial density (Hayduk, 1983). The former is achieved when the number of individuals in a given space is decreased while keeping the total walkable floorspace unchanged; the latter entails increasing the walkable floorspace while maintaining the number of people constant (Hayduk, 1983). As a consequence, in retail settings, managers need to restrict the number of simultaneous accesses to the store to lower social density or, alternatively, to increase the walkable space by altering the store layout to ensure a lower spatial density. It might be worth noticing that these actions do not necessarily affect store

crowding perceptions, but only the actual density of shoppers within the store space. Indeed, density is referred to the objective spatial limitation of individuals within a place, while crowd is a perceptual state which reflects the extent to which individuals feel constrained by the presence of other individuals within the same space (Stokols, 1972). Whilst the effects of store crowding have received a considerable attention in scholarly research (see the meta-analysis by Blut & Iyer, 2020), the relationship between density and consumer behavior still needs further investigations (Luck & Benkenstein, 2015).

Prior research has documented that shopping behavior is affected by the presence of other consumers (Grove & Fisk, 1997) depending on (i) the perceived similarity between the shopper and the other customers (Brack & Benkenstein, 2012), (ii) the behaviors of other customers while sharing the space among the retail shelves (Söderlund, 2011), and (iii) the actual number of customers moving through the aisles (Pan & Siemens, 2011; Uhrich, 2011). In this vein, previous studies have shown that the presence of other customers in certain areas of the store might both stimulate curiosity toward the products shelved in the area and deter from entering the areas because of the social density (Hui et al., 2009).

The unprecedented situation determined by a COVID19 pandemic forcing consumers to keep at distance from each other further alters the way consumers behave inside the store. As a consequence, their movements and the social and spatial density in the store would be strongly affected, with huge impact on the resulting shopping experience. Accordingly, understanding the spread of the virus would support better predictions about the right number of customers who can be safely allowed to enter, to prevent that their movements lead to the violation of the minimum interpersonal physical distance. Therefore, pandemic rebuilt the concept of distance and personal space in retail stores, requiring new investigations (Shankar et al., 2021).

2.2 The impact of the risk of contagious disease on physical distancing in retail stores

Previous studies have investigated the strategies that retailers can adopt to cope with an emergency spanning from the redefinition of the supply chain (Singh et al. 2020; Mollenkopf et al., 2020) to the collaboration with competitors to operate more efficiently (Crick & Crick, 2020). Similarly, literature has focused on how consumers respond to the strategies adopted by retailers both in terms of new behavioral patterns such as (i) unusual consumption (Laato et al., 2020), (ii) new payment mechanisms (Xu et al., 2020), (iii) compliance with new in-store signage (McNeish, 2020), (iv) reactance (Akhtar et al., 2020), and (v) panic (Naeem, 2020). Indeed, consumers have been found to develop new shopping habits during emergencies, whose effect is likely to persist over time (Donthu & Gustafsson, 2020). For instance, online shopping experienced a double-digit increase during the first months of the COVID-19 pandemic (Brem et al., 2020). Many offline retailers decided to increase their online sales to cope with the sudden decrease of in-store visits (Hall et al., 2020). At the same time, many customers accustomed to shopping offline had the chance to experience the unfamiliar benefits of shopping online with home delivery or in-store pick-up (Lee et al., 2020; Pantano et al., 2020). Simultaneously, the concept of in-store experience has dramatically changed, shifting the emphasis from the experiential side of shopping to the safety of the shopping experience (Roggeven & Sethuraman, 2020). With these regards, some hygiene factors which might have been almost overlooked by consumers and assumed as service standards before the spread of a contagious disease - such as the cleanliness of the place – have raised to the top of consumers' priorities in assessing the quality of a retail store experience (Rosenbaum & Russell-Bennett, 2020). Similarly, retailers started considering different solutions to prevent excessive density of customers across the stores and ensure a certain physical distancing, like one-way systems and predefined paths within the store (Prentice et al., 2020). However, how to implement a proper social distancing system during health emergencies is still an open line of inquiry (Shankar et al., 2021).

