Enhancing store layout decision with agent-based simulations of consumers’ density

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Abstract.
Customer concentration inside a store is of pivotal importance for retail management, acquiring controversial contributions about the best number of consumers in the floor space to ensure an enjoyable and pleasant experience. Indeed, the excessive concentration of people (crowd) might discourage from shopping in that location, while on the other hand, a certain traffic to the store generates profit for retailers.
The aim of this paper is to support retailers' informed decisions by refining our understanding of the extent to which store layouts influences consumer density. To this end, we conduct a large field study using a unique dataset covering customers in a real grocery store with agent-based simulations. Results clearly show the extent to which this kind of simulations help predicting the changes in store layout able to affect customer density in the areas, while ensuring the same number of individuals.

Keywords. Crowd; store layout; consumers' density; retailing; Probability Density Function; agent-based simulation

1. Introduction

The concept of customer concentration inside a store is a traditional topic in retail literature, acquiring controversial contributions about the best number of consumers in the floor space to ensure an enjoyable and pleasant experience (Aydinli et al. 2020). On the one hand, the excessive concentration of people (crowd) might discourage from shopping in that location (Machleit et al. 2000; Baker and Wakefield 2012); while on the other hand, a large traffic to the store generates profit for retailers (Aydinli et al. 2020; Ailawadi and Keller, 2004). With these regards, store layout plays a pivotal role in that, since it shapes customers' spatial perceptions and influences the paths followed by individuals while shopping, thereby affecting the likelihood of creating areas with excessive people density (Pons, Mourali and Giroux 2014).
The growing availability of in-store technologies is generating multiple opportunities to observe and model customers' behaviors. In this vein, recent literature has underlined the value of predictive analytics to profitably exploit the huge amount of customer data which can be collected in-store (Bradlow et al. 2017). For instance, prior studies have modeled customers' in-store traffic and movements by relying on multiple data sources, such as RFID tags (Larson, Bradlow, and Fader, 2005), 3D depth sensors (Vildjiounaite et al. 2014), etc. Similarly, a potentially fruitful avenue is

given by the combination of different sources of behavioral information such as POS and in-store sensors' data to optimize the effectiveness of the store layout (Inman and Nikolova 2017).

However, even if retailers are not equipped yet with motion sensors to measure the actual position and paths followed by customers, it would be still possible to make estimations by relying on agent-based methods, such as the Monte Carlo method (Hidalgo 2015; Misra et al. 2019). Indeed, agent-based modelling have proven to be effective in simulating individual movements in the space such as pedestrian traffic (Kerridge, Hine, and Wigan 2001), or tourists (O'Connor, Zerger, and Itami 2005). Accordingly, it might be considered an appropriate method to gain a deeper understanding of how consumers move across retail settings, largely characterized by a variation of the number of people across the day, and movements of consumers in the space.

However, to the best of our knowledge, there are no studies modelling consumers' density in the store as a function of a certain layout. The aim of this paper is to support retailers' informed decisions by refining our understanding of the extent to which layouts influences consumer density. In this way, our paper would investigate the usage of agent-based simulation to predict changes in the store layout able to still ensure the same number of consumers in the store (same profit) whilst modifying their density in the different areas. To this end, we conduct a large field study using a unique dataset covering customers in a real grocery store. Findings show how the simulations identify clearly to what extent the changes in layout allow distributing consumers' density more equally across the store, by reducing the crowded areas and populating the empty ones.

In the remainder of this paper, we fist review prior research on the store layout (section 2.1), and the effect of crowding on shopping behavior (section 2.2). We then report our empirical work based on agent simulation to model consumers' density and crowd in the store (section 3). We finally conclude with a discussion of our results, elaborate on the theoretical explanation, and identify practical implications for retailing (section 4).

2. Theoretical background

2.1. Store layout

Literature in retailing widely supports the notion that the choice of the store layout is of paramount importance, since it contributes to the creation of a positive and effective shopping environment for customers (Baker et al. 2002; Vrechopoulos et al. 2004), while affecting the retailer's operational efficiency (Baker, Grewal and Levy 1993; Lewison 1994). Specifically, research has found the huge effects of store layout on customers' perceptions and behaviors, spanning from price acceptability (Grewal and Baker 1994) to store loyalty (Merrilees and Miller 2001). In this vein, Garaus and colleagues (2015) empirically found that appropriate store layouts increase the amount of time spent in-store by customers leading to pleasurable experience. Indeed, an appropriate store layout does not fulfill only customers' utilitarian needs, such as assisting them to purchase more efficiently (Morales et al. 2005) or exploring the store more in depth (Mohan et al. 2012), but it extends also to the experiential side of shopping triggering positive emotions and satisfaction (Terblanche 2018). With these regards, Bonnin and Goudey (2012) referred to the ability of a shop to frame consumers' minds and to drive their movements and gestures as the kinetic quality of a retail store. Kinetic quality can be conceived both in terms of instrumentality of the layout to the movements and gestures required to follow a path through the space (Vilnai-Yavetz et al. 2005), and in terms of the extent to which it assists individuals in the performance of a specific task (Bonnin and Goudey 2012). Accordingly, retailers need to make sure that the layout of their store leads to a large store traffic whilst minimizing, at the same time, unnecessary or inefficient movements for customers. In other words, retailers are asked to arrange the interior spaces in terms of position, sequence and shape of the display areas to optimize a performance metric.

