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Analyzing store features for online order picking in grocery retailing: an experimental study

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Abstract:

The digital transformation is having a major impact on the consumer product market, pushing food retailers to foster online sales. To avoid large investments, e-grocers are tending to use their existing physical stores to undertake the online order picking process. In this context, these companies must choose in which traditional stores must prepare online orders. The aim of this study is to identify which store features affect order preparation times. The action research approach has been used at a Spanish e-grocer to analyze the characteristics that differentiate picking stores from each other; furthermore, the preparation times for a sample of online orders have been measured. The data were analyzed statistically using one-way ANOVA to define the optimal store in terms of size, assortment, backroom and congestion. The study shows that three of the four characteristics are significant on the preparation time. Therefore, e-grocers using a store-based model can use this information to focus their efforts on optimizing this process, assigning online order picking to the most appropriate stores. The approach used allows the study to be suitable for different retail context. Moreover, the results serve as support for strategic decision-making of researchers and e-grocers seeking to become more competitive in this continually growing market.

Key words:

E-grocery, omnichannel, store-based, picking, food retail, fulfillment.

1. Introduction

Online and traditional sales channels are increasingly connected, although it has been demostrated that the online sales are substituting the offline ones (Suel et al., 2018). This shift in consumer preferences appears to have accelerated in recent years and an increase in the use of technology has been observed. This behavioral change among consumers has been noted to a greater extent in the food sector.

E-commerce has been boosted by the effects of COVID-19, as consumer food distribution had to be adapted quickly (Forbes, 2020). On the one hand, border closures hindered the supply of some products. This issue became more critical in long-distance supply chains, where breaks in the chain provoked wholesale supply problems that led to stock-outs at retailers offering the online channel (Mahajan and Tomar, 2021). On the other hand, social restrictions resulted in the HORECA channel (Hotel, Restaurant and Catering) to close down. For this reason, the food sector underwent major growth in retail as consumers began to prepare more meals at home and eat out less (Hailu, 2020). This sudden change in consumer behavior highlighted more than ever the need to create sustainable and resilient supply chains that enable the adoption of alternatives to guarantee business continuity (Hendrickson, 2020).

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As a consequence of these breaks in the supply chain and the increase in omnichannel demand brought about by COVID-19, supermarkets encountered capacity problems in order to meet customer orders. That is why retailers who seek to increase omnichannel sales should pay special attention to their supply chain and new business models (Rodríguez-García et al., 2016). Within this scope, the digital transformation has become one of the most important strategies in order to mitigate the risks to the supply during the pandemic (Kumar et al., 2021). For that reason, supermarket chains are seeking to optimize their processes, concentrating their efforts on activities with the most impact on costs.

Looking at the online channel of grocery sellers, order preparation and transport are the most important activities, accounting for a large part of overall costs of stores (Tompkins et al., 2010). These activities are jointly known as e-fulfillment, and are especially important in this sector, which is based on handling food products that must meet a series of particular requirements (temperature control, expiry dates, traceability, etc.). Authors such as (Komijan and Delavari, 2017; Schoen et al., 2018) underscore the need to increase the proper conservation of sensitive products when it comes to managing the supply chain because there is increasing demand for greater speed. At the same time, online orders tend to be highly variable in terms of the number of items in them and often include products of a variety of sizes and weights, or that need to be kept at different temperatures (Zhao et al., 2020). To this end, products are often categorized into three groups: dry products (at room temperature), fresh products (kept above freezing), and frozen products (kept below freezing). Authors such as (Vazquez-Noguerol et al., 2020) state that order delivery is an activity that has been studied in detail by several authors, whereas there has been limited published research into improving the online order picking process.

In the extant literature, a distinction is commonly made between two strategic models that an e-grocer can adopt in order to meet demand, based on where preparation takes place: the warehouse-based model and the store-based model (Rai et al., 2019). Within each of these alternatives, specific peculiarities can be found or even hybrid models that combine features of both.