To date, physical distancing has been addressed as one of the most effective measures to reduce the risk of transmission of the virus (Fong et al., 2020; Remuzzi & Remuzzi, 2020) especially in closed environments such as stores, workplaces and schools. For instance, actual studies recommend

keeping a minimum distance of at least **1m** from each other in order to protect from contagion (Chu et al., 2020). Consequently, the implications for retail management are severe (Roggeven & Sethuraman, 2020; Pantano et al., 2020). Thus, retailers have to face the new challenge of restricting the number of customers allowed to enter the store simultaneously to provide a pleasant and rewarding shopping experience (Bove & Benoit, 2020). The restriction to enter a store is quite an unprecedented situation in retailing, at least for sanitary reasons. Yet, in the past some retailers experienced queueing out of their stores during the launch of new products (e.g., out of Apple Stores during the launch of new iPhone) or during exceptional sales periods (e.g., the Black Friday). However, the rationale for these queueing situations was driven by consumers' enthusiasm for shopping, while entrance regulation might be needed only to preserve the quality of the in-store experience. Conversely, the COVID-19 outbreak solicited new regulations to prevent consumers' gatherings of customers within the store for health and safety reasons.

Nevertheless, determining the maximum number of customers allowed to enter a store at any time is not a trivial issue. Indeed, it requires the efficient evaluation of the maximum space which can be occupied by human bodies within the entire walkable space under the constraint of physical distancing, and the dynamic nature of consumers' behaviour. This is to say, the capacity limit of retail stores is not defined anymore by the space required by customers not to touch each other while shopping (Timmermans, 2004), but rather by the space defined by roughly a certain radius around each customer that allows consumers to avoid touch, and which follows the consumers throughout the movements in the stores. It follows that consumer movements and interactions in store are radically changing due to the specific dimension of the usable space (Blut & Iyer, 2020). As a consequence, customers' perceptions of distances from other customers would result distorted (Menon & Kahn, 2002). Also, customers are typically not static entities in a store, they rather move following paths which are not necessarily linear (Luck & Benkenstein, 2015; Clarke & Kirkup, 1998). Simultaneously, the arrangement and the relative proportion of shelves and merchandise displays on the total store area further affects the customer density (Pons et al., 2016). Accordingly, the trade-off

between display and walkable space should be carefully calibrated in order to allow more customers to enter a store by constantly ensuring safe interpersonal distances and an assortment size in line with customer expectations. Building on this premise, recent studies have attempted to estimate the maximum number of people that can be allowed to simultaneously enter a store (Ntounis et al., 2020; Luck & Benkenstein, 2015). However, these models still fail in considering the dynamism of consumers paths, as they are entities continuously changing their physical location in the store. Thus, further developments are needed in order to realistically model the heterogeneity of customers' movements, which should include dynamic consumers' distribution in the store floorspace. In this vein, agent-based simulations would provide a potential opportunity to model consumers' movements in the space (consumer spatial behavior) (Vaanhaverbeke & Macharis, 2011).

3. Methodology of Research

Analythical methods and research on consumer behavior need to evolve to provide more efficient insights on consumers based on real data and real impact for practitioners and policy makers (Malter et al., 2020; Ding et al., 2020). This research aims at using agent-based simulations to model consumers' movements within a store, which better reflects the dynamic nature of their behavior and model accordingly their personal space while shopping in person during the risk of COVID-19 contagion. To this end, the research is based on two studies. First, it develops a classifier machine allowing to model the spread of COVID-19 contagion among consumers in a hypothetical (psychical) store (as exemplar scenario) (Study 1). Second, the research applies the model in a real case scenario within a grocery store (Study 2). In this way, the research demonstrates how the new model for consumer beahviour within a physical store would replicate their effective behaviours under the risks of disease contagious.

During COVID-19 pandemic, medical literature shows how non pharmaceutical interventions might (only) have some benefits in reducing the likelihood that a person with the infection passes it on in a closed space (Flaxman et al., 2021). Specifically, wearing (properly) a face covering (all time and

with specific protective requirements), limiting contacts with others, frequent washing hands, and further protecting eyes are strongly recommended measures to limit (not to stop) the spread of COVID-19 (Chu et al., 2020; Prem et al., 2020; Flaxman et al., 2020; Fong et al., 2020; Wendling et al., 2021). As a consequence, consumers might contract the infection if not wearing the mask properly (covering both mouth and nose) or wearing a not protective one, not protecting eyes, or touching others or products without immediately sanitizing the hands.

To date, observing the spreading of a virus in a store is not allowed. Specifically, Governments in many Countries do not allow to voluntarily infect a person in a point of sale, nor they allow aerosol/virus dispersion and related observation of what conditions the contagion occurs among individuals, in order to get real data on the spread of infection among consumers in a certain retail setting. For this reason, numerical simulations where agents mimic the possible consumers' behavior would provide an environment similar to the real one, where observing the phenomenon without risks for researchers or participants.