A typical and basic measure of retail space productivity is sales per square meter (Bogomolova, Szabo and Kennedy 2017; Page, Trinh, and Bogomolova 2019), which was found able to effectively capture the extent to which product placement on shelves and organization of the shelves within the store generates sales (Bezawada et al. 2009). Similarly, a separate stream of research proposed an additional set of customer-centric performance measures allowing to incorporate customer perceptions about the extent to which the store layout fulfills their emotional and kinetic needs (e.g., Baker, Grewal and Parasuraman 1994; Doyle and Broadbridge 1999; Backstrom and Johansson 2006). In this vein, Juel-Jackobsen (2015) advanced five parameters able to capture the perceptual side of customers' interactions with the retail space as defined by the specific store layout adopted by the retailer, namely visit-ability, destin-ability, comfort-ability, walk-ability, and compact-ability.

However, retailers strive to identify the optimal store layout maximizing the visibility of products to consumers and impulse buying tendencies (Grewal et al. 2003; Flamand, Ghoniem and Maddah 2012). With these regards, prior literature has examined different types of store layouts and their relative advantages given the benefits sought by the target market and the retail format (Ebster and Garaus 2011). For instance, a geometrically regular organization of displays with parallel aisles and counters – typically referred to as *grid layout* – is typical of grocery stores because it was found to ease routine and planned shopping (Levy and Weitz 2004). Similarly, a *spine layout* is characterized by a single large aisle running through the entire floorspace of the store with departments located on both sides of the aisle, and it is typically used by large scale retailers to facilitate customers in moving through the huge store area (Carpenter and Moore 2006). A *racetrack layout*, instead, consists of the organization of the store area into semi-detached spaces revolving around different concepts (e.g., kitchen, bedroom, living room in home-improvement centers), which consumers might go through by following a loop-like path (Foster and McLelland 2015). Racetrack layouts can be appropriate in order to create a more entertaining shopping experience as well as to guide consumers to shopping by concepts (Lewison 1994). Finally, the *freeform layout* is based on an irregular arrangement of displays with asymmetric aisles, so that customers are left free to browse the shop by following the path they wish (Hart and Davies 1996). These layouts are very common in boutiques and in the fashion industry since they increase the time spent in store by customers and encourage impulse buying whilst keeping high levels of hedonic shopping value (Fortin et al. 2011).

Therefore, the adoption of a specific store layout exerts a strong effect not only on the perceptions of consumers, but also on the behaviors they perform inside the store including -though not limited to – the paths followed to browse the merchandise displayed on the shelves (Hui, Bradlow and Fader 2009). However, testing and implementing alternative store layouts is a costly activity for retailers (Baker, Levy and Grewal 1992). With these regards, recent literature has proposed several technological solutions which might provide retailers with accurate data to monitor customers' paths inside retail stores (see Bradlow et al. 2017 for a review), albeit requiring impactful and expensive technological installations. While another stream of research proposed a methodological approach based on probability evaluation to model how individuals behave in large geographical areas as a function of the spatial elements which shape individuals' movements (e.g., Journel and Deutsch 1993; O'Connor et al. 2005). This modeling approach has been proven to be effective in predicting individuals' behaviors in large spaces without requiring, at the same time, the implementation of potentially intrusive and costly technological devices to track individuals' movements. Surprisingly, literature has not provided meaningful indications on the extent to which this approach can be effective in describing customers' movements within stores. The focus on retail stores is not trivial though, since probability prediction-based models might fail to fully incorporate individual behaviors in smaller and enclosed spaces. Accordingly, the present research aims to fill this gap by applying probability density functions to assess the impact of different store layouts on customers' in-store movements.

2.2. Spatial density and consumers' crowding perceptions

How consumers will spread through the available space determines the concentration level of customers per store area. The concept of customer concentration inside a store is typically referred to in retailing literature as social or spatial density (Knoeferle, Paus, and Vossen 2017). The former increases when the total number of customers populating a store area is higher, while keeping the total walkable floorspace unchanged; the latter, conversely, changes as a function of the walkable floorspace while maintaining the number of people constant (Mehta 2013). It might be worth of noticing that altering the total walkable space of a store does not necessarily affect customers' crowding perceptions, but just the actual density of shoppers within the store area. Indeed, density and crowding are two distinct concepts since spatial density reflects the objective spatial limitation of individuals within the space, whilst crowding is a perceptual state determined by the feeling of being constrained by the presence of other individuals within their same personal space (Stokols, 1972; Pons, Mourali and Giroux 2014). The effect of perceived crowding on consumers' in-store reactions and behaviors is quite controversial in the extant literature: on the one hand, literature has supported the increase of spatial density by brick-and-mortar retailers in order to attract additional customers to their stores with the ultimate goal of increasing their profitability (Kumar, Anand and Song 2017). On the other hand, prior studies have addressed the potential role of crowding as a stressor (Aylott and Mitchell 1998; Kim and Runyan 2011). Accordingly, multiple studies have reported negative effects of customers' crowding perceptions on store satisfaction (Machleit, Eroglu and Mantel 2000), shopping intentions (Baker and Wakefield 2012), time (Li, Kim and Lee 2009) and purchases (O'Guinn, Tanner and Maeng 2015). Yet, other studies showed that perceived crowding can turn even into positive reactions, such as an increase in hedonic and national brand products (Aydinli et al. 2020), or an increase in purchase intentions following employees' invasion of the customer's personal space (Esmark and Noble 2018). Accordingly, other studies have proposed an inverted-u-shape relationship between perceived crowding and customers' reactions (e.g., Pan and Siemens 2011; Knoeferle, Paus, and Vossen 2017). A recent meta-analysis performed by Blut and Iyer (2019) shed new light on the mixed findings reported in previous studies by distinguishing between spatial and human crowding, in line with the distinction formerly operated by Machleit, Kellaris, and Eroglu (1994). The former was found to exert several negative consumer reactions in terms of store evaluation, shoppers' perceived control and negative emotions; the latter, instead, was found to exert a positive effect on store evaluations and shoppers' emotions (Blut and Iyer 2019). Thus, retailers should strive to limit shoppers' perceptions of spatial crowding by means of an accurate design of the store layout (Mehta 2013).