Supermarket chains that choose the warehouse-based option have two different ways of operating: they can do their online order picking at their existing warehouses, or they can devote specialized infrastructures (known as dark stores) to the online channel. In both cases, investment tends to be greater than that for the store-based option due to the automation of handling means. In this respect, warehouses usually gain efficiency in the picking process, but the flexibility of the installation is reduced because automatic systems generally operate under very specific conditions.

In general, the viability of the warehouse-based model is usually conditioned by the volume of orders, particularly in those models that are exclusively devoted to the online channel (Rodríguez-García et al., 2021). In both warehouse- and store-based models, when the infrastructures are used to fulfil both on- and offline channels, a major advantage can arise. This is because order preparation resources can be shared and online orders can be prepared when the workload for the traditional channel is low.

Owing to this synergy between both channels, many supermarkets have opted for a store-based model, preparing online orders from their existing stores. This model has several advantages including that it allows flexibility in the face of variable demand and could avoid any major initial investment. However, one of the main disadvantages is that stores are not designed for the picking process to be done efficiently, but instead are aimed at the traditional sales channel. (Wollenburg et al., 2018). Add to this the fact that there is a great variety of features differentiating stores from each other, and so the same process may be very different in each store. The great diversity existing among stores gives rise to discrepancies in preparation times, which constitutes a potentially interesting problem to be studied. To date, there are no studies on e-grocery aimed at optimizing picking tasks by looking at store features. Nevertheless, knowing which features can favor or hinder picking tasks will provide information of great value that can help supermarket chains to decide which stores to use for online orders. Up to now, this strategical decision has been based on the proximity of the store and the customer; however, the closest store may not be the best alternative. Thus, it can be concluded that there is a gap in the literature. That gap is addressed by the current study and by answering the following research question:

RQ**:** How do the characteristics of stores affect the online order picking process?

In order to answer that research question, a study has been developed a statistical study using the Action

Research approach. A case study has been carried out at a Spanish firm with a store-based model. The time needed to prepare a sample of online orders has been measured taking as a reference the most representative stores of that e-grocer. The aim is to improve the online order picking process based on store features because this process needs to simultaneously achieving low costs, high accuracy, and high velocity (Hübner et al., 2019).

The remainder of the paper is organized as follows. Section 2 presents a review of the main publications about improving the online order picking process in stores. Section 3 describes the methodology used in the research process. The empirical analysis carried out is presented in section 4. Section 5 illustrates the findings of the statistical study. Section 6 discusses the results with what exists so far in the literature and finally section 7 presents the conclusions of the study.

2. Literature review

With regard to the two existing strategic order picking models, warehouse- or store-based, it should be noted that most e-grocers have opted for the store-based model (Ishfaq and Bajwa, 2019). This has mainly been due to the rapid growth in the online channel and the high costs of picking and transport. With the store-based model, e-grocers can make the most of this service to consolidate their market share without the need to make large initial investments by making good use of their existing physical sales points as order preparation centers (Mishra and Mukherjee, 2019; Dias et al., 2020).

In this strategic model, the work operation is as follows. A supermarket employee goes along the aisles of the store gathering the ordered products from the shelves to a trolley, just like any other client of the traditional channel. The main advantage of this model is that it allows the transformation to the online channel to be more gradual and flexible. Moreover, stores can adapt as demand increases. This is because, in order to carry out picking from the store, little else is required beyond staff training and any electronic devices. However, as mentioned previously, one main drawback of this strategic model is that these sales points are not designed for online picking (Rodríguez-García et al., 2021).

Firstly, stores tend to be designed on the basis of sales studies that encourage offline customers to buy more products as they go up and down the aisles. However, for an online order picker, the goal is to travel the minimum number of meters to complete an order, which is not something that is taken into account when designing traditional stores (Pires et al., 2021). The way products are presented on the shelves is also different because stores have products grouped in "families", whereas online picking is more efficient when the products are sorted in terms of their rotation, as they are in warehouses.

