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## Enhancing in-store picking for e-grocery: an empirical-based model

**Purpose** – This paper identifies, configures and analyses a solution aimed at increasing the efficiency of in-store picking for e-grocers and combining the traditional store-based option with a warehouse-based logic (creating a back area dedicated to the most required online items).

**Design/methodology/approach** – This study adopts a multi-method approach combining analytical modelling and interviews with practitioners. Interviews were performed with managers whose collaboration allowed the development and application of an empirically grounded model aimed at estimating the performance of the proposed picking solution in its different configurations. Various scenarios were modelled and different policies evaluated.

**Findings** – The proposed solution entails time benefits compared to traditional store-based picking for three main reasons: lower travel time (due to the absence of offline customers), lower retrieval time (tied to the more efficient product allocation in the back) and lower time to manage stock-outs (since there are no missing items in the back). Considering the batching policies, order picking is always outperformed by batch and zone picking, as they allow for the reduction of the average travelled distance per order. Conversely, zone picking is more efficient than batch picking when demand volumes are high.

**Originality/value** – From an academic perspective, this work proposes a picking solution that combines store-based and warehouse-based logics (traditionally seen as opposite or alternative choices). From a managerial perspective, it may support the definition of the picking process for traditional grocers that are offering - or aim to offer - e-commerce services to their customers.

**Keywords**: e-grocery, picking, logistics, e-retailing

## 1. Introduction

E-commerce is achieving significant volumes in different industries, and the food and grocery sector has recently shown the greatest growth rate in online sales (Eriksson et al., 2019). On one hand, online grocery initiatives are proliferating, and both start-ups and big dotcoms are entering the market (MacCarthy et al., 2019). On the other hand, in the realm of the COVID-19 emergency, many previously sceptical customers have experienced online purchases and are now inclined to change their grocery shopping behaviour in favour of e-commerce (Vazquez-Noguerol et al., 2021). In this scenario, traditional grocery retailers have started to offer e-commerce services to stay competitive (Li et al., 2021).

The two most common logistics solutions for fulfilling online grocery orders are warehouse-based and store-based models. In the warehouse-based model, online orders are prepared in purpose-built warehouses dedicated to the e-commerce channel (Colla and Lapoule, 2012). Instead, in the store-based option, online orders are fulfilled in existing stores where offline customers also do their shopping (Li and Yousept, 2004).

In the warehouse-based model, facilities are designed to optimise picking activities, avoiding interferences from traditional customers during the picking journey (Hübner et al., 2016). According to Colla and Lapoule (2012), the preparation of an order made of 50-60 items in a dedicated warehouse might require at least 40% less time than it would in a store. In purpose-built facilities, it is also possible to raise the level of automation (Hübner et al., 2016), and real-time data about product availability are easily collected, thus reducing stock-outs (Colla and Lapoule, 2012). Consistent with these considerations, the warehouse-based model implies a more efficient and effective picking process.

Conversely, the store-based model is characterised by certain problems that become much more relevant as online demand increases. There is a high risk of incurring stock-outs: an item, available when the customer issues the order online, may be out of stock when the picker has to retrieve it (Fernie et al., 2010). Layouts in traditional stores are designed to display products and not to achieve high operational efficiency; accordingly, their marketing-oriented placement may require longer distances to be travelled during picking (Di Francesco et al., 2021). The presence of people within the aisles also hinders pickers' activities, and this implies a high picking time (Hübner et al., 2016). In addition, employees bother customers walking in stores, creating congestion and negatively affecting their shopping experience (Scott and Scott, 2008). Based on the above, the store-based model has significant limits in terms of scalability (Hübner et al., 2016) and it is less profitable than the warehouse-based solution (Hackney et al., 2006).

Nevertheless, including a new facility in the network requires significant investment, which represents a barrier for many traditional grocery retailers (Li and Yousept, 2004). As a result, they implement this solution only when their online volumes are significant enough and prefer, in the initial stages of the business, to manage operations in physical stores (MacCarthy et al., 2019). Based on the above, numerous grocery retailers are striving to find an efficient and effective way to keep up with the rapid evolution of e-commerce by leveraging their stores without investing a huge amount of resources (Vazquez-Noguerol et al., 2021).

The literature on warehouse-based picking is very rich and allows us to derive interesting insights. Nonetheless, the in-store problem is much different, and the proposed solutions should be carefully adjusted to fit stores. Considering instead the limited number of works addressing the buy-online-pickup-in-store (BOPIS) model for e-grocers, most of them analyse or optimise a pre-defined traditional picking process without proposing any alternative or novel solutions. Few scholars have proposed solutions to improve the in-store picking process. Vazquez-Noguerol et al. (2021) recommended moving picking activities to the closing hours of the store. This shows how the absence of offline customers significantly decreases the picking time per order, improving overall picking performance. Gorczynski and Kooijman (2015) suggest dedicating an ad hoc area to bulky and heavy items to save the picker time and energy, and whose activities are also not hindered by people. This contribution shows how—beside the presence of offline customers—two of the main obstacles to picking efficiency are the not-optimised product location and the higher stock-out risk, which can be avoided in an ad-hoc area. Based on these proposed solutions and in line with the FPA warehouse-based field of research (suggesting the creation of devoted and optimised picking areas), a question may be raised about the convenience of dedicating an ad-hoc area to the picking of a higher number of products (the most required online items). Accordingly, it could be interesting to define a new intermediate model for e-grocery that combines the logistics behind warehouse-based and store-based solutions, typically presented as two opposite choices.

The present work intends to propose and analyse a solution to increase the efficiency of e-grocery in-store picking based on the creation of an area dedicated to the most required online canned and non-food items in the back of the store. In other words, it addresses the following research question: how, and to what extent, can in-store picking for e-grocery be improved, creating a back area dedicated to the most required online canned and non-food items?

The remainder of this paper is organised as follows: Section 2 summarises the results of the literature review; Section 3 presents the research design; Section 4 illustrates the model application; Section 5 discusses the results; and Section 6 summarises the stemming conclusions.

## 2. Literature review

### 2.1 Warehouse-based solutions to increase picking efficiency

Picking has always captured the attention of scholars who have been striving to find ways to increase the efficiency of this process. Seminal literature in the field focuses on warehouses, where traditional players mainly manage customer orders. In this context, the work by De Koster et al. (2007) presented a comprehensive review of extant knowledge, illustrating the main solutions to improve picking performances. Three main areas can be identified.

- *Storage assignment*: it designs how items are organised within the warehouses and thus is strictly related to the facility layout and organisation. Two main levels of decision pertain to this domain:
    - *Forward-reserve allocation*: the potential division between the areas dedicated to the bulk stock (reserve area) and the picking stock (forward area or forward picking area (FPA)) (Taljanovic and Salihbegovic, 2010). Setting up an FPA (and thus reducing the dimension of the picking area) may strongly increase picking efficiency, as the pickers travel shorter distances (De Koster et al., 2007). This "warehouse within a warehouse" needs to be correctly sized, including the right items, considering both their demand and their volume (Walter et al., 2013).
    - *Storage policy*: the assignment of items to the storage locations. One "extreme" solution is "random storage," in which items are randomly located in the storage area (Caron et al., 1998). Other solutions instead allocate items to increase picking efficiency. Among them, an efficient option is "class-based storage": items are grouped into (usually two to four) classes, mainly based on their access index, that is., the picking frequency or dedicated space ratio (Rouwenhorst et al., 2000). These classes are assigned dedicated areas, with the fastest-moving items typically stored close to the input or output point (Manzini et al., 2007).
- *Routing policy*: it refers to the logic according to which the picker moves within the aisles. The two opposite solutions are the traversal (the picker travels the entire length of the aisle once entered (Petersen and Aese, 2004)) and the return policy (the picker comes back on the same side the aisle was entered, once the farthest item has been picked (Yu and De Koster, 2009)). The most suitable option depends on various factors, such as the length of the racks, the expected number of picks per aisle and the storage policy (Caron et al., 1998). Some intermediate solutions also exist that may reduce the travelled distance but are typically more complex to both design and implement (e.g., S-shape, largest gap, mid-point) (De Koster et al., 2007).