However, determining the optimal store forces retailers to define the maximum space which can be occupied by human bodies within the constraint of the store walkable space. First, the store layout should enable customers not to touch each other while shopping (Timmermans, 2004). Indeed, previous studies have clearly documented that the physical movements are significantly influenced by the way store space is managed (Kim and Runyan 2011). Accordingly, the trade-off between display and walkable space should be carefully calibrated in order to allow the maximum number of customers possible to enter a store by guaranteeing, at the same time, compliance with personal space requirements and an assortment size in line with customer expectations. Secondly, customers are typically not static entities in a store; instead, they move following paths which are not necessarily linear (Luck and Benkenstein 2015), influenced by the way the store layout is designed (Hui, Bradlow and Fader 2009). Drawing upon this literature, recent studies have attempted to estimate spatial density accounting for the dynamic nature of customers' interactions within the store space (e.g., Ntounis et al. 2020; Luck and Benkenstein 2015). However, these models still fail in acknowledging the heterogeneity in customers' movements within the retail store. To fill this gap, the present work addresses agent-based modeling as a simulation approach enabling to simulate consumers' movements in the space (Vanhaverbeke and Macharis, 2011), thereby allowing the prediction of how customers are expected to flow through the store by following their paths to move between the different attractions in a store as a function of the store layout.

Table 1 summarizes the actual literature in the topic, and highlights the main gaps emerging from both store layout and spatial density streams of research.

Table 1: Main studies on store layout and spatial density.

Topics	Main findings	Description of gaps	Key studies
Store layout decisions	• Store layout affects both the utilitarian and the experiential side of shopping. • Retailers need to make sure that the store layout generates a large store traffic whilst minimizing, at the same time, unnecessary or inefficient movements for customers. • Probability prediction-based models are effective in analyzing how individuals behave in large geographical areas as a function of the spatial elements which shape individuals' movements.	• Anlysis of the effects of alternative store layouts on customers' in-store behaviors, and technological solutions to track them. • Approach based on probability density functions which has not been applied to model customers' in-store movements as a function of the store layout.	Journel and Deutsch 1993; O'Connor et al. 2005; Grewal et al. 2003; Vrechopoulos et al. 2004; Garaus et al. 2015; Bradlow et al. 2017; Bogomolova, Szabo and Kennedy 2017
Spatial density and consumers' crowding perceptions	• Density and crowding are interconnected since the former reflects the objective spatial limitation, whilst crowding is a perceptual state. • Physical movements are influenced by the way store space is managed: the trade-off between display and walkable space should be carefully calibrated to maximize the number of store visits by guaranteeing, at the same time, compliance with personal space requirements and an assortment size in line with customer expectations. • Customers are not static entities in a store, but they move following paths which are not necessarily linear but are rather influenced by the way the store layout is designed.	• Attempts to estimate spatial density accounting for the dynamic nature of customers' interactions within the store space. However, these models still fail in acknowledging the heterogeneity in customers' movements within the retail store space defined by the store layout.	Timmermans, 2004; Hui, Bradlow and Fader 2009; Kim and Runyan 2011; Mehta 2013; Pons, Mourali and Giroux 2014; Knoeferle, Paus, and Vossen 2017; Blut and Iyer 2019

3. Methodology of research

3.1 Methods

This research aims at using agent-based simulations to predict changes in the store layout in order to ensure the same number of consumers in the store (same profit) whilst modifying their density within the store space. To this end, the research pipeline is based on multiple steps (Figure 1). The pipeline starts with the definition of the settings, in terms of store dimension (floorspace), different areas (i.e., bakery, fish, etc.), distribution of consumers in the different areas (according to the purchases). The second step consists of measuring the level of crowd based on the evaluation of consumers' density in the actual store layout (Study 1), and in a new scenario (Study 2), with the related entropy value per each scenario. Finally, the comparison of results between the two scenarios would actually describe the extent to which possible changes in the layout would lead to a better distribution of consumers in each area of the store (in other words, reducing the maximum density and increasing the minimum one).