Because the traditional channel continues to predominate over the online one, changing store layout to optimize picking routes would not seem to be the best option. However, firms can act on other factors, such as choosing to assign online order picking to the optimum stores (Pires et al., 2017). When supermarket chains decide to implement the store-based model, a strategic decision must be made to select the stores to be used for picking online orders. To date, picking has usually been done in the stores nearest the customer and in locations where there is a greater population density of online orders. However, each store has features that could hinder or favor the picking task.

The chief differences between stores are found in size, in selling concepts, in backroom availability and in congestion (Seidel et al., 2016). The same authors focused one study on categorizing stores by size and distinguished three types of stores. Although there is no unanimity about the defining limits for size, supermarket chains can categorize their stores from the smallest to the largest surface area as: convenience stores (also known as discount stores), supermarkets, and hypermarkets (Seidel, 2021). In terms of picking, convenience stores tend to be the least efficient as their grid layout will cause pickers to take longer routes thereby increasing the picking time (Do and Omdahl, 2018). Similarly, it can also be reasoned that supermarket-sized stores would increase the travel distance as they have a greater surface area. This aspect would become even more relevant in the case of hypermarkets, which are not only the stores with the largest area but also stock other products not found in supermarkets, such as household appliances. It seems reasonable that the main objective of the stores is to minimize the travel distance of pickers and consolidation effort of orders (Hübner et al., 2019). The aim of such a consolidation effort is to reduce the process time by preparing several orders simultaneously, either by grouping orders that must be sent in the same time slot or grouping products from several orders by category (e.g., dry, fresh, and frozen). However, this is a little used model as it often gives rise to confusion and errors among the various orders being prepared at the same time.

This travel distance also usually depends on the assortment. For that reason, it is very important to define the assortment in the store properly, as this will limit the online assortment because online orders will be picked from the shelves in the physical stores (Gallino and Moreno, 2019; Rooderkerk and Kök, 2019). Thus, stores with a wider range of products will need a greater number of shelves to display them. As the number of shelves increases, so does the number of aisles in the store and, in turn, the distance in meters on the route of a picker. It is not clear whether it is better to offer a large or limited assortment. The former increases customer service, even though this lengthens search and route times. The latter reduces search times, although this may increase congestion of pickers and customers in the aisles; moreover, it may reduce the level of service (Fernie et al., 2010). Another question to bear in mind when integrating both channels is management of products on offer as this could trigger an increase in demand and affect availability of the products on the shelves. Furthermore, those offers and promotions are not usually the same in both channels.

Another characteristic that tends to differentiate stores is backroom availability, as this space allows the store to be supplied when there are stock-outs as orders are being prepared (Pires et al., 2017). Some stores even use this space to speed up online order preparation and avoid contact with offline customers (Mangiaracina et al., 2018). One of the greatest drawbacks of this model is that the time devoted to picking is usually increased as case packs are not divided into customer units (Broekmeulen et al., 2017). As a result, the pickers have to divide the units in their packaging or even unpack parts of pallet loads, which can lead to increases in picking time. This problem becomes even clearer when multi-item pallets are used, where the pickers have to handle several products in order to collect the particular reference they require. Add to this the fact that backroom pallets are not always at picking height. They can be stored high up and need handling equipment to be reached. In contrast, not having a backroom can lead to decreased customer service due to there being less capacity for replacement (Paul et al., 2019). Between the two options, there is an intermediate model, in which the store does have a backroom (and thus some capacity for replenishment but it is not used for online order picking. The handling problems are avoided with this picking option.

The last factor identified in the literature that affects stores is congestion. This variable refers to the store traffic, specifically the aisle traffic. Picking time is expected to slow down as customer traffic increases because in the hours of greater offline activity, the speed of the picker can be reduced owing to interaction with customers sharing the same space. However, the picking time does not have to increase significantly when the picker spends more time standing still picking up products from shelves and less time travelling between aisles (Salgado, 2015).

In summary, the extant literature has been used to identify the store features that appear to influence order picking time. These are: size, assortment, backroom availability, and congestion. This information can be used to determine which options are the most favorable for speeding up the picking process and thus define the optimum stores to serve the online channel.