3.1 Study 1: Consumers' contagion in a hypothetical scenario

3.1.1 Experiment setting

First, we consider the hypothetical scenario of a generic store. Accordingly, we define the size of the store of 400 square meters. Since retailing is characterized by a variation of the number of people across the day, and (unpredictable for retailers) movements of consumers in the floorspace, thus consumers cannot be considered static entities in the space (Pantano et al., 2021). Therefore, there is a need of deeper understanding of how consumers move across the retail setting, and how the risk of contagion increases/decreases accordingly. To this end, we employ an approach based on agents simulations using the Montecarlo method to reflect the nature of consumers' movements within the store (Hidalgo, 2015; Misra et al., 2019).

Secondly, we consider six main areas in the store of **5m** each (with more areas the movements in the store would be very limited, while less areas are not very realistic). Each consumer in the store will tend to spend a certain amount of time in one area and move to the next one.

Thirdly, we assume that maximum 100 consumers enter the store (less than the maximum physical capacity of the store) not considering social distancing measures. Thus, consumers' movements might lead to social gatherings in certain area. Each consumer will access only three areas out of the six. In the hypothetical scenario, we specifically assume that each consumer visit on average three areas of the store and that the time spent in each area is the same (temporal distance of 100 steps), stay in each area up to 1/3 of the total time, and move of half meter for each temporal step after each area.

3.1.2. Agents-based simulations

To run the simulations, we used Wolfram Mathematica software. This software supports technical computing environments and workflows, since it provides 5,000 built in functions covering different areas of technical computing, including pre-trained machine learning algorithms. For this reason, it has started being used also in marketing research, to make prediction (Pantano et al., 2017), evaluating tourist behavior (Giglio et al., 2019), and explore consumers' online communications to extract insights (Pantano, 2021).

For this research purpose, the software simulated a random behavior of consumers across the six areas through the Montecarlo method, without considering any form of pre-determined physical distance among consumers. In other words, this software simulates consumers' random paths in floorspace, with the possibility to have contacts (e.g., talk, approach, etc.) with other consumers or salespersons through Montecarlo method.

Established compartmental epidemic models such as the Susceptible-Infected-Susceptible (SIS) or Susceptible-Infected-Recovered (SIR) and contagion theory (Rapp, 2013) describe the evolution of disease transmission among individuals, considering Susceptible (S) as the persons who might contract the disease, Infected (I) the persons who got the disease, and Recovered (R) as the persons

who got it and recovered. Specifically, these models show how the individuals of a fixed population are Susceptible (S), Infected (I) and Recovered (R), by modelling the spread of the contagious disease (Osborne et al., 2018; Pantano, 2021). It is realistic to assume that the point of sale would be visited by at least one infect, since COVID19 symptoms can be showed up to 15 days after having a contact with an infect, and many infects do not show symptoms even if they already contracted the disease (Chu et al., 2020). In the present study we assume that one consumer is the infect (I) entering the store (in red in Figure 1), while the other consumers who have contacts with the infect are susceptible of contracting the disease (S) (in black in Figure 1). Thus, Figure 1 shows that some social gatherings occur when consumers (agents) reach specific areas.
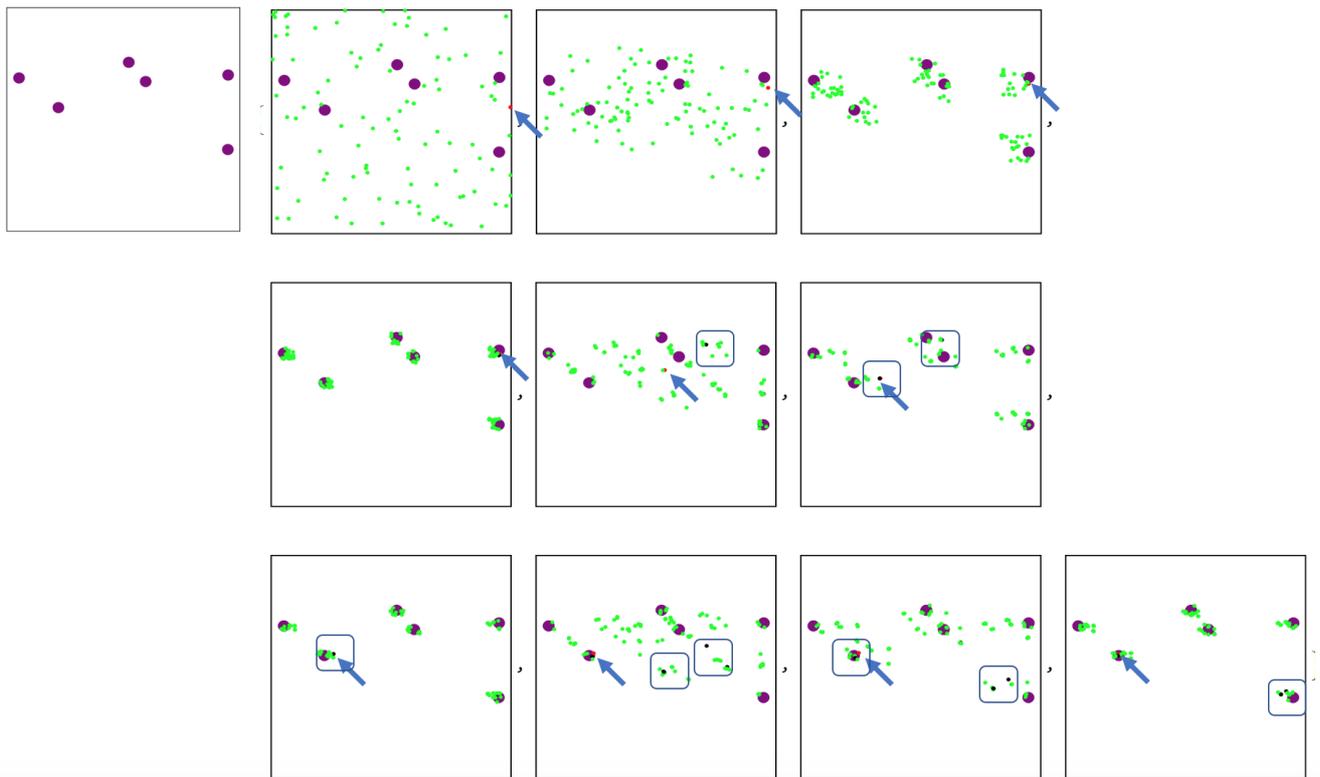
Figure 1: Each consumer would visit three areas in a temporal distance of 100 steps, stay in each area up to 1/3 of the total time, move of half meter for each temporal step after each area, and there