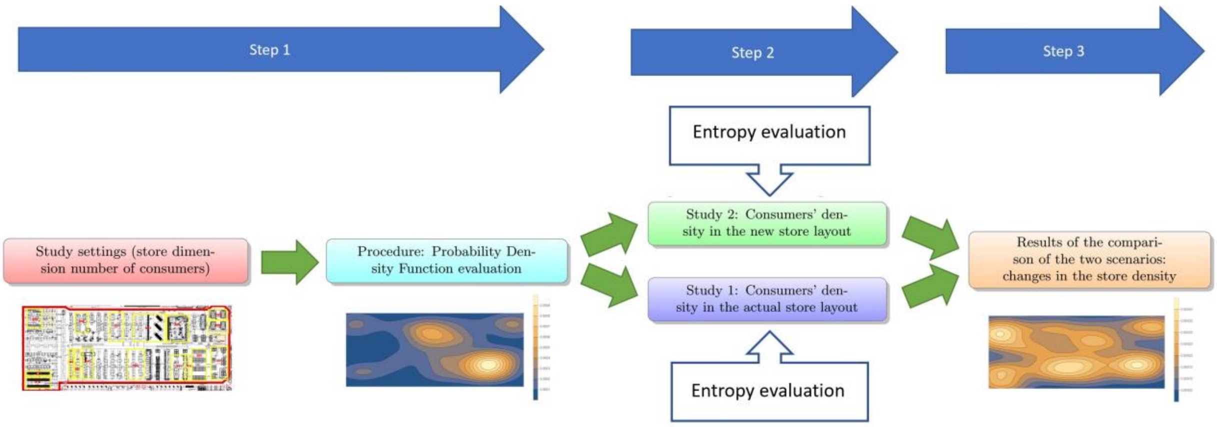

Figure 1. Research pipeline.

3.2 Study settings

The present research investigates a (real) grocery store within a large shopping center in Northern Italy. Specifically, the grocery walkable floorspace is 3,805 sq (the effective surface removing the space allocated to shelves, walls, etc.). Based on the number of products sold in each part of the store, there are 15 main areas of interests for consumers, contributing differently to the grocery profit (Table 2).

Area of interest	Relevance in the total store sales
Tins and Cans	**0.1374**
Cleaning Cupboard and Laundry	0.0462
Beauty	0.0423
Drinks	**0.0973**
Health and Medicines	0.002
Fresh Meat	0.06
Bakery	0.0781
Fish	0.0247
Ready Meals	0.0723
Salami and frozen food	**0.12**
Fruits and vegetables	**0.1217**
Electricals and technology	0.0131

Kitchen and dining	0.0117
Books and stationery	0.0091
Toys	0.0046
Others	0.0159

Table 2: Main areas of interests for consumers and related weight in the grocery profit (highlighted the four main profitable areas).

Appraising the numbers of receipts per hour per day of each week between January and July 2020, the peaks of clients (the highest number of clients entering the store) almost occur at the same hour (5.00-6.00 p.m.) every day, with the highest peak on Saturday. On this day, at 5.00 p.m., on the 25th of January 2020, the store witnessed the entrance of 385 clients, who actually bought at least one product.

3.3. Procedure

Since *Wolfram Mathematica* software supports data computation, mathematical modelling, and simulation and has started attracting the attention of scholars also in the field of marketing and tourism for understanding consumers' brands (Pantano and Dennis 2019) and tourists' behaviour (Giglio et al. 2019; Pantano et al. 2017), the present research employed this software to distribute consumers on the floorspace based on the map of the store, the location of each area, and the weight of each area. Since consumers are dynamic entities moving around during the time, the 385 customers navigate the store differently between 5.00 p.m. and 6.00 p.m. according to the relevance of each area (Table 1). To this end, we assume that each consumer made at least one purchase (in other words, there is one receipt per consumer). However, 66 consumers bought "others", thus they cannot be allocated to a specific area. Accordingly, Montecarlo method allows distributing them in the different areas, while 66 out of 385 are randomly located in the floorspace not close to a specific area. To this end, we run the simulation of consumers' movements 1,000 times. An average of the emerging different distributions of people in the store are presented in Figure 2, where the squares indicate the effective location and dimension of each relevant area and the points each consumer.

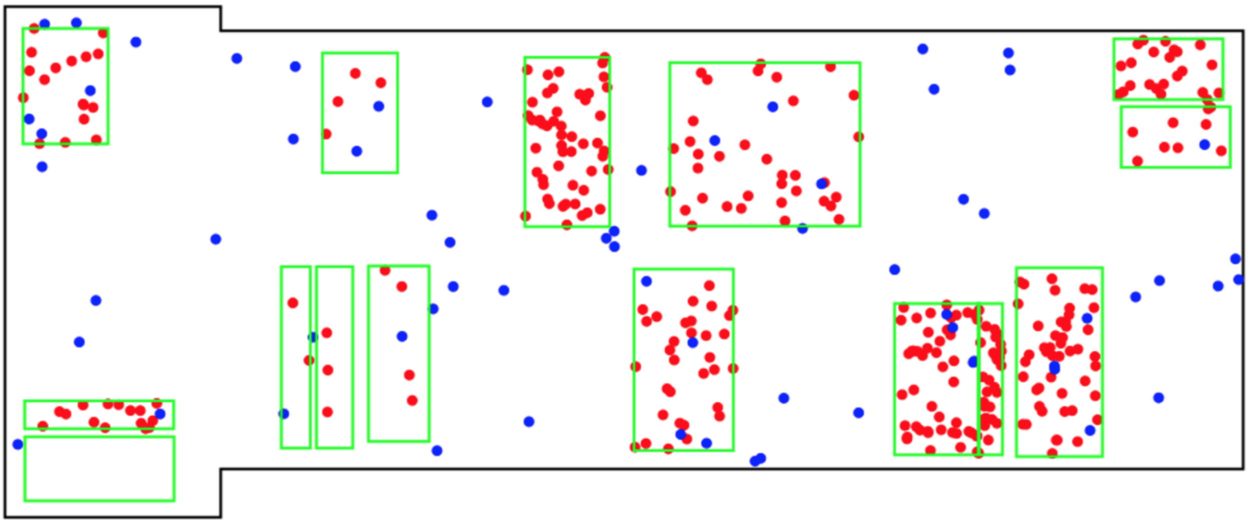

Figure 2: Average of the different distributions of consumers (1,000 simulations) in the store between 5.00 and 6.00, based on the highest number of people (385) and the relevant of each area of interest (represented as squares)[1]

This initial distribution confirms that few of the most profitable areas are located in proximity to each other, while some areas are quite populated and others are almost empty (i.e., bottom left on Figure 1).

