The role of brick-and-mortar stores in an omnichannel environment

PhD Thesis

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PhD Thesis submitted to the Universitat Politècnica de Catalunya – BarcelonaTech in accordance with the requirements of the PhD. program in BUSINESS ADMINISTRATION AND MANAGEMENT in the Department of Management.

ACADEMIC YEAR: 2018-2019

ABSTRACT

Context: Retail is changing as technology is growing. The traditional way of shopping has evolved thanks to mobile devices, and retailers are struggling to avoid customers' attrition. Customers are immersed in a seamless omnichannel experience that allows them to switch from channel to channel and search for the most convenient way of shopping at all times. In this context, retailers have to compete not only with other brands but also with other channels of the same brand, and this situation makes it difficult for them to develop new ways of engaging the customers and create loyalty programs to make the most of their investments in the stores.
Effective product recommendation has become one of the key selling strategies employed everywhere, from brick-and-mortar stores to omnichannel retail, in order to increase sales and revenues and to increase repeat purchases from the same retail store and brand.

Objectives: The goal of this PhD Thesis is divided into two interrelated purposes: (1) to identify which are the trigger factors that motivate customers on the choice of each shopping channel and (2) to provide retailers with an algorithm that optimises the mix of recommended products in a brick-and-mortar store so as to provide the customer with an additional experience and engage them to the retail store.

Method: To reach those objectives we have analysed the different trends in the purchase process online and offline under the multichannel or omnichannel strategies. The methodology combines an exhaustive revision of academic literature about omnichannel strategies as well as reports from specialised consultant companies so as to define the trends and the factors that motivate customers towards one or another shopping path. As for the second study, with the goal of maximizing the total attractiveness value for the visiting customers to retail shops, and considering a multi-period tie horizon, we have studied how to determine an assortment of products to be included in display tables. In order to deal with the underlying optimization problem, a biased-randomized heuristic is proposed. In a first stage, it constructs an initial feasible solution. In a second stage, this initial solution is improved by employing a local search mechanism. A set of instances has been generated to test the approach. Different product-selection methodologies have been tested to illustrate the potential benefits of the proposed algorithm.

Results: The findings of the first study indicate that there are common trigger factors for every shopping channel and for every stage of the purchase path. Regarding the second study, recommending a set of correlated and attractive products on retail display tables that vary often is a promising way to engage customers with such an attractive experience.

Implications: The result of this research will allow retailers to face omnichannel strategies in such a way that they manage to engage and retain customers avoiding attrition and optimising their investments. Being able to know what is the best selection of products that best appeal to customers, provides a rationalization of the stock shown at every store and increases productivity of the employees in charge of such stock decisions.

DEDICATION AND ACKNOWLEDGEMENTS

There are some people without whom this thesis might not have been written, and to whom I am greatly indebted. To my husband David, for believing in me and for pushing me to finish this enormous project, for his love and patience. I know it has not been easy to share time with me. To my advisor Vicenç Fernández for guiding me when I was lost, for sharing his knowledge when I most needed it, and specially for teaching me that less is more. To Dolors Puig, who always thinks I can. To Belen Derqui, for trusting my success and encouraging me to go on.

I would also like to dedicate this work to my mother, my father and my aunts who would have been proud to see me here today.

This work has been partially supported by the Spanish Ministry of Economy and Competitiveness and FEDER (TRA2015-71883-REDT), and the Erasmus+ programme (2016-1-ES01-KA108- 023465).

AUTHOR'S DECLARATION

I declare that the work in this PhD thesis was carried out in accordance with the regulations of the Universitat Politècnica de Catalunya – BarcelonaTech and the requirements of the Ph.D. program in Business Administration and Management in the Department of Management. Except where indicated by specific reference in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

SIGNED: DATE:

Maria J. Màrmol Pérez 7th. April 2019

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CHAPTER 1

INTRODUCTION

It is deeply known that retaining customers is much more difficult than attracting a new one. The figure is different according to different sources but on average, acquiring a new customer is anywhere from 5 to 25 times more expensive than retaining an existing one (Gallo, 2014). Not only is the cost of retaining an existing customer less than the cost of acquiring a new one but also existing customers cost less to maintain than newly acquired. Dawkins & Reichheld (1990) found that a 5% swing in customer retention can impact profits from 25 to 85% across a wide array of industries. Zeithaml, Berry, & Parasuraman (1996) stated that reducing consumer defection is a more profitable strategy than cutting costs or increasing market share. Therefore, customer loyalty and retention is one of the main concerns for all kind of businesses, from products to services to places like malls and retail stores. And, in today's world, with so many purchase possibilities online and offline, the matter is increasingly important. Loyalty programmes are commonly used in forms of discounts, presents and personal communications among other practices. In this context of increasing competition and financial difficulties, loyalty is a key factor for survival and success (Schlesinger, Cervera, & Pérez-Cabañero, 2016). But unfortunately, loyalty is not the same as retention nor a synonym of repeat purchases.