- *Batching policy*: this defines how different orders are assigned to the picking tours. The three most common policies are as follows:
    - Order picking: one picking tour is assigned one order, and the picker picks all the pieces belonging to one order (Petersen and Aese, 2004).
    - Batch picking: one picking tour is assigned more than one order, and the picker picks all the pieces belonging to all the orders included in the batch (Hong et al., 2012).
    - Zone picking: picking tours are performed within specified zones in the storage area. The picker picks all the pieces of different parts of the orders belonging to the assigned zone. In the end, the different parts of the order need to be consolidated (De Koster et al., 2007).

    The batch and zone picking options have different advantages compared with order picking. Among them, the average travelled distance per order is lower due to an increase in picking density (Caron et al., 1998). Moreover, order batching generates "overlapping lines" (when the same item is requested in different orders belonging to the same tour), implying a further time reduction: the picker who has already reached the proper location can pick the pieces for more than one order (Yu and De Koster, 2009).

The "generic" picking process is critical, but it becomes even more challenging when considering the additional complexities entailed by e-commerce and grocery shopping, respectively. Concerning e-commerce, orders are typically very small, the order frequency is variable and unpredictable, and the handled unit is neither a pallet load nor a carton, but a single piece (Eriksson et al., 2019). As a result, different solutions need to be implemented to make traditional warehouses more efficient in managing online orders (e.g., introducing automated solutions (Kembro and Norrman, 2020)). Concerning grocery, products may be fresh, frozen or fragile, thus implying stringent storage and handling requirements (Kämäräinen and Punakivi, 2002). Therefore, the e-grocery picking problem (including both e-commerce and grocery shopping) is considerably different from the traditional problem addressed by many scholars so far (e.g., De Koster et al. (2007)).

### 2.2 BOPIS model

While seminal literature on picking is focused on warehouses, the advent of e-commerce has generated a new fulfilment model in which online orders are prepared in stores (BOPIS) (Di Francesco et al., 2021). Not only customers but also retailers could benefit from this omni-channel solution, which often entails better performance (Jones et al., 2021).

The BOPIS option generates different criticalities. First, stores are typically organised according to a marketing-based expository logic, aimed at displaying products to customers and not at increasing picking efficiency (Hübner et al., 2016). Second, there are offline customers in the aisles of the stores doing their shopping. On one hand, they hinder picking activities; on the other hand, they are bothered by the pickers (Colla and Lapoule, 2012). Third, control over inventory levels was much lower when compared with those in dedicated warehouses. Stocks are often shared with offline customers whose purchases are not known in advance (Xu and Cao, 2019). Fourth, the efficiency of fulfilment activities is significantly variable, as it depends on many factors that are not stable over a day or a week (e.g., the number of offline customers walking within the aisles) (Zhang et al., 2019). As a result, the BOPIS model may be very beneficial for customers who aim to order online and then collect their parcels, and the proximity to customers may sometimes generate advantages in terms of delivery costs for retailers (Lin et al., 2021), it is unquestionably more expensive when considering picking activities (Ishfaq and Raja, 2018), especially for the grocery sector (Kämäräinen et al., 2001).

While different contributions may be found in identifying the criticalities of the BOPIS model, fewer scholars have investigated solutions to address them, especially when considering picking. MacCarthy et al. (2019) estimated the number of picking waves a retailer should launch in an ordering cycle and their timing. Di Francesco et al. (2021) developed a model to define the amount of time to allow for batching of online orders prior to starting the in-store picking process and the optimal number of pickers and packers for a sports equipment shop in New York. Both of these works did not consider the specificities of the grocery sector, neither in terms of products (fragility or temperature requirements (Fernie et al., 2010)), nor the peculiar layout (wide surface, different areas for product categories, such as ambient, fresh, frozen or deli (Hübner et al., 2016)). Moreover, neither proposed solutions to improve the picking process, but they both aimed to find a way to optimally manage a fixed and predefined picking configuration (batch picking performed in the store).

Considering the main contributions proposing potential solutions to BOPIS, the novel work by Vazquez-Noguerol et al. (2021) focused on e-grocery. Based on the test of some "practices" that could be implemented to enhance in-store picking, they suggested moving picking activities when the store is closed to the public. Despite the interesting suggestions, this work examined the store as it is, with no changes in its layout or in its logistics (which could lead to more sustainable advantages in the case of higher online demand). Gorczynski and Kooijman (2015) suggested dedicating an ad hoc area to bulky and heavy items. This solution saves the time and energy of the picker, whose activities are not hindered by people walking there; moreover, the location of products may be optimised based on picking efficiency. Nonetheless, heavy and bulky items typically constitute only a small portion of grocery orders, and the associated advantage could be significantly increased if the proposed solution is applied to a higher number of products.

## 3. Research design

This work adopts an empirical-based multi-method approach, combining interviews with practitioners and the development and application of an analytical model. This method has its foundation in two main methodological papers: Reiner (2005) and Mangan et al. (2004).

Reiner (2005) recommends using "quantitative model-driven empirical research", developing and applying analytical models to real-life data collected through interviews. Calculating or estimating the results instead of observing them is preferable if they are very difficult to collect (and this is the case with the proposed innovative picking solution). Mangan et al. (2004) suggest using "methodological triangulation", which consists of a multi-method process based on three main phases. Step i (qualitative): to gain in-depth insights into the market of interest through desk-based market analyses or interviews. Step ii (quantitative): to answer the research questions, based on analytical modelling. Step iii (qualitative): to propose a validation and refinement of the obtained results, thanks to the Delphi method or interviews.

The methodology adopted in this paper is a combination of these two approaches; the main steps, the adopted methods and their outcomes are detailed in Figure 1.

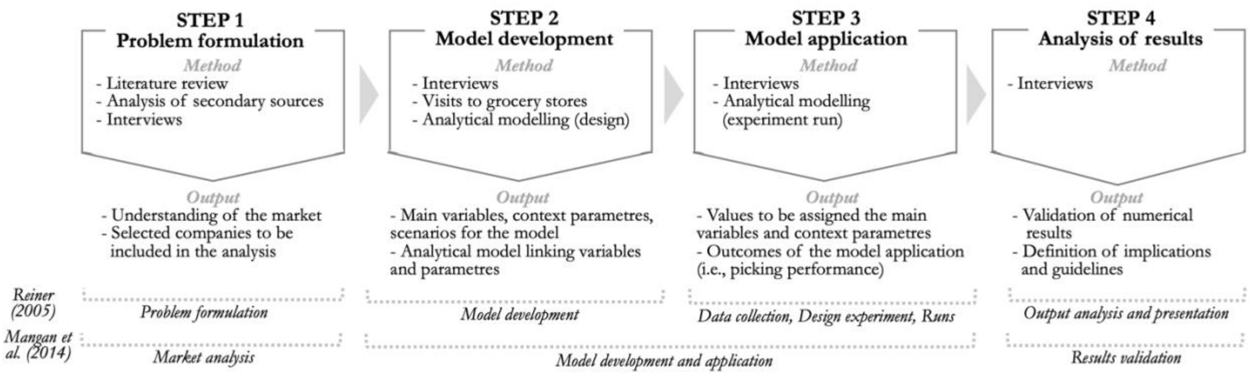


*Figure 1*

In Step 1, an analysis of the e-grocery context was conducted to gain a picture of the market and select the companies to be included in the analysis. In Step 2, a model to estimate the performance of the picking solutions was developed. The different variables, parameters and choices, in terms of layout and policies, were identified and modelled, and the formulas to compute the associated picking performances were defined. In Step 3, the model was applied to a representative case. An exemplary e-grocery case was defined based on interviews, which allowed the assignment of realistic numerical values to the defined variables or parameters. In Step 4, the numerical outcomes of the analyses were validated and interpreted with practitioners, and conclusions were drawn.