3.3.1 Crowd evaluation

Since the number of consumers in each area of the stores would change across time, we evaluate the Probability Density Function (PDF), which is the estimation of the probability of the number of consumers in each area (Bertacchini et al. 2020; Santos et al. 2010). To this end, it is possible to adopt the Density Kernel Estimator Method (Sheather and Jones 1991; Botev et al. 2010). This method has been especially used in the spatial geostatistics, with the aim to identify a distribution of probability from sets of punctual data (geographical data) (Daley and Vere-Jones, 2007; Baddeley et al., 2015). In other words, this method allows shifting from a "discrete" distribution of points to a "continuous" distribution of points in a certain space. For this reason, it has been used to evaluate the distribution of traffic accidents (Hashimoto et al., 2016), criminal hotspots (Hu et al., 2018), animals in a certain habitat (Wood et al., 2000), etc.

In our context, areas of the stores are spatial data, while a single consumer in the storefront is a "punctual datum", and we assume that consumers are distributed in the store proportionally in the

[1] Areas are identified with the square without the specific name to avoid any reference to the specific grocery store involved in the research.

areas of the product that they buy. Thus, the Density Kernel Estimator Method provides the Probability Density Function from points c (consumers) that are distributed in the space (store):

$$p_c(y) = \frac{1}{c\,h}\sum_{i=1}^{c} K\left(\frac{y-y_i}{h}\right) \text{ (1).}$$

Where $Y = \{y_i, i = 1,2, \dots c: y_i \in S\}$ represents the sets of all points in the space, and $y \in S$ is the spatial variable K (smooth and symmetric) as the kernel function, and h is the bandwidth parameter. The value of entropy is usually considered to understand the spatial distribution of events (Journal and Deutsch 1993; Davison and Shiner 2005). Thus, the further evaluation of the entropy would help understanding the degree of disorder or randomness in a certain configuration. In other words, the entropy would help understanding how the areas of the store would be populated. Specifically, if we have *M* events occurring in *m* different modalities x_i, and each event is repeated $rip(x_i)$, thus entropy is defined as:

$$E = \sum_{i=1}^{m} -\frac{rip(x_i)}{M}\ln\left(\frac{rip(x_i)}{M}\right) \text{ (2).}$$

If *M* (number of events) and *m* (number of different modalities) have the same value (*M*=*m*), the event occurs only once, and all the events are different, thus $rip(x_i) = 1$, leading to:

$$E = \sum_{i=1}^{M} -\frac{1}{M}\ln\left(\frac{1}{M}\right) = \ln(M) \text{ (3).}$$

If the modality *x* is only 1 (m=1), thus the *M* events are the same (occurring more times), $rip(x_i) = M$, leading to:

$$E = \sum_{i=1}^{m} -\frac{rip(x_i)}{M}\ln\left(\frac{rip(x_i)}{M}\right) = -\ln(1) = 0 \text{ (4).}$$

As a consequence, the entropy of a system of *M* events occurring in different modalities x_i has a total value between 0 and ln(M). If further considering the value of entropy as the relationship between the entropy and maximum value $\mathrm{E} = \frac{E}{\ln(M)}$, the entropy values range between 0 and 1, we can compare the order/disorder between different systems.

4. Results

4.1. Study 1: Consumers' density in the actual store layout

Drawing upon (1), the evaluation of the Probability Density Function (1) for the actual store layout is graphically shown in Figure 3 (3D plot).

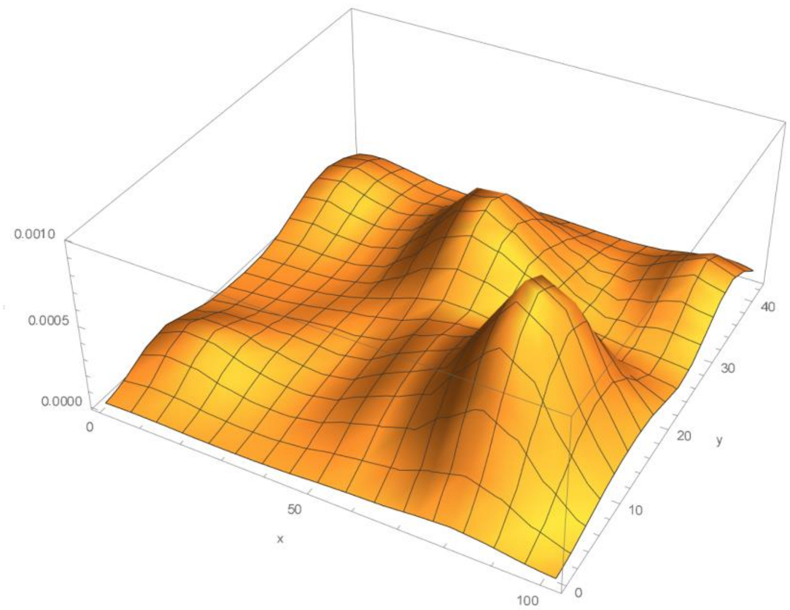

Figure 3. 3D plot of the Probability Density Function of 385 consumers.