is one infect (each frame is captured after 10 temporal steps from each other, the row helps

visualizing the infect (I), and the square the susceptible consumers (S)).

A further simulations plot would better describe the spread of the virus among consumers. In this scenario, we used Montecarlo method to reflect consumers' movements across the store. Since the number of consumers might vary according to the day/time, we run more simulations by varying the number of consumers. In particular, we evaluate different scenarios with 20 customers (a), 40 (b), 60 (c),… 180 (l), and 200 (Figure 2 and Table 1). Figure 2 shows the results of the different simulations, where the x axis describes the time, and the y axis describes the number of consumers who would have contacts with the infect.
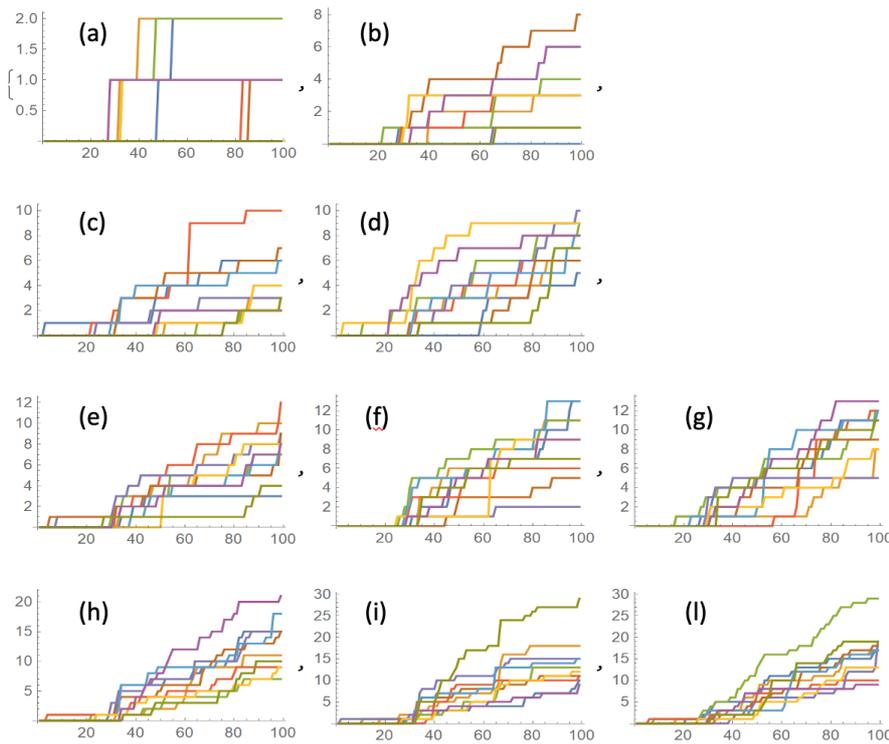
Figure 2: The evolution of the number of susceptible consumers (S) through Montecarlo simulation with 20 (a), 40 (b), 60 (c), … 180 (i) and 200 (l) consumers who freely move across the store.