3. Methodology

This section describes the methodology employed throughout the study. The first part contains a description of the research process and an explanation of the different stages followed in the proposed approach. Subsequently, the second part presents the case study selected for the analysis of the order picking process.

3.1. Research process

To carry out this study, the researchers have used the well-known action research approach. Authors such as Shani & Coghlan (2019) define it as a research process in which applied scientific knowledge is integrated with existing organizational learning and employed in real-world problems. A researcher using the action research approach is not just a mere observer of the process of change but a participant that is directly involved in it, acting as an agent of change (Prado-Prado et al., 2020).

Under these considerations, the research process begins with a contextualization phase. Firstly, authors conduct a literature review with the aim of identifying which store features can affect the picking process. Then, to undertake the study, we choose a sample of pilot stores classified according to the characteristics defined above. With the aim of determining the optimal store for the online picking process, studies of methods and times are carried out in the most representative omnichannel stores.

The time measured for each order is that corresponding to carrying out all the tasks that form a part of the online order picking process, from downloading the orders to the devices pickers work with to the packing process for later dispatch to the end consumer. Due to the large amount of collected data, it is necessary to use statistical tools in order to draw conclusions about the time studies. For this analysis, one way ANOVA is used, which is a statistical technique for assessing how several explanatory variables affect a continuous response variable (Hofmann and Meyer-Nieberg, 2018). In this respect, one-way ANOVA is applied to determine the effect of each store characteristic (explanatory or independent variables) in the order picking time (response or dependent variable). Since the objective of the study is to reduce the picking process time, those store characteristics that speed up the preparation will be considered as the best option.

3.2. Case selection

The firm of the study is a supermarket chain with stores throughout Spain, which has an annual sales figure of €5bn. The case study has been limited to two regions where sales are more representative: Galicia and País Vasco. This firm is a reference in e-commerce as it has been offering the service for 10 years, although only 13% of its stores offer this sales channel. The traditional stores used for picking have been selected based on their location, all of them being situated in the greater population density, where the online demand is usually concentrated.

In a first phase of analysis, the stores selected for the study were classified according to their size, product assortment, backroom and traffic or congestion; these differences are the product of non-standardization. Based on this information, the stores were categorized according to their characteristics. As a result, a representative sample of their online demand was selected. The sample obtained consisted of 200 orders, which corresponds to the average daily demand of the stores studied. Because the firm is continually growing, and the online demand is steadily increasing, optimizing the online order picking process is vital to maintain leadership.

4. Empirical analysis

This section deals with the description of the problem. First, the initial considerations of the study are justified. Then, the store features under observation that affect the online order picking process are described.

4.1. Field problem

The first stage of the case study focuses on investigating the problems linked to the stores and their work method. First, it should be pointed out that for this study only the preparation process has been taken into account, and any other activity related to replenishment and transport has been excluded. Regarding the stores, we identified that the management is the same for all of them. In this respect, the online order picking process is always carried out with the store open to the public and the frequency and method for replenishment are similar at all stores. At a technological and operational level, the stores can be considered similar, as they all have the same working method and the same type of devices.

At the beginning, pickers download online orders onto a mobile device. They carry the device with them during the process because it indicates the items and quantities of the products to pick up. Just as if they were an offline customer in the store, the pikers walk through the aisles, stopping at the locations of the products indicated by the device, and placing them into a trolley. Although the layout of the stores may vary depending on the size or the product range, the route of the pickers is very similar in all stores. They all start by picking up the dry products, continue with the fresh products, and finally complete the order with the frozen products. At the end of the process, the order is packed and ready for shipment. It should be noted that in all stores the order picking is done individually, this means that each order is prepared by a single picker and that each picker only prepares one order at a time. Finally, it is worth remarking that all measurements were taken at stores located in city centers, where most online orders are prepared. Moreover, these stores are the ones with the longest experience in preparing online orders, so all the pickers have received training and have a similar level of experience.