This probability density can be further represented in the floorspace as a colorized scale output, in which larger values are shown lighter (Figure 4). To this end, we use the function "Contour Plot" (algorithm) already available in the software.

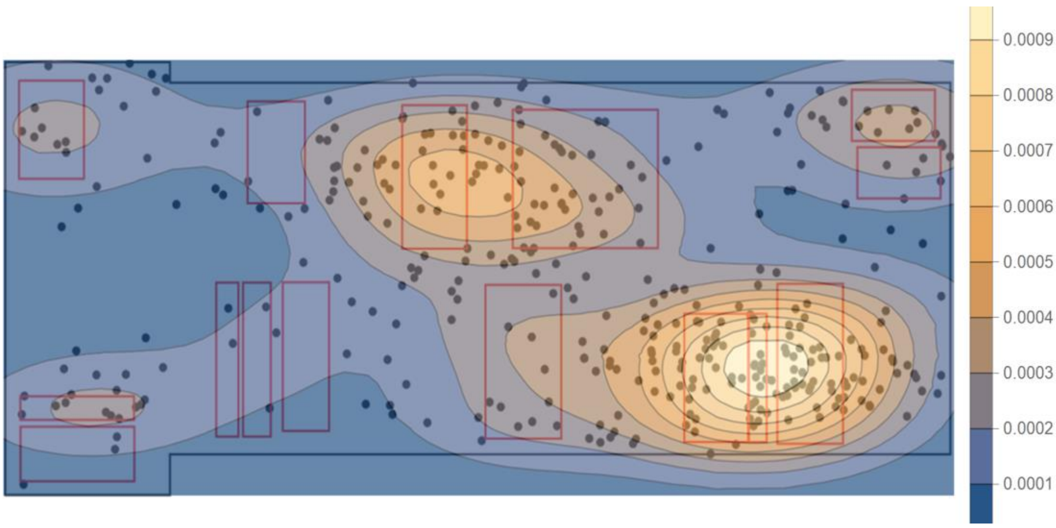

Figure 4: Probability density of (385) consumers in the floorspace, with reference to the different areas interest in the actual store layout.

From consumers' density evaluation, we clearly notice that there are some areas with high density (up to 0.0009) and others empty (between 0.0001 and 0.0002). This result means that some areas are more populated than others, while consumers do not populate the whole store surface. In other words, some areas could be better exploited, while others involve large crowds. It is possible to further evaluate the level of order or disorder of the actual configuration. To evaluate the entropy the actual our store layout, we used the built-in algorithm (function) ("Entropy[list]") based on (4), leading to the value E= 0.33384.

4.2. Study 2: Consumers' density in the new store layout

To reduce the density peaks, while ensuring that the same number of consumers (385) can access the store and the same areas of interest, a new store layout might consider the introduction of a certain distance between the more populated areas. To this end, we assume that (i) the different areas of the stores are flexible and might be moved around the store, and (ii) the resources needed (financial, technological and human resources, and time) are affordable by the retailer.

As in the previous store layout (the real one), we use Montecarlo method to distribute consumers, while 66 out of 385 who bought at "others" are randomly located in the floorspace not close to a specific area. To this end, we run again the simulation of consumers' movements 1,000 times. An average of the emerging different distributions of people in the store is presented in Figure 5, where the squares indicating the location of each area are located differently in the new configuration.