Number of consumers per scenario	Max (number of S)	Min (number of S)	Mean	Median	S.D.
(a) 20	2	0	1	1	0.82
(b) 40	8	0	3	3	2.49
(c) 60	10	2	4.6	3.5	2.59
(d) 80	10	5	7.4	7.5	1.65
(e) 100	12	3	7.7	8	2.67
(f) 120	13	2	8.6	9	3.6
(g) 140	13	5	10.1	11	2.51
(h) 160	21	7	13	13	4.5
(i) 180	29	9	14.3	12,5	5.83
(l) 200	29	9	16.8	17	5.59

Table 1: Summary of number of consumers and susceptible ones (S) per each simulated scenario.

The simulations show that there are some peaks occurring with a similar trend in each scenario, implying that there is a correlation between the number of consumers and the number of consumers susceptible to contract the deases from one infect. This correlation can be modelled. To this end, Wolfram Mathematica provides the "Time Series Model Fit" function, a pre-trained machine learning algorithm, which automatically analyses the data against the available family (group) models (e.g., autoregressive model family, moving-average model family, autoregressive moving-average model family, integrated etc.), and identifies the most suitable and efficient technique for the particular dataset object of the study accordingly. The result is formula (1), consisting of the best model of the correlation between the number of consumers in the store and the number of consumers susceptible of contracting the disease (S):

$$y = 1.22 + 1.65\,x \qquad (1).$$

From this formula, a specific linear correlation between the number of consumers in the store and the number of consumers susceptible to contract the disease emerge. In other words, our results confirm that the higher the number of consumers allowed to enter the store simultaneously, the higher the number of susceptible consumers (S) and infects (I) (without distancing measures), thus the higher the risk of contagion.

3.2 Study 2: Consumers' contagion in a real grocery store

3.2.1: Experiment settings

The present research investigates a (real) grocery store located within a shopping center in Northern Italy. Specifically, the grocery walkable floorspace is 3,805 square meters (which is the effective surface removing the space allocated to shelves, walls, etc.). The areas of the stores are: (1) tins and cans, (2) cleaning cupboard and laundry, (3) beaty, (4) drinks, (5) health and medicines, (6) fresh meat, (7) bakery, (8) fish, (9) ready meals, (10) salami and frozen food, (11) fruits and vegetables, (12) electricals and technology, (13) kitchen and dining, (14) books and stationery, (15) toys, and (16) others.

Appraising the numbers of receipts per hour per day of each week between January and April 2021, we considered the maximum number of consumers who actually bought at least one product identifying the maximum number of clients as 289. Subsequently, we distributed the (real) clients in the stores according to the visited areas emerging from the receipt (Figure 3).
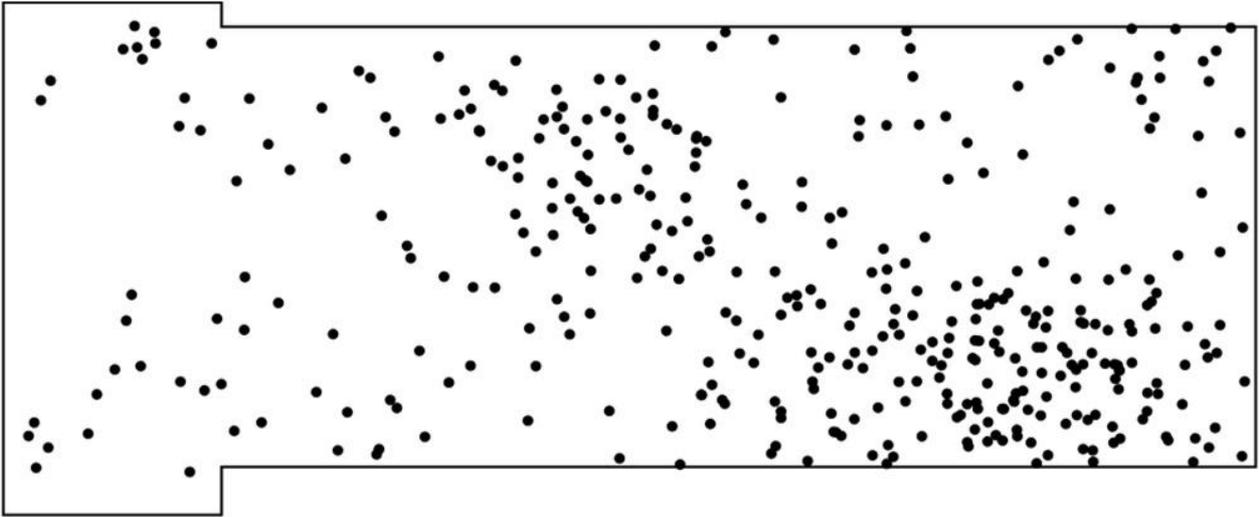
Figure 3. Consumers' distribution (289) in a real grocery store[1].