The two main methods used (interviews and analytical modelling) are illustrated below.

### 3.1 Interviews

Both the analytical model and its application to a realistic case rely on interviews with five practitioners from five Italian grocery companies. The focus on Italy has both managerial and academic reasons. From a managerial viewpoint, the Italian e-grocery market is one of the least mature markets in Europe, and the majority of operators still rely mainly on the store-based model (B2C Observatory, 2020). At the same time, it is very dynamic and open to testing new solutions. From an academic viewpoint, the choice to focus on one country is aligned with previous literature addressing picking for e-grocery: Eriksson et al. (2019) addressed Sweden, while Vazquez-Noguerol et al., (2021) focused on Spain. The alignment with extant literature is also valid with relation to the number of considered companies: Eriksson et al. analysed three grocery retailers (2019), while Vazquez-Noguerol et al., (2021) focused on only one.

Table 1 summarises the main features of the participants (both the managers and their firms will stay anonymous for reasons of confidentiality).

| | Phase | Objective | Methodology | Mangan et al. (2004) | Reiner (2005) |
|---|---|---|---|---|---|
| 1 | Problem formulation | Set the boundaries and goals of the research, analyse the context | Interviews round (i)<br>Literature review | Market analysis | Problem formulation |
| 2 | Model development | Develop the model (defining the layout and policies), identify the most significant variables and parameters to be varied | Interviews round (ii)<br>Analytical modelling | Model development and application | Model development |
| 3 | Model application | Collect the data to food the model, run the analyses | Interviews round (iii) | | Data collection, Design experiment, Runs |
| 4 | Analysis of results | Analyse and interpret the obtained results | Interviews round (iv) | Validation and refinement of results | Analysis of output, Presentation of results |

*Table 1: Multi-method approach*

The interviews had different goals in the four steps of the research and therefore followed specific approaches and protocols.

In Step 1, exploratory group interviews were performed to gain a deeper understanding of the e-grocery market, of the main logistics challenges faced by traditional retailers fulfilling online orders in their stores and of the potential solutions implemented to address them (Mangan et al., 2004).

In Step 2, interviews were aimed at identifying the main variables, parameters and alternatives to be included in the model, and to define the links among them. Practitioners were interviewed in a group using a semi-structured approach. Their discussion was guided by one moderator, while two researchers took notes and recorded the meetings. Group interviews are more effective in phases where the significance of the results depends on the mutual collaboration of the participants, who share their experiences and knowledge on the topic addressed (Urciuoli and Hintsa, 2017).

In Step 3, the goal of the interviews was to collect data to feed the model. In line with previous similar works (Seghezzi and Mangiaracina, 2020), participants were first interviewed individually to gather data about their specific context, avoiding influences from the other e-grocers. A group interview was then performed to design a representative "exemplary" case for the model application. Defining a base exemplary scenario in collaboration with practitioners is an increasingly diffused practice in logistics research, since it helps derive results that are both reliable and interesting for a large number of managers (Pinto et al., 2019). These interviews were structured and supported by checklists reporting all the main variables and parameters for which numerical values were needed (Nutting et al., 2002).

In Step 4, the aim of the interviews was to gain a comprehensive interpretation of the outcomes and accordingly derive managerial guidelines. In addition, in this case, it was a group interview, as the discussion provided valuable contributions, benefitting from the mutual collaboration of the participants (Reiner, 2005).

### 3.2 Analytical model

Figure 2 displays the main logical elements behind the model.

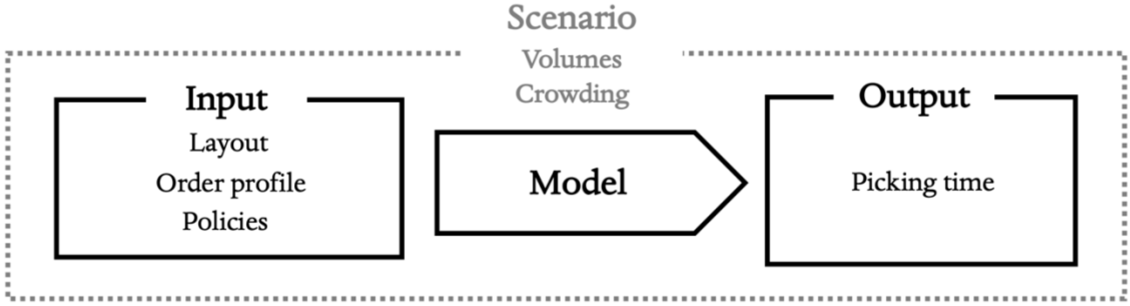


*Figure 2*

The "***scenario***" refers to the context in which the model is applied. From the interviews with the practitioners, it was recommended to include two dimensions.

- The online volumes, representing the e-commerce demand to be fulfilled; more specifically, the managers suggested distinguishing between two scenarios—high volumes and low volumes—based on their impact on picking performances. Low demand values do not allow efficient batch orders, whereas high volumes grant a sufficient number of orders to be grouped in the same picking tour.
- The crowding in the store, that is, the density of offline customers present at the point of sale. In this case, the interviews suggested considering three scenarios: the best case (low crowding level), the worst case (many people in the store) and an average case. These configurations have a different impact on waiting times in picking activities.

The "***input***" variables describe the picking problem to be modelled and analysed. These include:
- The layout of the store, that is, the layout and organisation of the areas inside the store.
- The order profile, that is, the average number of items and pieces per order for the different product categories.
- The adopted policies, which are the storage, routing and batching policies.

The "***model***" is the core element of the architecture. It aims to compute the picking time for both the store-only and the store + back picking solutions. Formulas estimating the picking time in the different configurations—based on the combination of the literature analysis (mainly resorting to the seminal works by Caron et al. (1998) and Yu and De Koster (2009)) and interviews with practitioners—are displayed in Appendix A. The unit of analysis is the single picking tour, and the different policies to be compared are thus individually analysed. The picking time per order is the sum of four main components:
- Set-up time: time needed by the picker to prepare the tour (e.g. read the picking list, prepare the cart) (Henn, 2012).
- Retrieval time: time spent to identify, retrieve the products from the shelves, check and put them into the cart. This depends on both the number of items and the number of pieces to be picked (Hong et al., 2012).
- Travel time: time spent by the picker travelling along the aisles, reaching all the different items and going back to the storage of online orders. It is the sum (for all the different zones) of the time needed to reach the different aisles and the time needed to travel within the aisles themselves (Parikh and Meller, 2010).

- Stock-out management time: time needed to manage missing items. It depends on both the average rate of stock-out and the duration of the activities performed to manage them (Fernie et al., 2010).