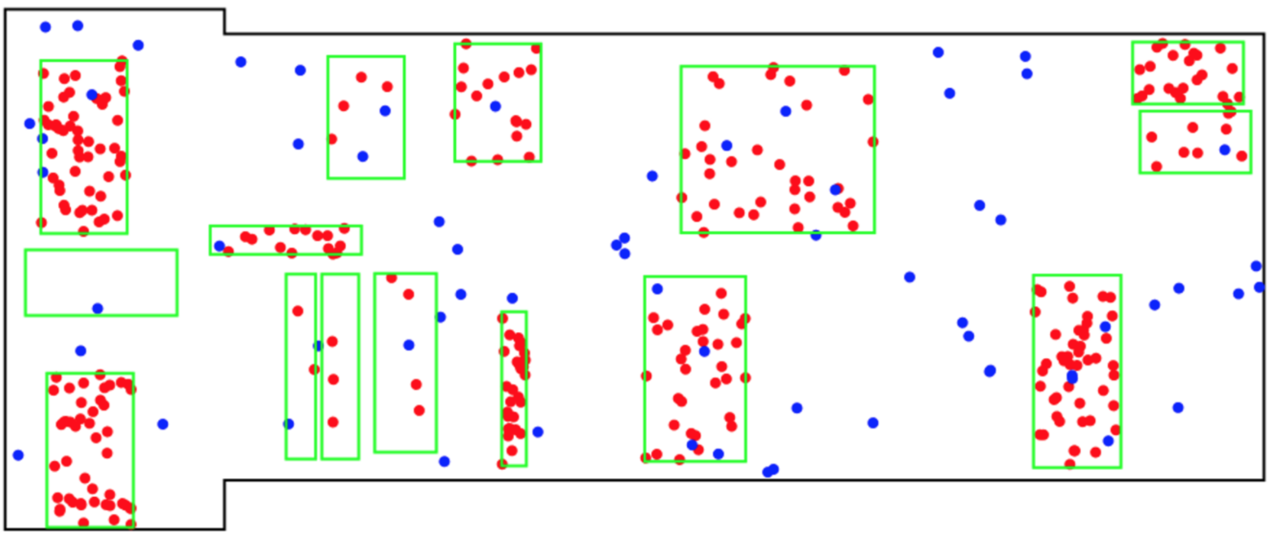

Figure 5: Average of the different distributions of consumers (1,000 simulations) in the store between 5.00 and 6.00, based on the highest number of people (385) and the new location of each area of interest (represented as squares).

To estimate the PDF, also in this case, we evaluate the Density Kernel Estimator Method using (1) (Figure 6):

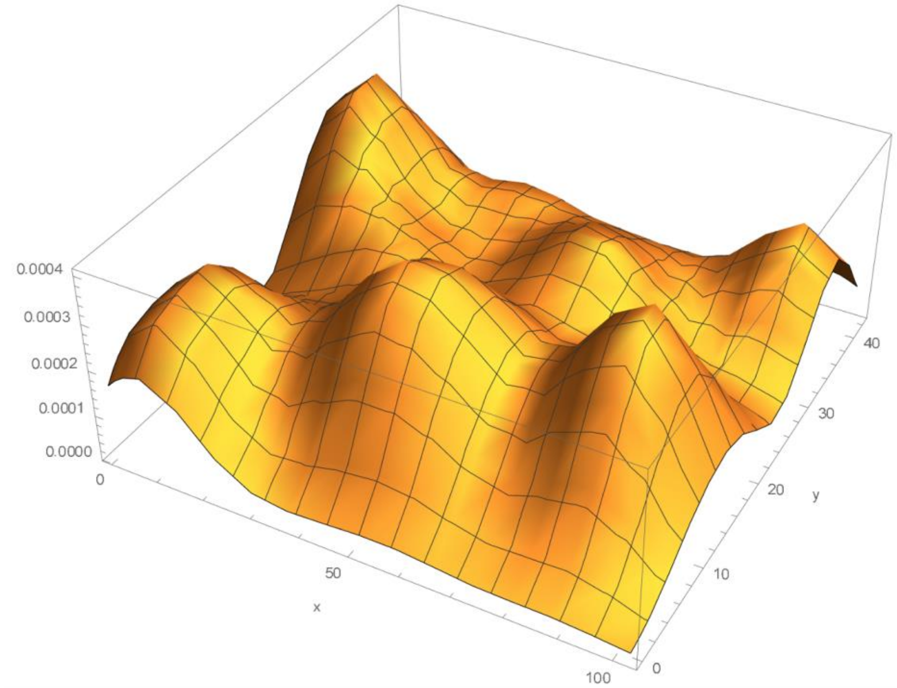

Figure 6. 3D plot of the Probability Density Function of 385 consumers in the new store layout.

In this case, we note that the peaks are lower than 0.0004, while in the previous layout they reached close to 0.0009. Thus, this analysis provides a first indication of consumers' density on the storefloor. The contour plot (Figure 7) shows the effective density in the new layout by showing the presence of more peaks if compared with the previous layout, but counting for a lower value.

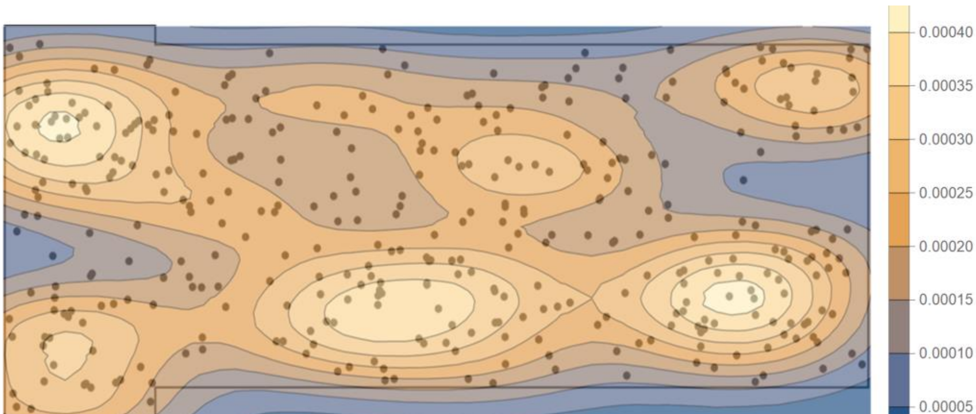

Figure 7: Probability density of (385) consumers in the floorspace, with reference to the different areas of the new store layout.

From consumers' density values, we clearly notice that the areas of the stores resulting more populated in the previous scenario have a lower density (up to 0.0004 against the 0.0009 with the "old" layout) and less empty areas (lower than 0.0002). This result means that the new store layout leads to a better distribution of consumers on the storefloor. Thus, the new configuration would show simultaneously less crowed areas and less empty areas.

Drawing upon (4), the entropy value in this case (*E*) is 0.3474, which is higher than the value in the previous configuration. Thus, the new layout resulted in a higher disorder if compared with the real layout. If considering a random distribution of consumers in the store, without considering any area of interest, the final value of entropy is *E*=0.34975, which is the maximum value of the entropy in store with this size, shape and number of consumers. Therefore, the entropy of the new store is very close to the maximum value of entropy for this store.