Taking all these considerations into account, and with the objective of collecting comparable measurements, the researchers paid special attention to the day and time slot when preparation took place in order to avoid bias as a result of the weekly seasonality of the sector (Hübner et al., 2015). For that reason, in addition to taking into account that the chosen stores were similar (in terms of demand, work method and location), all the measurements of the orders assigned to each store were made on a single day. This last factor is relevant because omnichannel and the substitution effect between channels cause discrepancies between online and offline sales.

4.2. Design of intervention

Regarding the initial considerations, four store variables were identified for each order that affect the online order picking process (independent variables). Analysis of this information, together with the measurements taken, made it possible to determine the type of store that provided efficient online order preparation.

The first store variable was size. The firm itself classifies its stores in three groups: convenience stores have a surface area less than 700 m^2, supermarkets covers 700 to 2000 m^2, and hypermarkets cover a surface area of up to 2000 m^2.

The second variable was the product assortment on offer. After analyzing the distribution of the assortment size in the different stores, the following categories of assortment were established: small, fewer than 32000 items, medium, between 32 000 and 40 000 items, and large, over 40 000 items.

The third variable was the availability of a backroom. If the store has a backroom, it is also analyzed whether this facility adjacent to the store is used for online order preparation. The difference between these last two options is that the one that does have a backroom will have a greater replenishment capacity, even though picking is only carried out in the aisles of the store.

Finally, the fourth variable defined corresponds to store customer traffic or congestion. For this, an indicator of daily orders per square meter of the store was defined. The orders considered in this indicator correspond to the customers of the offline channel, that is, the customers who physically visit the store to make their purchase. In the store-based model, the traffic of online order pickers can be distributed throughout the working day, taking advantage of the times when the store has less workload. However, the traffic of customers visiting the store is a variable that cannot be acted upon. This variable was also sorted into three ranges because of the distribution of the indicator values at the stores of the firm: low, when the indicator is below 0.3 daily orders/m^2; medium, when it is between 0.3 and 0.5 daily orders/m^2; and high, when it is over 0.5 daily orders/m^2. Once the identified variables have been described, Table 1 shows the distribution of a sample of 200 online orders. In addition, the picking process time has been considered as the dependent variable to determine which alternative is more efficient. Those characteristics that allow a shorter picking time will be more favorable. To this end, the preparation time of the orders that make up the sample has been measured.

Given that the time for preparing an order depends mainly on the number of items, the total time for the order has been divided to obtain a suitable indicator for preparation time (Chintagunta et al., 2012). The number of items per order in the sample ranged from 4 to 69, with an average of 36 items per order.

Table 1. Store features description and sample distribution.

Store features	Alternatives	Range	Sample (n=200)
Store size	Convenience	< 700 m^2	24 (12%)
	Supermarket	700 < store < 2000 m^2	95 (47.5%)
	Hypermarket	> 2000 m^2	81 (40.5%)
Assortment	Small assortment	< 32000 items	56 (28%)
	Medium assortment	32000 < assortment < 40000 items	60 (30%)
	Large assortment	> 40000 items	84 (42%)
Backroom	No		36 (18%)
	Yes		95 (47.5%)
	Yes and picking		69 (34.5%)
Congestion	Low traffic	< 0,3 daily orders/ m^2	51 (25.5%)
	Medium traffic	0,3 < traffic < 0,5 daily orders/ m^2	75 (37.5%)
	High traffic	> 0,5 daily orders/ m^2	74 (37%)

Table 2. Individual ANOVA results (n=200).

Store features	Sum Sq	Df	Mean Sq	F-value	*p*-value
Store size	11018	2	5509	10.07	< 0.001***
Assortment	19636	2	9818	19.50	<0.001***
Backroom	5012	2	2506.2	4.34	0.014*
Congestion	2184	2	1092.1	1.85	0.161

5. Findings

After defining the sample and the variables, studies of methods and times were undertaken on the orders of the pilot sample. Then, a one-way ANOVA statistical analysis was carried out in order to determine the effect of each characteristic on the picking time per item. Table 2 presents the findings obtained.