The "***output***" refers to the picking performance of the considered solution. In line with former works pursuing the same goal in other contexts (e.g., Yu and De Koster (2009) for warehousing), the estimated measure is the average time needed to pick an order.

## 4. Model application

This section describes the representative case considered for the model application, detailing the scenarios (paragraph 4.1) and the numerical values for the input variables (paragraph 4.2).

Four different picking solutions were explored, based on the possibility of implementing a dedicated area for online orders in the back: store picking only and store + back, with the percentage of picks in the back being 60%, 70% and 80%, respectively. These percentages designate the share of picks (on the total number of items to be retrieved) managed in the back. They only refer to items stored at ambient temperature (details about this choice are presented in the following section).

### 4.1 Scenario

#### 4.1.1 Scenario: Volumes

The two volume scenarios (low and high) were integrated into the model through the number of orders that may be aggregated in the same picking tour. The higher the volume, the higher the number of orders that can be batched. Accordingly, two different picking configurations were defined for the high and low saturation cases (details follow in Section 4.2.3 in correspondence with all the considered picking policies).

#### 4.1.2 Scenario: Crowding

The crowding in the store may imply a "waiting time", which is the additional time spent in a picking tour due to the congestion (which depends on the density of people in the store and its dimension). The effect of the crowding level was included in the model in both:

- The retrieval time: if the crowding increases, the retrieval time per line (RTL), that is, the fixed time spent in front of the picking location (positioning, checking, etc.), increases. The average values of RTL are 8 s/line for average crowding, 6s/line and 10s/line for low and high crowding, respectively.
- The travel time: if the crowding increases, the speed of the picker Sp is reduced due to congestion on the picker's way. The average values of Sp are 1.3 m/s for average crowding, 1.5m/s and 1m/s for low and high crowding, respectively.

### 4.2 Input

#### 4.2.1 Input: Layout

The layout is composed of the sales floor of the store and the back area (in the store + back solution). For the sales floor, the layout was modelled based on a representative grocery point of sale defined during the discussion with the grocers. The back area needed to be designed instead. To avoid significant investments in setting up a wide area, only some items from the canned and non-food category are managed in the back. This makes it much easier and faster to arrange a back area. As a matter of fact, this category of products does not have specific storage and management needs and accordingly does not require additional equipment, such as fridges or freezers. Hence, the only condition is the presence of space to place some shelves. This decision is aligned with the objective of this research, which addresses grocers who need to approach online commerce without huge investments.

To define the items to be stored in the dedicated area, class-based criteria were applied. canned and non-food items were clustered into A and B classes, based on their access index for online sales. Forward reserve allocation and the class-based storage policy (De Koster et al., 2007) were applied, assuming the same space dedicated to each item belonging to the same category. A-class items (representing the small portion of products responsible for the majority of online sales) were allocated to the back area. Therefore, the picking process for e-commerce orders is two-phased: A-class items for the canned and non-food category are picked in the back area, while the remaining items are picked in the store.

The access index (the Picking frequency/Dedicated space ratio (Rouwenhorst et al., 2000)) is one of the measures academic literature proposes to decide the location of the items in a storage or picking area. Implementing class-based storage relying on this ratio allows the “fastest moving” items to be distinguished with respect to the space dedicated to them (De Koster et al., 2007). While the concept is consolidated in warehouse-focused works (Yu and De Koster, 2009), its implementation in stores is novel. When this approach was proposed to the managers, all five agreed. The two additional choices that were discussed with them concerned the number of classes of items and what class(es) should be stored in the back. Most scholars recommend using two to four classes (Petersen and Aase, 2004), ideally two or three (Yu and De Koster, 2009), dedicating a zone to each of them. The approach used to identify the classes works as follows: the AI for each item is computed and the average among them is derived; the items whose AI is higher than the average AI compose the A class. (De Koster et al., 2007). As a result, A-class items are the “fastest moving” ones. All the managers agreed to define two classes and store only Class A items in the back area. The expected marginal benefit (in terms of picking-time reduction) of storing class B items in the back is lower than the costs of the space required (and existing stores often do not offer much room to set up a back area).

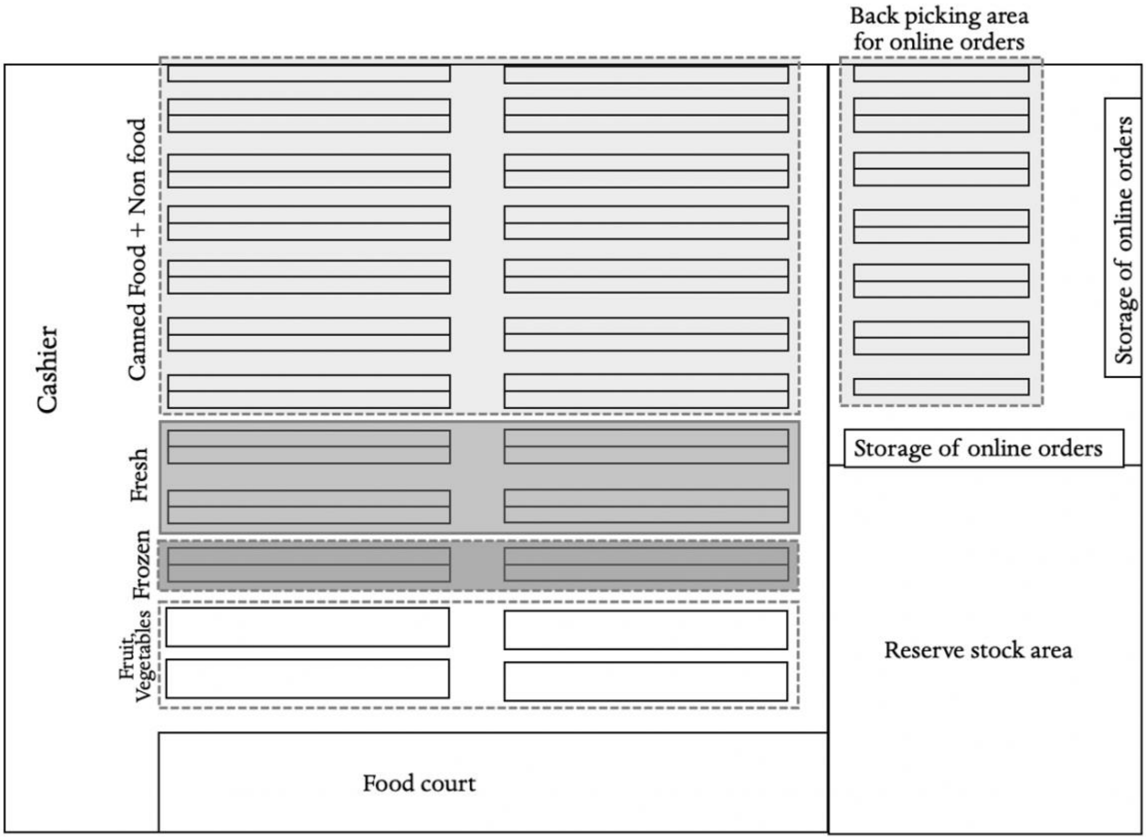


*Figure 3*

The general configuration of the considered layout is shown in Figure 3 and the related measures in Appendix B. The store includes an area for each of the main product categories: canned and non-food, fresh products (stored in fridges), frozen products (stored in freezers), fruit and vegetables (typically variable weight) and the food court (where store operators provide freshly prepared meals, such as deli or meat). Concerning the back, in addition to the traditional area dedicated to reserve stock (Fernie et al., 2010), there is a space dedicated to the storage of already picked online orders and shelves to store the A-class items in the event of the innovative store + back solution.