Understanding customers' decision-making processes to predict their future intentions and behaviour has been the goal of many psychology, marketing and consumer-behaviour theories (Han & Ryu, 2012). In order to maximize customers' repurchase intentions, managers need to know the success factors influencing repurchase intent and their relative importance (Frank, Enkawa, & Schvaneveldt, 2014). The different purchase process theories vary on the basis of consumers' priorities and the intensity of need and wants of a particular product (Prasad & Jha, 2014). That is why we have created a model for Repurchase Intentions in which we establish some constructs that affect every stage of the process.

Based on Engel, Kollat and Blackwell model of purchase process (Blackwell et al., 2006) (Figure 1) , we have developed a "repurchase model" to further apply it to a "brick and click process". Bearing in mind that buyers go through a purchase process, or better, a "repurchase process", we would like to identify those elements that are key when buyers face the decision of repeating a purchase. Repurchase intention is the individual's judgement about buying again a designated service from the same company, taking into account his or her current situation and likely circumstances (Hellier, Geursen, Carr, & Rickard, 2003). In this context, we have conducted an exploratory research to gather preliminary information that will help define problems and suggest hypotheses. The basis of the research will be to test a model that wishes to describe the extent to which repurchase intention is influenced by certain proposed moderating variables (brand reputation, quality, complementary services, atmosphere, price and distance, among others). When we speak about "brick and click" we refer to the fact that retailers have presence in both online and offline environments. Obviously, applying a purchase process or a repurchase process to a brick and click business means to adapt the existing models to a more complex one.