5. Discussion and conclusion

The amount and concentration of store visits plays a critical role in retailing. On the one hand, maximizing the number of store visits and consumers in the stores is a profitability source for retailers (Aydinli et al. 2020; Kumar, Anand and Song 2017; Ailawadi and Keller 2004). On the other one, an excessive customer density might lead to undesirable crowding perceptions from the consumer side, which might ultimately lead to lower store satisfaction and patronage intention (Machleit, Eroglu and Mantel 2000; Baker and Wakefield 2012). Accordingly, retailers strive for the optimal balance between the number of customers attracted by the store and crowding perceptions. Although, testing and implementing alternative store layouts is a costly activity for retailers (Baker, Levy and Grewal 1992) as it likely involves moving shelves and changing planograms. For this reason, recent literature has addressed the role of several technological solutions enabling an accurate monitoring of customers' paths inside retail stores (Bradlow et al. 2017). Drawing upon these studies, the present research advances a solution to the problem of estimating traffic flows and spatial density without requiring the installation of any technological device/sensor. Our research method makes use of checkout data to estimate a) the number of customers inside the store at any given time of the day, and b) the attractiveness of each store area. Specifically, the approach presented in this research allows estimating the probability of the number of consumers in each store area by means of a Montecarlo simulation. In this way, our model provides a measurement of how a new layout allows better distributing people in the store at each time. This distribution emerges as a function of the relative attractiveness of each store area.

Moreover, an appropriate store layout increases the amount of time spent in-store by customers and enjoy a pleasurable experience (Garaus et al. 2015), including the positive role of walkability (Juel-Jackobsen 2012). Our results add new knowledge by providing a new way to design the store layout based on a new distribution of the areas of interest. This approach makes the same number of consumers to populate the store with less crowded areas. Results further show clearly that changes in store layout affecting customer density in the store areas might be predicted through agent-based simulations, by ensuring the same total number of customers present in the store. These results might be a solution to the problem of ensuring a certain walkable floorspace while maintaining the number of people constant (Mehta 2013).

Moreover, our research considers consumers following paths which are not necessarily linear (Luck and Benkenstein 2015), while reducing consumers touch to each other while shopping, as encouraged by previous studies (Timmermans 2004). Specifically, findings demonstrate the extent to which a store layout maximizing the distances between the most attractive areas facilitates the reduction of the overall density of customers inside the store, thereby potentially limiting crowding perceptions by customers during their shopping experiences. With these regards, our approach combines the information about customer density with a measure of entropy capturing the extent to which product areas are ordered in the space, through agent-based simulation. The higher the entropy, the higher the disorder in the areas. Given that higher disorder in areas/shelves layout might discourage customers, by making the search of the products more effortful (Morales et al. 2005; Garaus et al. 2015), our pave the way for a modelling approach which allows to take simultaneously into account both the potential social density–identified by the probability density function – and the store navigation clarity – indicated by the level of entropy. Accordingly, the approach suggested in the present research allows predicting the optimal balance between customer density and layout effectiveness by minimizing the former and maximizing the latter.

Finally, the present study employs the probability density function as basic measure of customer density inside the store which has proven to yield meaningful indications when applied to spatial geostatistics for large geographical areas (Journel and Deutsch 1993; Wood et al. 2000; O'Connor et al. 2005). To the best of the authors' knowledge, this is the first time that this approach, based on geospatial statistics, is adopted to describe and predict customers' movements inside a, smaller and enclosed space (retail store).

Retailers might consider our approach to effectively evaluate if the actual configuration of their store generates peaks and if new layouts might reduce these peaks (leading to high consumers' density and perception of crowd), while better populating the almost empty areas. Similarly, the agent-based simulation supports them in predicting consumers' distribution in different layouts before the actual changes in the real layout, supporting the measurement and comparison of the effectiveness of new solutions while virtually testing multiple configurations.

The results of the present study should be read in the light of its limitations that delineate avenues for new lines of inquiry. First, the present study measures the number of consumers based on the number of receipts at check-out, thus it counts only consumers who effectively made a purchase in the store. New studies might consider evaluating the number of consumers through other tools like cameras (e.g., CCTV) or sensors to also embrace those consumers who enter the sore but not make any purchase. Secondly, the present study evaluates the store density that might lead to the crowd perception. However, it does not collect effective data with consumers to investigate the value of consumers' crowd perception in the new scenario. Thus, future research might triangulate our results with qualitative and quantitative data emerging from in-depth interviews or surveys with consumers. Similarly, new studies might evaluate if the changes suggested by the simulation would provide the same/higher/lower profit when put into practice in the real point of sale. Comparisons between the hypothesized new configurations and the effective new configuration in the real store would corroborate the validity and reliability of our approach. Finally, the present study considers the changes in the layout as free of cost for the retailer. However, it would require some investments (i.e., time to actually move the areas/shelves, employees to perform the job, etc.). Thus, future research is needed to understand if and to what extent the additional costs are offset by the profits brought by the change in the layout towards a better configuration of the areas. Furthermore, moving some product categories (e.g., products requiring to be refrigerated) within the store layout could be more or less difficult and expensive than others. For these reasons, additional comparisons including predictions of costs as new constraints of the model are encouraged.

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