### 4.2.2 Input: Order profile

All four grocers who were already offering e-commerce highlighted how the average online basket was larger than the average offline basket, while the composition in terms of the different categories was aligned (Colla and Lapoule, 2012). The typical profile of an online order is as follows:

- Canned and non-food: 20 lines, 1.3 pieces/line;
- Fresh: 8 lines, 1.2 pieces/line;
- Frozen: 4 lines, 1.1 pieces/line;

- Water: 2 lines, 1 piece/line;
- Fruit and vegetables: 3 lines, 3.2 pieces/line;
- Food court: 2 lines, 1 piece/line.

This profile was defined during the interviews in Step 3, and it was also in line with the few contributions found in the literature on the topic (e.g., Eriksson et al., 2019) and related secondary sources (B2C eCommerce observatory, 2020).

The canned and non-food category encompasses all the products (excluding water) stored at room temperature, including pasta, snacks, home and healthcare products. Fresh products include milk, yogurt, cheese and all the other products stored at a temperature between 0°C and 10°C, while frozen items need what is referred to as "negative cold" (lower than 0°C). In the food court all the food products that are not pre-packed are found, which require the work of an operator for the preparation (e.g., fresh ham or prepared meals).

#### 4.2.3 Input: Policies

Besides the storage assignment choices, the literature designates two main policies to be defined: the routing (how the picker moves within the aisles (Yu and De Koster, 2009)), and batching policies (whether or how different orders are managed in the same tour (Hong et al., 2012)). Adapting the findings presented in the literature to e-grocery implied some changes or refinements (which are illustrated in the following paragraphs) and were defined based on interviews with managers.

*Routing.* The traversal routing policy was adopted in both the store and the back area: pickers must completely traverse the entire aisle once it is entered (Petersen and Aese, 2004). It is the most suitable option for the store because of the expository logic of the shelves, which are designed to force customers (and thus also the picker) to visit all aisles (Henn et al., 2012). The same solution is implemented in the back area, since traversal routing is recommended if the number of picks per tour is high (Yu and De Koster, 2009), as is supposed to happen in an area dedicated to products with high AI (Rouwenhorst et al., 2000).

*Stockout management.* Managers also discussed the stock-out management policy, that is, how pickers manage the absence of ordered items. The interviews originally allowed us to identify three potential options. The first is the absence of stock-out management: if the required items are not available, no alternatives are proposed and the order is delivered incompletely (Pan et al., 2017). Second, the phone call: when there are missing articles, the picker calls (or texts) the customer proposing alternatives that can be accepted or not. This option was immediately discarded by practitioners who experienced it in the past: it is very time-consuming, and it implies a tremendous reduction in picking efficiency (Milioti et al., 2020). The third is the picker choice. During the picking tour, when there are missing items, the operator picks a substitute product, which is then proposed to the customer during the delivery phase. Even if time-consuming, different marketing-oriented studies show the benefits of proposing alternatives in customer satisfaction (Fernie et al., 2010). Moreover, managers who had already implemented e-commerce clearly stated that having the possibility to avoid a stock-out is fundamental for many online customers. As a result, the modelled stock-out management scenario is the third scenario (picker choice).

*Batching*. As illustrated in the literature review section, there are typically three batching policies, (defining how to allocate different orders to the picking tours (De Koster et al., 2007; Petersen and Aase, 2004)): order picking (one order per picking tour), batch picking (different orders per picking tour) and zone picking (picking tours performed within specified zones). The structured interviews in Step 3 allowed for the definition of such policies in the considered exemplary case, with reference to both the number of orders and the percentage of lines overlapping. The values (shown in Table 2 for the store and Table 3 for the store + back option) were defined by the managers based on their experience and on the analysis of the orders fulfilled by their companies. An ad hoc picking tour was assigned to fruit and vegetables and to the food court (as also recommended by Vazquez-Noguerol et al., 2021). As a result, the picking time associated with these two categories does not change with the chosen batching policy (which thus needs to be detailed only for the other categories).

<table>
<tr><th rowspan="9">STORE</th><th colspan="2">Policy</th><th>Orders per tour</th><th>Lines overlapping</th></tr>
<tr><td>Order</td><td>(All)</td><td>1</td><td>0</td></tr>
<tr><td>Batch</td><td>(All)</td><td>2</td><td>10%</td></tr>
<tr><td rowspan="3">Zone (high volumes)</td><td>Canned + Non food</td><td>5</td><td>5%</td></tr>
<tr><td>Fresh</td><td>10</td><td>2%</td></tr>
<tr><td>Frozen</td><td>12</td><td>2%</td></tr>
<tr><td rowspan="3">Zone (low volumes)</td><td>Canned + Non food</td><td>2</td><td>3%</td></tr>
<tr><td>Fresh</td><td>4</td><td>1%</td></tr>
<tr><td>Frozen</td><td>4</td><td>1%</td></tr>
</table>

*Table 2: Policies – Store option*

| | | Policy | | Orders per tour | Lines overlapping |
|---|---|---|---|---|---|
| **STORE + BACK** | **BACK** | **Batch** | Canned + Non food | 6 | 5% |
| | **STORE** | **Batch** | (All) | 3 | 10% |
| | | **Zone** | Canned + Non food | 12 | 5% |
| | | | Fresh | 10 | 2% |
| | | | Frozen | 12 | 2% |

*Table 3: Policies – Store+Back option*

As anticipated in section 4.1.1, scenarios do not refer to specific numbers in terms of orders, but to the ability to saturate the picking tours (which depends on various elements, e.g., the demand, the space available to store already picked orders, the service level and the dimension of the store). Therefore, the goal in defining the high or low volume scenarios is not to analyse specific demand data. Conversely, it is to shape two saturation scenarios for the model application and to evaluate the picking performances accordingly, considering the number of orders per tour (and not the specific overall number of daily orders). In other words, the unit of analysis of the work—and of the model—is a picking tour and not the overall volume managed on a daily basis. In the picking policies, the two volume scenarios resulted in a different number of orders to be picked on a tour for the zone picking policy (details are presented in the following paragraphs).

In the store-based model (Table 2), three alternative batching policies were considered. First, order picking, with one order per tour. The second is batch picking. In this case, two orders are considered to be picked per tour, generating 10% lines overlapping. In line with the literature on this topic (e.g., De Koster et al., 2007), the overlapping refers to orders belonging to the same picking tour; as a result, pickers concurrently retrieve the pieces for the different orders, applying a sort-while-pick logic (Petersen and Aase, 2004). The third is zone picking. In this case, three zones are managed: canned and non-food, fresh and frozen. The orders are managed in three different picking tours, one for each zone. The average number of orders that can be managed in a tour consequently increases compared with the batch picking case (2). As a result, should the demand be high enough to allow for the saturation of the tour, there are 5, 10 and 12 orders per picking journey for the canned and non-food, fresh and frozen categories, respectively. A higher number of orders is assigned to the zones for which the average number of pieces per order is lower (since they occupy less space on the picking cart).

Conversely, considering the low-volume scenario, the batching of orders cannot often be managed efficiently; as a result, the number of orders to be picked in a tour is lower, and the previous configurations (saturating the picking cart) cannot be reached. In the model, lower demand values result in a lower number of orders that can be managed in the zone picking policy: it is not possible to aggregate 12 (or 5) orders in a picking tour in the frozen zone (or in the fresh one), and a new zone picking configuration was defined with the managers for the low saturation case, with up to 4 orders per tour.