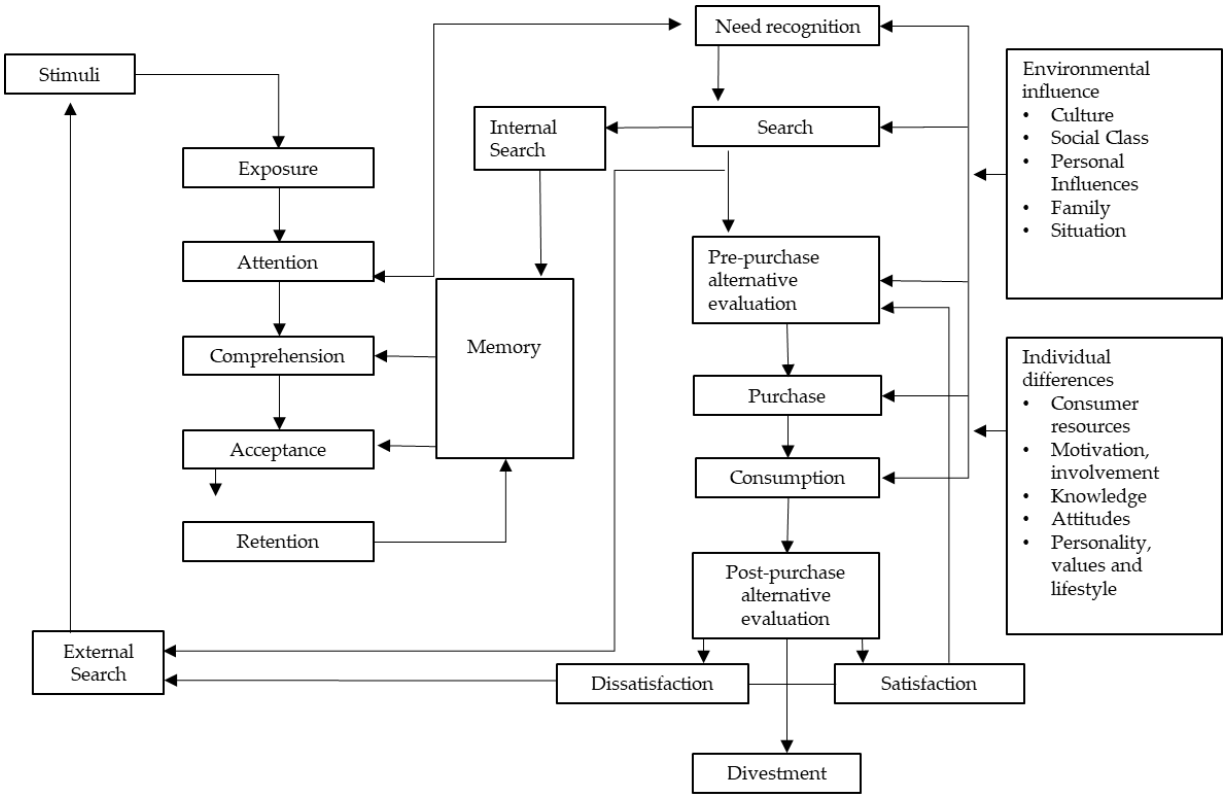

Figure 1 Consumer behaviour model (Blackwell et al., 2006)

In order to address these questions, we have gone through a number of reports made by important consultancy companies so as to have a clear idea of how customers behave during the purchase process and in what percentage the factors we have considered as important are really considered as such.

We have identified the phases of the classical consumer behaviour model (need recognition, information search, alternative evaluation, purchase and post-purchase) (Kollat, Engel, & Blackwell, 1970) under an omnichannel approach in all possible combinations, i.e. shopping in the store,

webrooming, showrooming, BOPIS (Buy Online Pick up In Store), online shopping and mobile shopping. The simultaneous use of different communication channels by customers is facilitating the emergence of new behaviours, such as showrooming and webrooming (Mosquera, Olarte-Pascual, & Juaneda-Ayensa, 2017). That is why, in most cases, customers start on one channel to end the purchase in another one.

1.1 The repurchase process. What makes customers buy again?

For a long time, customer satisfaction management has been the key factor to consider to retain him (Ganiyu, Uche, & Elizabeth, 2012). Customer satisfaction in this context, is the attitude resulting from the comparison of the expectation of performance and the perceived performance of the service experience (Oliver, 1980). The belief among many executives is that measuring satisfaction is the best indication of repurchase intention (Kenney & Khanfar, 2009) but although satisfied customers tend to be loyal, loyal customers are not necessarily satisfied (Fornell, 2016). Determining the link between satisfaction and intent to repurchase has been troublesome for firms (Mittal, 2013).This disconnect between satisfaction and intent to repurchase prohibits practitioners from making accurate estimations (Olsen, 2002). Future purchase intentions cannot accurately be estimated based on past behaviour (Andreassen & Lervik, 1999).

In the marketing literature, future repurchase intention is recognized as a positive consequence of customer satisfaction (Anderson, 1994; Cronin, Brady, & Hult, 2000; Zeithaml et al., 1996), but a closer look at the link between customer satisfaction and future repurchase intention has indicated weak and sometimes non-existent relationships between these constructs (Hennig-Thurau & Klee, 1997). Embedded in future repurchase intention lies satisfaction with the last encounter, the sum of previous experiences, and knowledge of other alternatives (Andreassen & Lervik, 1999). Repurchase intention is defined as the individual's judgement about buying a service again, the decision to engage in future activity with a service provider and what form this activity will take (Hellier et al., 2003). After all, repurchase is the key to a firm's long-term success (Han & Kim, 2010). Repurchase involves satisfaction, loyalty, memory, perceptions, evaluation and attitudes. Nevertheless, high levels of perceived quality and customer satisfaction are not sufficient to promote customer loyalty in many industries (Olsen, 2007). In fact, 71% of consumers claim that loyalty programs do not engender loyalty at all (Accenture, 2017).

A lot has been written and researched about the purchase process (Ajzen, 2011; Howard, & Shethe, 1969) but there is a lack of theories on repurchase models in the academic literature. In a normal purchase process, a customer identifies a need, looks for information, evaluates alternatives and makes a decision (Blackwell et al.,2006). As regards repurchase intend, the process is somehow different as the customer has already had previous experience at a certain place or with a certain product or service. That is why the nature of the relationship between the customer and the brand is becoming increasingly important given the need to retain customers in a highly competitive global sector. Every stage includes variables that should be considered and that have been adapted to the repurchase model we are proposing.