3.2.2: Agents- based simulation

Following the same steps of the hypothetical scenario, we hypothesized one infect (I) entering the store. As per the hypothetical case, we ran further 100 simulations to reflect consumers' movements across the store and to model the spread of the virus among consumers. Specifically, each consumer would visit the areas according to the purchases in the receipt, stay at each attraction a certain time (given by the number of areas visited according to the receipt), and move of half meter for each temporal step after each area, and there is one infect (I). The simulation shows that after a certain time, some consumers had contacts with the infect (S) (Figure 4).

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[1] Specific areas are not indicated on the map to preserve the anonymity of the store.
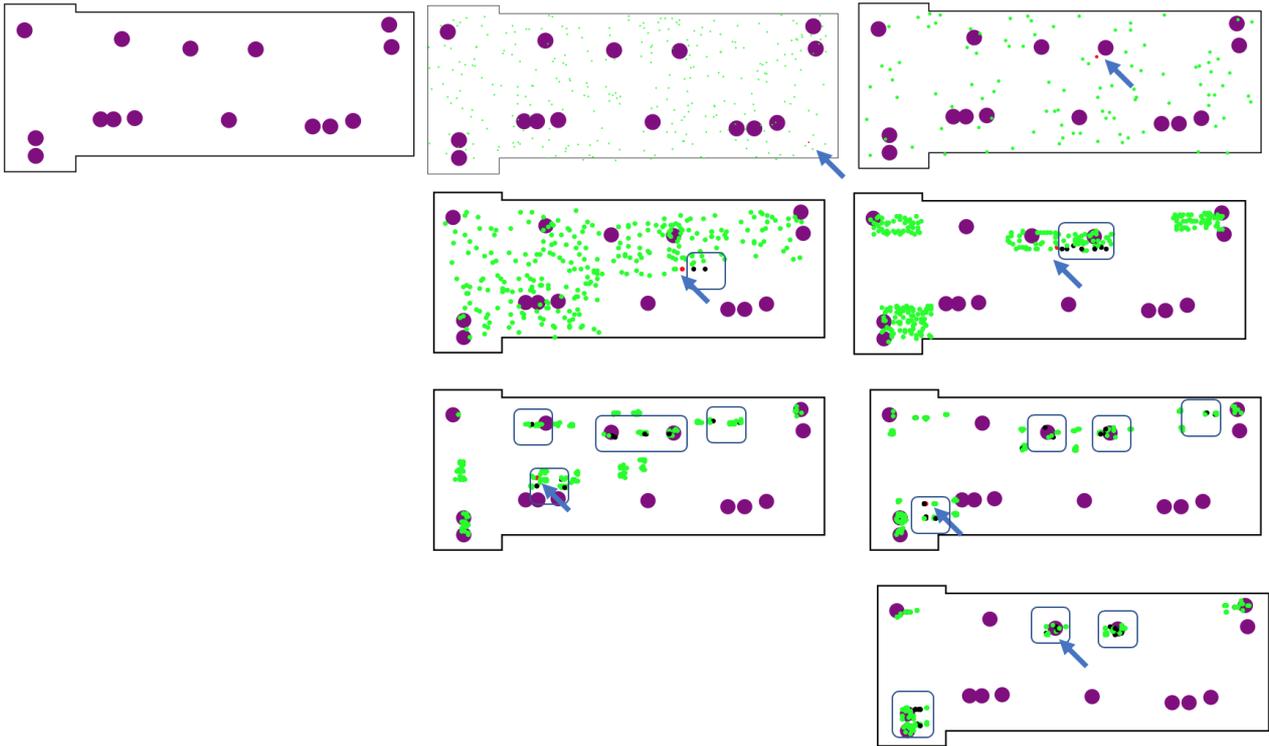
Figure 4. Spread of contagious disease among consumers (289) in a (real) grocery of 3,805 square meters (the row helps visualizing the infect (I), and the square the susceptible consumers (S)).