Clarification is needed to explain the way these numbers were derived during interactions with the managers. The maximum number of orders that can be picked in a tour is constrained by the maximum number of boxes that can be set up in the picking cart. When picking e-grocery orders, operators typically rely on carts containing 12 boxes (3 layers * 4 boxes/layer) (Mangiaracina et al., 2018). Each box is filled with items belonging to one single zone and to one single customer order; one zone, as picked ambient, fresh and frozen items are subsequently stored separately on shelves, in fridges and in freezers, respectively (Eriksson et al., 2019); one single customer order, since a sort-while-pick policy is adopted (Vazquez-Noguerol et al., 2021). Hence, based on the number of boxes, the number of customer orders and their profile (expected number of pieces for each product category), it was possible to estimate the average number of orders to be assigned to a tour.

In the new store + back solution, two different combinations of policies were contemplated, which arose from the following: for the share of products picked in the store, both the batch and the zone picking were evaluated; in the back, only batch picking was performed. As a result, the two possible combined configurations are batch in both the store and the back or batch in the back and zone in the store.

The reason why zone picking was not contemplated for the back area is twofold: on the one hand, only items from the canned and non-food category are managed in the back, and they belong to just one zone. On the other hand, the dimension of the back area (and the number of differently managed items) is low, and thus the conditions for which zone picking is recommended are not met. In addition, order picking is not considered in the store; a great number of the items are picked in the back, thus resulting in a lower portion of items to be retrieved in the store. Relying on order picking in the store would imply inefficient picking tours, with the picker travelling along the aisles for a very low number of items to be retrieved.

## 5. Results and discussion

### 5.1 Base case

The table in Figure 4 illustrates the results of the model application to the presented case in terms of the average picking time (minutes) per order in the different scenarios and configurations. The rows indicate the combinations of the volumes (low, high) and crowding (low, average, high) scenarios. The four major columns refer to the four analysed solutions (the store-only case and three potential alternatives for the store + back option, with 60%, 70% and 80% of the online ordered ambient items picked in the back area, respectively). The best case for each combination of picking configuration and volumes or crowding scenario and for each analysed solution is highlighted in bold and underlined. Considering, for instance, the first row and column, that is, low volumes and low crowding for the store-only case, the best performance is associated with batch picking, with 21.5 minutes per order vs 26.7 for order picking and 23.3 for zone picking.

***Results of the model application***

*Picking time (min/order)*

| *Volumes* | *Crowding* | Store-only | | | Store+Back | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | 60% picks in the back | | 70% picks in the back | | 80% picks in the back | |
| | | *Order* | *Batch* | *Zone* | *Batch* | *Zone* | *Batch* | *Zone* | *Batch* | *Zone* |
| *Low* | *Low* | 26.7 | **21.5** | 23.3 | **19.4** | 19.9 | **19.2** | 19.7 | **18.8** | 19.5 |
| *High* | *Low* | 26.7 | 21.5 | **19.6** | 19.4 | **18.5** | 19.2 | **18.4** | 18.8 | **18.3** |
| *Low* | *Average* | 29.5 | **23.5** | 25.4 | **20.7** | 21.1 | **20.4** | 20.9 | **19.9** | 20.6 |
| *High* | *Average* | 29.5 | 23.5 | **21.3** | 20.7 | **19.7** | 20.4 | **19.5** | 19.9 | **19.3** |
| *Low* | *High* | 35.7 | **28.1** | 30.1 | **23.7** | 24 | **23.1** | 23.6 | **22.4** | 23 |
| *High* | *High* | 35.7 | 28.1 | **25** | 23.7 | **22.1** | 23.1 | **21.8** | 22.4 | **21.5** |

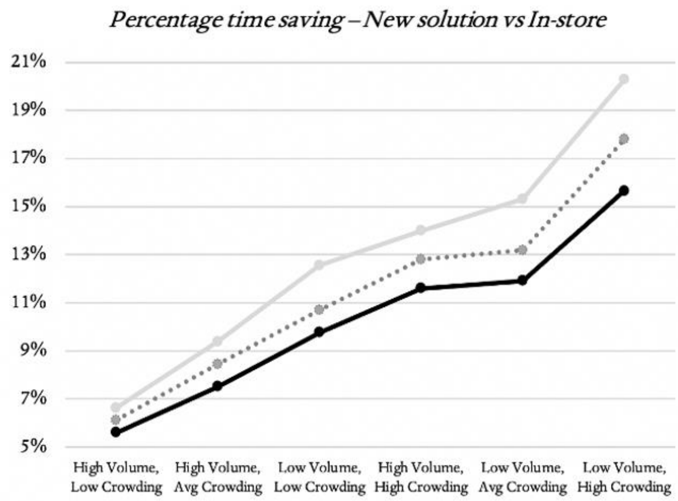


*Figure 4*

Besides providing a quantitative evaluation of the average time needed to pick an order (which is a piece of information all the managers were interested in), this analysis derived some key considerations concerning the store + back option and its comparison with the traditional store-based solution.

First, the picking solution with the dedicated back area is always more efficient than traditional store-based picking. The graph at the bottom of Figure 4 represents the percentage time saving (new solution vs traditional in-store solution) when considering the best case for both options. They are batch picking for low volumes and zone picking for high volumes (corresponding to the results reported in bold). The value of this benefit varies between 6% and 16% for the store + back (60%) option. This range becomes 6%–18% for the store + back (70%) and 7%–20% for the store + back (80%). The lowest savings (for all the picking configurations) are associated with high volumes-low crowding, while the highest advantages are associated with low volumes-high crowding. The main benefits in terms of time reduction may be attributed to three main reasons:

- Lower travel time: the pickers move faster in the back area since there are no offline customers creating congestion in the aisles.
- Lower retrieval time: on one hand, in the back area there are no customers hindering the retrieval of products; on the other hand, products in the back are stored on the shelves according to a picking-optimisation logic, and not to an expository one.
- Lower time to manage stock-outs: in the back area, there are not offline customers picking the last piece of an item for which an online order is already placed.

Second, the new intermediate solution is more efficient than the store-based solution, independent of how crowded the store is when picking activities are performed (also in the low crowding case). However, in line with expectations, as crowding in the store increases, the benefits gained by picking products from the back become more significant. In fact, the presence of more people in the store boosts the negative effects they have on picking activities.

Third, implementing the proposed solution is convenient for both volume scenarios. Nonetheless, as expected, higher benefits are associated with higher volumes. On one hand, higher volumes allow for more efficient saturation of the picking tours. On the other hand, the advantage in terms of a lower picking time per item is multiplied by a higher number of items.

Fourth, the benefit entailed by the store + back solution increases when the percentage (and thus the number) of items stored in the back increases. Nonetheless, the additional time savings are not significant; the great advantage of the solution is already achieved with a lower percentage of items stored in the back. The marginal benefit stemming from storing a higher number of items in the back is limited (in line with the ABC curve). As a consequence, managers should carefully evaluate the extent to which it can be convenient to increase the number of products stored in the dedicated back area.

Fifth, these results allow for the evaluation and drawing of conclusions about the convenience of the different batching policies.

- Order picking is always outperformed by both batch and zone picking policies, as they allow for the reduction of the average travelled distance per order (due to a higher picking density). As a result, as soon as the volumes allow it, e-grocers should aggregate different orders in the same picking tour, independently of the demand and the crowding level of the store.
- Zone picking is more efficient than batch picking when demand volumes are high for both the store-only and store + back options. Moreover, this is true for any crowding level. In fact, high volumes saturate the picking tours in the different zones, including those associated with fewer items per order (fresh and frozen).