Based on the above mentioned EKB (Engel, Kollat and Blackwell) decision making model, we have constructed my own research model to explain repurchase process and how a customer repeats an operation with the same retailer or service supplier. We are aware that models are very helpful, but they also have limitations. They show a global vision, help to identify information areas, and allow the quantification of variables. Therefore, they are not exhaustive and they cannot show all the elements of the process. Apart from that, the importance of the elements can be different for different products or services and for different individuals and also vary according to the complexity of the purchase. Despite

all the difficulties, we have proposed a model that can be applied to different sectors, different processes and different complexities.

The EKB model starts with a "need recognition" stage. Need recognition is the first step in customer buying behaviour. In our model, this need is soon transformed in "want" and information search. Nowadays, the search for information can be done online or offline. The combination of both worlds is what is called "omnichannel", a form of retailing that, by enabling real interaction, allows customers to shop across channels anywhere and at any time, thereby providing them with a unique, complete, and seamless shopping experience that breaks down the barriers between channels (Juaneda-Ayensa, Mosquera, & Sierra, 2016). In both cases, external sources like marketing efforts made by the brands, peers and family opinions and word-of-mouth can be determinant of a decision made by a customer (Khan et al., 2015). Online channel loyalty has been observed to be more toward products that belong to a "search category" rather than to an "experience category"(Kim & Forsythe, 2007). It is the stage of alternative evaluation the one that is going to be more deeply considered in our work. In a repurchase process, most of evaluation criteria come from a past experience. We have proposed eight variables after a deep literature revision: brand reputation, product range, complementary services, service quality, atmosphere, price and convenience. The evaluation of these variables will lead to a repurchase intention and are explained in detail here below:

- **Brand reputation**: Customer value perceptions influence brand preference both directly and indirectly via satisfaction (Hellier et al., 2003). In a repurchase process, after the customer has tried other brands (either because they are cheaper or for other reasons), reputation can be a clear variable that can make a customer buy again. This also involves loyalty to a certain brand, cultural reasons or past experiences. Brand reputation also plays a vital role in preventing custom defection (Anderson, 1994). Effectively, a strong brand can help insulate companies from the negative ramifications of service breakdowns (Kenney, & Khanfar, 2009).
- **Product range:** The fundamental reason for shopping is to buy the product or the service, and this is guided by factors such as availability, quality and variety of merchandise (Rajamma, Paswan, & Ganesh, 2007). This will also be a key factor when we apply our model to the Omnichannel system. Research will probably show that one of the reasons for preferring online purchases is the variety of offer that cannot be found in physical stores. Store traffic and assortment may also influence the online and offline retailers' pricing strategies (Li, Lu, & Talebian, 2014). Customers do not make a second attempt if their first choice is out of stock.
- **Complementary services**: We would like to mention complementary services meaning all these actions taken by retailers that can lead to a clear preference by the customer: delivery, personalisation, after sales service, and so on. Applying this point to the omnichannel model, if the product can be delivered quickly at a relatively low cost, the online channel is preferred whereas if the delivery cost is high and customers are impatient, the traditional channel is better (Li et al., 2014). A 35% of UK shoppers would be interested in attending a lifestyle lessor or club at their favourite store (Westfield, 2015)
- **Service Quality**: Several studies have determined that high customer satisfaction and service quality result in higher customer loyalty and willingness to recommend the firm to another person (Bolton, 1991; Boulding, Kalra, Staelin, & Zeithaml, 1993; Rust et al., 2013). In our research, we take this recommendation as a way of reassuring the customer that his is a good choice.
- **Atmosphere:** The increasing use of customer supportive technologies and applications within the physical retail store in the context of the omnichannel retailing era has enhanced shopping experience and store atmosphere (Chris Lazaris, Vrechopoulos, Doukidis, & Fraidaki, 2015). Feeling the right personal experience at a certain retail store can be a very important evaluative factor and lead the customer to repeat a purchase to feel the experience again. In the same way,

a web atmospheric cue is comparable to a brick-and-mortar atmospheric cue and can be defined as any web interface component that stimulates one's senses (Dailey, 2004).