As the results show, three of the four store features identified are statistically significant. On the one hand, Store size and Assortment, are significant at the 0.01 level (*p*-value<0.001), while Backroom is significant at the 0.05 level (*p*-value=0.014). On the other hand, no interaction effect is detected for the store congestion feature (*p*-value=0.161). Means and standard deviations for the dependent variable are reported in Table 3.

At this point, it is not possible to identify the alternatives that minimize the preparation time. Although the mean time per item is known and very different, deviations must also be taken into account. This first stage of analysis only indicates that the differences among the alternatives of the store size, assortment and backroom are significant. In order to complete the study, it is necessary to carry out a second stage of pair analysis, comparing the results obtained for the alternatives of each group. Means and standard deviations and ANOVA results for pair analysis are shown in Table 4.

Regarding the store size variable, it can be seen that the lowest values are obtained in convenience stores (M=61.1). These stores present significant differences at the 0.01 level, in times per item, com-pared to the supermarkets (M=81.2) and hypermarkets (M=85.4). The two larger store types do not show significant differences between them (*p*-value=0.465). Thus, the statistical analysis shows that the option that minimizes preparation time is the assignment of convenience stores.

For the Assortment variable, the highest values are obtained with a large assortment (M=92.1), as

Table 3. Mean scores and standard deviations for the dependent variable (n = 200).

Store features	Alternatives	Mean (SD)
Store size	Convenience	61.1 (7.0)
	Supermarket	81.2 (26.4)
	Hypermarket	85.4 (22.7)
Assortment	Small assortment	73.7 (18.8)
	Medium assortment	70.7 (19.9)
	Large assortment	92.1 (26.0)
Backroom	No	73.8 (16.1)
	Yes	78.3 (26.4)
	Yes and picking	87.0 (24.1)
Congestion	Low traffic	85.9 (26.2)
	Medium traffic	77.7 (23.4)
	High traffic	79.6 (23.9)

Table 4. Pair analysis results for the variable Store size.

Store features	Pairs	Mean (SD)	*p*-value
Store size	Convenience	61.1 (7.0)	<0.001***
	Supermarket	81.2 (26.4)	
	Convenience	61.1 (7.0)	<0.001***
	Hypermarket	85.4 (22.7)	
	Supermarket	81.2 (26.4)	0.465
	Hypermarket	85.4 (22.7)	

Table 5. Pair analysis results for the variable Assortment.

Store features	Pairs	Mean (SD)	*p*-value
Assortment	Small	73.7 (18.8)	0.741
	Medium	70.7 (19.9)	
	Small	73.7 (18.8)	<0.001***
	Large	92.1 (26.0)	
	Medium	70.7 (19.9)	<0.001***
	Large	92.1 (26.0)	

Table 6. Pair analysis results for the variable Backroom.

Store features	Pairs	Mean (SD)	*p*-value
Backroom	No	73.8 (16.1)	0.592
	Yes	78.3 (26.4)	
	No	73.8 (16.1)	0.021*
	Yes and picking	87.0 (24.1)	
	Yes	78.3 (26.4)	0.059
	Yes and picking	87.0 (24.1)	

there are significant differences at the 0.01 level, not only with the medium assortment but also the small assortment. However, the difference between the means of medium assortment (M=70.7) and low assortment (M=73.7) is not significant (*p*-value=0.741). Therefore, it cannot be guaranteed which of the two options is better; although it can be pointed out that the most unfavorable of the three options is the large assortment.

For the Backroom variable, significant differences were only observed at the 0.05 level (*p*-value=0.021) between having or not having a backroom and, furthermore, undertaking picking in it. What seems to be clear is that the lowest values are obtained when picking is undertaken in the aisles of the store (M=73.8, without backroom; M=78.3, with backroom for replenishment).

Finally, the different alternatives of the congestion variable have not been studied by pair analysis, since in the first stage of the analysis this variable did not turn out to be significant.

6. Discussion

This statistical study presents valuable information for supermarket chains that meet online demand with a store-based model. Authors have identified which store characteristics speed up the online order picking time. As a result, it seems that the most agile way to carry out this process is in a convenience store, with a small or medium assortment of products and using the aisles of the store for the picking process. With respect to the influence of customer congestion, no significant interactions with picking time have been observed. In this section, these results are compared and discussed with the previous literature.