Sixth, the presented reduction in the picking time implies a great—and proportional—reduction in the cost of the workforce (still compared with the traditional in-store baseline). In fact, both the literature (e.g., Di Francesco et al. 2021) and interviews revealed how the wage of the pickers is hourly-based. According to the interviewed grocers, the average hourly cost paid for a picker is around 20€. As a result, the percentage time savings are valid for the cost savings as well (e.g., 19.6 vs 18.5 minutes per order and 6.5 vs 6.2€ per order for a 6% saving; 32.7 vs 28.1 minutes per order and 10.9 vs 9.4€ per order for a 16% saving).

## 6. Conclusion

### 6.1 Theoretical contribution

The purpose of this study was to understand how and to what extent in-store picking for e.-grocery can be improved by combining the logistics behind warehouse-based and store-based solutions. Accordingly, the present work contributes to the literature by defining and investigating a solution aimed at improving the efficiency of e-grocery in-store picking based on the creation of an area in the back of the store dedicated to the most required online items. Compared with the extant literature, the developed model moves a step forward in a twofold direction. On the one hand, it considers an intermediate picking model combining store-based and warehouse-based logistics options, traditionally seen as two opposite alternative choices so far. On the other hand, it extends previous work aimed at increasing the efficiency of in-store picking. Extant contributions have mainly proposed solutions to improve the process in the current store layout without contemplating more structural modifications. The major findings recommend either moving picking activities during the closing hours or locating heavy or bulky items in an ad hoc area not accessible to offline customers. This work builds on the principle that picking activities are more efficient if there is no one walking in the aisles and if the position of the items in the racks is optimised. It extends these solutions, implementing the principle behind them to the most required online items (applying FPA and AI principles from the warehouse-based literature). In addition, it examines different managerial policies derived from warehouse-based contributions and evaluates the performances of the most promising ones.

The picking solution with the dedicated back area is always more efficient than traditional store-based picking, and the associated benefit varies between 6% and 16% for the store + back (60%) option, up to 7%–20% for the store + back (80%). The new intermediate solution is more efficient than the store-based solution (i) independently of how crowded the store is when picking activities are performed (even if the best performances occur with high crowding levels) and (ii) for both volume scenarios (but higher benefits are associated with higher volumes). Finally, despite the fact that the benefit entailed by the back area increases with a higher percentage of items stored in the back, the additional time saving is not significant (since the great advantage of the solution is already achieved with a lower percentage of items stored in the back). Considering the batching policies, order picking is always outperformed by batch and zone picking because they allow for the reduction of the average travelled distance per order. Conversely, zone picking is more efficient than batch picking when the demand volumes are high for both the store-only and store + back options.

### 6.2 Managerial contribution

From a managerial perspective, this research and the presented results provide some practical insights that may be useful to grocers that are offering, or aim to offer, e-commerce.

- Grocers should consider implementing an ad hoc area dedicated to the most required online items, independent of the number of offline customers visiting the store and the e-commerce volume. Such a solution allows for a decrease in overall picking time, independent of crowding and demand conditions. The canned and non-food items should be clustered into three classes based on their access index, and A class items should be allocated in the back. When designing the back area, managers should carefully evaluate to what extent it can be convenient to increase the number of products stored in the dedicated back area. Storing the items responsible for about 60% of online sales is expected to convey the greatest portion of the efficiency gain.
- Considering the batching policies, e-grocers should evaluate implementing a two-step path. First, as long as the volumes do not allow for the saturation of picking tours in the zones

characterised by a lower number of items (fresh and frozen), opt for batch picking. Second, when the saturation condition is met, switch to zone picking whenever possible. This twofold process should also be applied during the day: batching orders when there are few orders to be fulfilled and implementing a zone picking in moments where the volumes get higher.

- The dedicated back area implies lower picking times and accordingly lower picking costs. When evaluating its implementation, grocers should consider both its associated investments and costs. The main investments are the creation of the area and the purchasing or installation of the shelving. Investments depend on the baseline of the store (e.g., the availability or existence of the area). The main costs are instead the "coordination" costs (costs related to the management of the different parts of the order to be assembled after the picking activities in distinct areas) and general services (e.g., air conditioning, energy). The differential costs compared with the traditional in-store store are almost negligible, with the picking activity performed in the same way, while the expected benefits have proved to be significant.
- The creation of the back area is strictly linked to the emerging phenomenon of micro-fulfilment centres (very small logistics hubs located next to urban areas, devoted to e-commerce orders, typically characterised by a high automation level). On the one hand, they pursue the same goal based on some common features: both aim to rapidly fulfil online orders, thanks to high picking efficiency (absence of offline customers, optimised product storage and picking process) and fast deliveries (proximity to final customers). On the other hand, the dedicated back area may be seen as an antecedent of micro-fulfilment centres. Such centres, especially e-grocery, are often located in already existing stores (to leverage their widespread distribution in the territory). As a result, the manually managed dedicated area created at the back of the store could, if demand and space allow, be subsequently transformed into a micro-fulfilment centre, introducing automated solutions.

### 6.3 Limitations and future research

This work presents some limitations that suggest directions for future research. First, the study considers a single picking tour as the unit of analysis to estimate the average picking time per order (in line with previous contributions analysing picking performances e.g., De Koster et al., 2007). As a result, the different policies are individually analysed and compared and the shift perspective was not included. Nonetheless, further research could extend the model to test combinations of different policies and enlarge the unit of analysis to the overall volumes managed daily. A day could be divided into time slots, and the picking slots could be assigned specific orders issued before the cut-off. A model could then be developed, providing as an output, the number of orders to be picked in each picking slot and their optimal allocation in picking tours. Such tours could then be applied to the results of the present work to estimate the associated time performances. Second, the model was applied to a representative case scenario built in collaboration with practitioners. The outcomes for the in-store picking resulting from such average input values were confirmed by the grocers who had already implemented such solutions and may thus be considered reliable. Future work could perform real-time simulations to account for the different forms of uncertainty affecting the pickers' speed. Although the overall average results will be aligned, this could help in analysing and providing suggestions for specific situations (e.g., a high number of customers concentrated in a specific zone for discounted products). Third, the analysis was based on scenarios and input data, defined based on interviews with five practitioners operating in the Italian market. This is aligned with previous contributions in the field (which typically focus on one country and fewer than six companies). In addition, it is coherent with the scope of the work, addressing an e-grocery market for which the store-based model is still predominant (exactly as it happens in Italy). To improve the external validity of the obtained outcomes and their generalisability, further work extending the geographical scope (including a higher number of interviewees from different countries) could be used. Fourth, the proposed solution could not be feasible for some retailers (due to a shortage of space in the back) or imply a high degree of uncertainty (for instance, the products to be stored in the back could change quickly in the case of seasonal variations). Future works could aim to include and examine the impact of such sources of uncertainty on the performance of the picking solution based on the back area to encompass additional considerations.