Similarly to what done in the hypothetical scenario, we ran further simulations by considering the (real) number of consumers in the same day at different hour (Table 2) to evaluate the different number of potential risky contacts among consumers (Figure 5).

Hour	Number of clients
8.00 a.m.	26
9.00	156
10.00	234
11.00	289
12.00	194
1.00 p.m.	123
2.00	123
3.00	141
4.00	201
5.00	256
6.00	289
7.00	269
8.00 p.m.	74
	(TOTAL) 2.375

Table 2. Number of clients per hour per day (from opening at 8.00 a.m. to closure at 9.00 p.m.), in the day of the week with the highest number of consumers.

As in the hypothetical scenarios, Figure 5 shows the results of the different simulations per hour, where the *x* axis describes the time, and the *y* axis describes the number of consumers meeting the infect. Each curve is associated with a specific hour of the day.
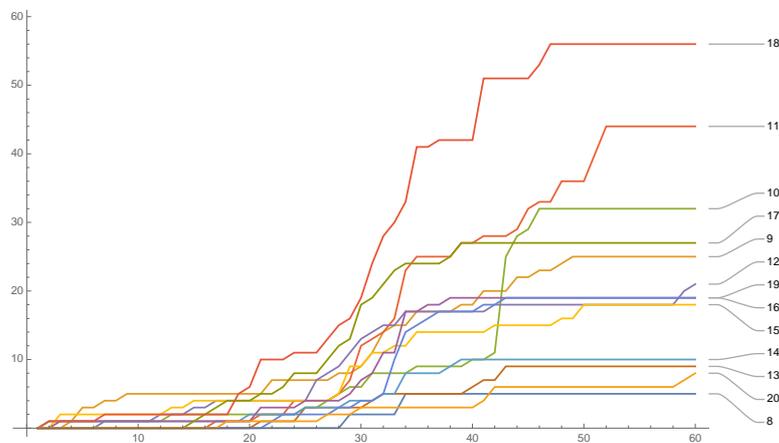
Figure 5: Different spread of the virus according the number of consumers at specific hours of the (same) day.

The simulations in the real scenario show the similar trend of peaks occurrence in each scenario, confirming that the peaks occur at the same time of the hypothetical scenario, further confirming the reliability of formula (1).

4. Discussion and Conclusion

Considering consumers as agents able to move throughout the space, and simulating their behaviour within the store, our study shows that limiting the number of consumers' access to a store does not

avoid possible social gatherings inside. Results of the two scenarios (Study 1 and Study 2) show the extent to which the virus would spread among consumers in a certain retail setting, which is even greater in certain areas. Findings also show similar consumers' gatherings in certain areas at the same time, which ultimately increase the risk of contagion. Specifically, the spread of contagion follows a linear trend (see formula (1)). Therefore, the occurrence of any form consumers' (social) interaction with others in the store expose them to a high risk of contagion while shopping. Thus, in the present research, the size of individuals' personal space is exogenously imposed because as a regulation to contain the contagion. In this vein, the present research provides the unprecedented opportunity to estimate how individuals move within a store area under the exogenous constraint of social distance to prevent the risk of COVID19 contagion at different degrees of social density. In particular, study 1 investigates a hypothetical point of sale in 10 different scenarios with the number of consumers from 20 (scenario a) to 200 (scenario l); while study 2 focuses on a real point of sale at different hour per day, for instance from 26 consumers at 8.00 a.m. to the peak of 289 (at 11.00 a.m. and 6.00 p.m.). Both studies confirm the relationship between the number of infects I and the numbers of susceptible (S), modelling the risk of contracting the disease while shopping (formula (1)).

4.1 Contribution to the Literature

Past studies on the Theory of Personal Space (Hall, 1966; Sommer, 1969) identify the personal space as a sphere or a bubble whose radius defines the minimum threshold of physical distance that individuals require to perceive the presence of others in the same space without eliciting negative reactions. According to the same theory (Hall, 1966; Sommer, 1969), the size of the *individual's bubble* is endogenous, whilst distancing due to the risk of contagion reflects an exogenous constraint on consumers. Thus, our research extends the concept of personal space and distancing in physical stores in time of a contagious disease (as during the COVID19 outbreak), by estimating how individuals move within a store area under the exogenous, rather than endogenous, constraint of keeping other customers distant. Our findings extend these studies by showing that the personal space

defined with a certain space is a dynamic entity, following consumers during each step of the in-store path. Thus, our study assigns to the personal space the attribute of *dynamic*, as emerged in the simulations of consumers' in-stores paths in study 1 and 2. Drawing upon past studies on consumers' paths within stores (Luck & Benkenstein, 2015; Clarke & Kirkup, 1998), our research adopting agents-based simulations provides a more realistic representation of consumers' movement in a fixed shopping area, taking into consideration not linear paths. This dynamic representation adds new knowledge to the first attempts to model the number of people in the store (Ntounis et al., 2020; Luck & Benkenstein, 2015).