On the one hand, convenience stores seemed to be the least efficient stores for carrying out picking (Do and Omdahl, 2018). However, our results show that this type of store can lead to a reduction of up to 40% of the total order picking time, due to the reduction in the distance traveled by the pickers.

Furthermore, some of the doubts existing in the literature regarding the assortment size have been resolved, as this study shows that picking time can increase by up to 30% if the assortment is large. This result coincide with the study by Wollenburg et al. (2018), in which the authors have identified that a wide range of products involves a greater travel of the pickers and, consequently, an increase in the costs of the activity.

On the other hand, our statistical analysis shows that preparing in the aisles of the store is the most effective alternative. However, the literature highlighted that preparing in the backroom speeds up the preparation of online orders by avoiding contact with the offline clients (Mangiaracina et al., 2018). Even though this alternative can reduce the customer service due to possible stock-outs, the process is more agile because the products are collected in customer units, avoiding double handling.

Regarding the store congestion variable, it has been demonstrated that this is not a relevant variable. This result agrees with that presented by Salgado (2015), who sustains that store congestion is less of a problem when picking density is high and the pickers have to stop more often because the pickers spend more time collecting and less time travelling.

In summary, the results of our study show discrepancies with the extant literature in two aspects: on the one hand, in relation to the optimal size of the stores in which to prepare online orders; on the other hand, about whether or not to use the warehouse for this task. Furthermore, authors confirm that congestion is not a variable that has a significant effect on the picking time, despite the fact that the literature on this subject is very limited. Finally, the results are in line with previous studies defining low or medium product ranges as the best options to minimize picking time.

7. Conclusions

By undertaking this study, it has been possible to determine which features of traditional stores affect online order picking time. This information is of great value for supermarket chains that are opting for a store-based model and want to optimize picking times. In this sense, the study has important implications at a strategic level as it permits improvements in the decision to assign orders to preparation stores. To date, the only decision criterion used by stores have been the distance of the store from the customer and the population density, which may not be the best options.

The results obtained by applying a one-way ANOVA statistical analysis show that the most efficient stores for picking are those that have a smaller surface area (convenience stores) and a range that is not excessively large. Stores of this type reduce the time and route length when searching. The results also indicate, although with a lower level of dependency, that carrying out picking in the aisles of the store itself is a better option than in the backroom. Finally, the congestion variable linked to store traffic was not shown to be significant in the efficiency of the process. All these results have been contrasted and discussed with reference to the extant literature.

Thus, the proposed research question has been answered by defining the store features that will optimize the online order picking process. Similarly, this publication makes it possible to resolve future lines for research presented in the literature (Vazquez-Noguerol et al., 2021) by identifying the best store to minimize picking time and determine how traditional sales affect the online order picking process. There are some limitations in this study, which also provide an opportunity for future research. First, in order to define the store characteristics, the ranges of values used were those defined by the firm on which the case study was based. However, these ranges of values could vary if another firm were analyzed and this could lead to slightly different results. Second, regarding the online orders selected for measuring timings, these were only broken down in terms of the number of items. No distinction has been made as regards the type of products: dry, fresh, or frozen.

Future research could focus on determining how order characteristics can affect picking times. Thus, the time and resources needed for e-fulfilment could be estimated and anticipated. Once the approximate picking time for an order is known, demand predictions could be made in order to optimize order planning and increase control over picking costs. This would all be of great interest at a strategic level to analyze the growth in online demand and, if this reached a sizeable volume, to propose a change to the warehouse-based model. Another important line of research would be to study how technological developments affect the efficiency of picking processes. In this sense, comparative studies could be undertaken on the timing and efficiency of order picking in several scenarios using distinct levels of automation.

In conclusion, this study and the lines of future research proposed are intended to serve as a reference for the optimization of the processes in supermarket chains operating in the online channel. This information will be of great value for sustainable growth in an environment of digital transformation in which there is strong competition between companies and where consumer requirements are increasingly demanding.

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