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## Appendix A

**Average Picking Time per Order = Set-Up Time (SUT) + Retrieval Time (RT) + Stock-Out Management Time (SOMT) + Expected Travel Time (ETT)**

(SUT) = set-up time per picking order, i.e. time needed to prepare the picking mission

$(RT) = \sum_c (NL_c \cdot RTL_c + NP_c \cdot RTP_c)$

Where:

c = category of products (e.g., Canned+Non food; Fresh)

$NL_c$ = number of lines from category c per order

$RTL_c$ = retrieval time per line (i.e. time needed to read and check the picking list, and to position in front of the picking location) for items from category c

$NP_c$ = number of pieces per line from category c

$RTP_c$ = retrieval time per piece, i.e. time needed to pick an item and put it in the cart, for items from category c

$(SOMT) = \sum_c (SOTL_c \cdot NL_c \cdot \%SO_c)$

Where

$SOTL_c$ = stock-out management time per line (i.e. time needed to select the substitute product, and to position in front of the related picking location) for items from category c

$NL_c$ = number of lines from category c per order

$\%SO_c$ = average percentage of lines in stock-out for products from category c

(ETT)

Store case: $(ETT) = (ETT_{store})$

Store + back case: $(ETT)$ = % picked in the store $\cdot (ETT_{store})$ + % picked in the back $\cdot (ETT_{back})$

**STORE**

*ORDER PICKING POLICY*

$(ETT_{store}) = L_{Iorder} + L_{Eorder} / Sp$

$L_{Iorder} = \sum_c (l_{Ic} + w_{Ec}) \cdot v_c$

$L_{Eorder} = D_{I/O} + 2 \cdot \sum_c (a_c/2 - 1) \cdot w_{Ic} + D_{c-1;1}$

$L_I = (l_{ICNoF} + w_{ECNoF}) \cdot v_{CNoF} + (l_{IFre} + w_{EFre}) \cdot v_{Fre} + (l_{IFro} + w_{EFro}) \cdot v_{Fro}$

$L_E = D_{I/O} + 2 \cdot (a_{CNoF}/2 - 1) \cdot w_{Iz} + D_{CNoF\text{-}Fre} + (a_{Fre}/2 - 1) \cdot w_{I\text{-}Fre} + D_{Fre\text{-}Fro} + (a_{Fro}/2 - 1) \cdot w_{I\text{-}Fro}$

Where:

c = category of products (e.g., Canned+Non food; Fresh)

Sp = Speed of the picker

$v_c = \sum_{i=1}^{a_c} [1-(1-p_i)^{N_c}$

$N_c$ = number of lines per order for items from category c

$w_{Ec}$ = width of the cross aisle between two aisles dedicated to products from category c

$a_c$ = number of aisles dedicated to products from category c

$p_i$ = probability to visit the i-th aisle

$l_{Ic}$ = length of the aisles dedicated to products from category c

$w_{Ic}$ = width of a aisle dedicated to products from category c

$D_{I/O}$ = distance between the input/output point and the centerline of the nearest aisle in the first category of products

$D_{c-1;\,c}$ = distance between the centerline of the last aisle of a category (c-1) and the centerline of the first aisle of the subsequent one (c)

*BATCH PICKING POLICY*

$(ETT_{store}) = (L_{Ibatch} + L_{Ebatch})/NO_c \cdot Sp$

$L_{Ibatch} = \sum_c (l_{Ic} + w_{Ec}) \cdot v_c$

$L_{Ebatch} = D_{I/O} + 2 \cdot \sum_c (a_c/2 - 1) \cdot w_{Ic} + D_{c-1;1}$

$L_I = (l_{ICNoF} + w_{ECNoF}) \cdot v_{CNoF} + (l_{IFre} + w_{EFre}) \cdot v_{Fre} + (l_{IFro} + w_{EFro}) \cdot v_{Fro}$

$L_E = D_{I/O} + 2 \cdot (a_{CNoF}/2 - 1) \cdot w_{Iz} + D_{CNoF\text{-}Fre} + (a_{Fre}/2 - 1) \cdot w_{I\text{-}Fre} + D_{Fre\text{-}Fro} + (a_{Fro}/2 - 1) \cdot w_{I\text{-}Fro}$

Where:

c = category of products (e.g., Canned+Non food; Fresh)

Sp = Speed of the picker

$NO_c$ = number of orders per tour for items from category c

$v_c = \sum_{i=1}^{a_c} [1-(1-p_i)^{N_c \cdot (1-\%O_c)}/NO_c]$

$N_c$ = number of lines per batch for items from category c

$\%O_c$ = lines overlap due to the batch policy for items from category c

$w_{Ec}$ = width of the cross aisle between two aisles dedicated to products from category c

$a_c$ = number of aisles dedicated to products from category c

$p_i$ = probability to visit the i-th aisle

$l_{Ic}$ = length of the aisles dedicated to products from category c

$w_{Ic}$ = width of a aisle dedicated to products from category c

$D_{I/O}$ = distance between the input/output point and the centerline of the nearest aisle in the first category of products

$D_{c-1;\,c}$ = distance between the centerline of the last aisle of a category (c-1) and the centerline of the first aisle of the subsequent one (c)

*ZONE PICKING POLICY*

$(ETT_{store}) = \sum_z [(L_{I_z} + L_{Ez})/NO_z] / Sp$

$L_{Iz} = (l_{Iz} + w_{Ez}) \cdot v_z$

$L_{Ez} = 2 \cdot (f_z - 1) \cdot w_{Iz} + D_{I/Oz}$

Where:

z = picking zone (e.g., Fresh)

$NO_z$ = number of orders per tour for items from zone z

Sp = Speed of the picker

$v_z = \sum_{i=1}^{a_z} [1-(1-p_i)^{N_z \cdot (1-\%O_z)}$

$N_z$ = number of lines to be picked in a tour for items from zone z

$\%O_z$ = lines overlap due to the zone policy for items from zone z

$a_z$ = number of aisles in zone z

$p_i$ = probability to visit the i-th aisle

$l_{Iz}$ = length of the aisles in zone z

$w_{Ez}$ = width of the cross aisle between two aisles in zone z

$f_z$ = expected farthest aisle to be visited in zone z

$w_{Iz}$ = width of a aisle in zone z

$D_{I/Oz}$ = distance between the input/output point and the centerline of the nearest aisle in zone z

$f_z$ = expected farthest couple of aisles to be visited in a picking tour in in zone z

**BACK AREA**

$(ETT_{back}) = (L_{Iback}+L_{Eback})/NO_{back} \cdot Sp$

$L_{Iback} =(l_{Iback} + w_{Eback}) \cdot v_{back}$

$L_{Eback} = 2\ [D_{I/Oback} + (f_{back} - 1)\cdot w_{Iback}]$

Where:

Sp = Speed of the picker

$NO_{back}$ = number of orders per tour for the back area

$v_{back} = \sum_{i=1}^{a_{back}} [1-(1-p_{iback})^{N_{back}\cdot (1-\%O_{back})}/NO_{back}\ ]$

$N_{back}$ = number of lines per tour for the back area

$\%O_{back}$ = lines overlap due to the batch policy for items in the back area

$w_{Eback}$ = width of the lateral aisle in the back area

$a_{back}$ = number of aisles in the back area

$p_{iback}$ = probability to visit the i-th aisle in the back area

$l_{Iback}$ = length of the aisles in the back area

$f_{back}$ = expected farthest aisle to be visited in the back area

$w_{Iback}$ = width of a aisle in the back area

$D_{I/Oback}$ = distance between the input/output point and the centerline of the nearest aisle in the back area

## Appendix B

Average dimensions of the layout (metres)

| | Store | | | | Back |
|---|---|---|---|---|---|
| | Canned and No-Food | Fresh | Frozen | Fruits and Vegetables (Water) | Canned and No-Food |
| **we** | 4.2 | 4.2 | 2.5 | 0 | 2 |
| **a** | 20 | 3 | 2 | 1 | 4 |
| **li** | 22 | 12 | 18 | 30 | 7.5 |
| **wi** | 3.4 | 4 | 3.4 | 2 | 3.2 |

$D_{I/O} = 34$ m

$D_{c-1;\, c} = 4$ m

$D_{I/Oback} = 5$ m