Moreover, according to the Theory of Personal Space (Hall, 1966; Sommer, 1969) we model the effects of violation of consumers' personal space in terms of health, as the risk of COVID19 contagion. This health risk should be further added to the traditional list of factors shaping the personal space (e.g., culture, perceived familiarity and/or affinity with others, and situational factors) (Evans & Howard, 1973). In other words, under a pathogen treat, the personal space in the stores in terms of physical distance is not only a psychological barrier (Martin, 2012), but it represents the physical limit of the safety zone. In this way, our findings contribute to the definition of retail physical distance during pandemic emergencies as the spatial distance among consumers taking place in the physical store and the absence of physical interactions with other consumers. In this way, our findings reply to the recent call for investigations on rebuilding the concept of distance and personal space as required by COVID-19 pandemic (Shankar et al., 2021).

4.2. Implications for practitioners

From a managerial point of view, this research suggests an alternative method for estimating the safe number of in-store customers, based on agents-based simulations, which incorporates the heterogeneity of shopping paths. Indeed, our approach predicts the extent to which consumers would enter in contact to each other within the store (social gatherings), while the linear correlation between the number of consumers in the store and the number of consumers susceptible to contract the disease

should push retailers to avoid any form of interaction between consumers in any area of the store. The specific application or our model in a real store shows the feasibility of the system that retailers could put into practice to better evaluate the maximum number of consumers who can simultaneously access the store during a pandemic (and avoid temporary closures of the stores). Thus, simulating scenarios with different number of agents allow managers to predict the higher/lower occurrence of social gatherings as a function of the number of consumers. Specifically, our approach allows managers to understanding the risk of social gatherings in what specific areas of the store. Accordingly, managers could insert some "traffic lights" or temporary displays (as a form of constrain) to limit the access to those areas, or "alarms" that ring if the distance between consumers is less than 1m.

Summarizing, our findings provide an effective and scalable solution to practitioners, with emphasis on store managers, since an overestimation of the number of customers might put at risk customers' and employees' health, whilst an underestimation might lead to possible profit loss. Our work aims at soliciting managers' awareness of the potential risk of contagion occurring in-store, and adapt the strategies accordingly to provide new (safer) shopping experience that might persist also when the pandemic will be over.

4.3 Limitations and future research direction

Despite these contributions, this research is not without limitations. First, the present simulations do not take into consideration possible changes in consumer's behaviour if crossing another customer's path. Thus, future models might enrich our findings by considering additional scenarios such as (i) consumer stops and waits until there is again enough space to access that area, or (ii) consumer changes path, which implies no access to that area in the near future.

Secondly, this paper considers the risk of social gatherings in the store as effect of consumers' density. However, it ignores the effect of consumers density on their perception of crowd and the extent to which this perception would push them to change behaviour. In other words, from the receipts we

evaluated the possible path in the store, but we have no information about the extent to which the path has been altered due to the presence of others. Future investigations might focus on the effect of store density on consumers' in-store paths.

Thirdly, our study does not take into consideration that consumers' awareness of potential contagion in the stores would alter their behaviour in terms of shopping channel preference (i.e., online or physical store), modality of shopping (i.e., store browsing or only pick-up), store size preference (i.e., large sized store or smaller ones), store attachment and loyalty. Future research might involve consumers to deeply investigate these possible reactions and the related drivers (through in-depth interviews, survey, or direct observations).

Fourthly, we consider in both studies the presence of only one infect (I), thus the simultaneously presence of more infects would dramatically increase the risk for consumers. Additional investigation might quantify the individual risk for consumers, based on the risk of contact with one and more infects.

Finally, in Study 2 we assume that each receipt is assigned to one consumer. However, only a limited number of stores oblige consumers to shop alone (during the COVID19 pandemic), thus our study excludes the presence of families or couples buying together. Similarly, the evaluation of receipts implies that each consumer bought at least one product. However, it is possible that few consumers entered the store and did not buy anything. As a consequence, our study 2 might underestimate the effective number of consumers in the store, which might lead to an even higher risk of contagion. Future research might develop more effective measures to evaluate the number of consumers in the store, like the usage of cameras or movements sensors, etc. Also, they might investigate the effective in-store paths, and compare and contrast with the one simulated through the agents to provide a detailed measure of the reliability of this approach.

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