- **Price**: Nowadays, the increasing availability of comparative price information online make customers more price-sensitive (Degeratu, Rangaswamy, & Wu, 2000). Even if price seems to be one of the most important criteria to evaluate a purchase, it can be less considered if the other factors we have mentioned are important for the customer (for example atmosphere, distance or brand). Although the online population becomes comparable to the general population, the combined effects of price and promotion seem to be stronger in regular stores than in online stores (Degeratu et al., 2000).
- **Convenience**: A geographically proximal convenience store will offer an assortment of consumable products with a greater degree of convenience with respect to time and distance, but usually charge a price premium for these goods (Dholakia et al., 2010). The literature has identified the convenience dimension as a key motivator for selecting a retail type (Evanschitzky et al., 2004)

It can be considered that purchase is also influenced by other factors like time, affordability and the quantity of effort the customer has to devote to the action of purchase. The buyer must weigh the consequences of investing time and energy in finding another alternative (Blackwell et al., 2006).The process does not end with the purchase itself but with the use and experience of the good or service. Satisfaction or dissatisfaction will inevitably lead to a post purchase feeling that will meet the customer's expectations and therefore, take him to a new purchase. The above explanation is summarized in Figure 2.

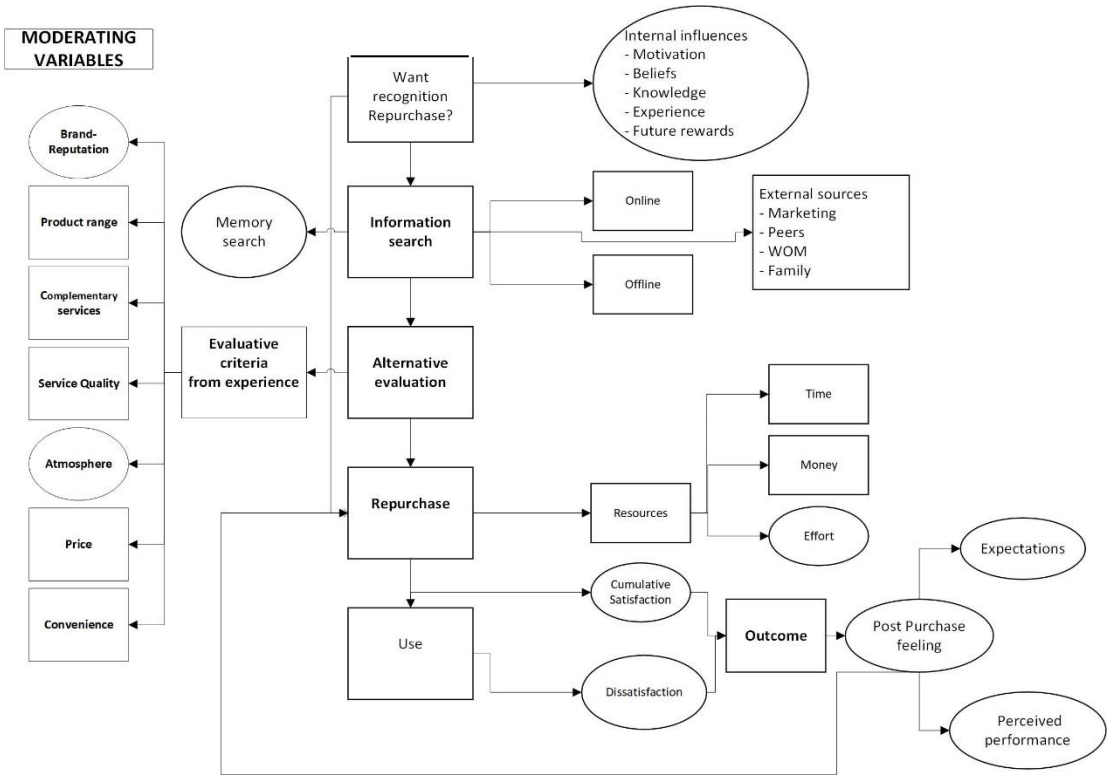

Figure 2 Repurchase Process

1.2 Shopping in an omnichannel environment

Customers are changing where, how and even why they shop (Nelson & Leon, 2012). The future of retail is all about using technology to strengthen customer relationships and improve the customer experience (Eisenberg et al., 2016).It is said that they prefer to shop online from a retailer of good repute, which favours the multichannel retailing strategy compared to the pure online retailing strategy (Piercy, 2012). Nevertheless, the notion that increases in customer loyalty as a result of proper order fulfilment leads to a stronger motivation to shop at a given outlet is true for physical stores as well as for online retailers (Agnihotri, 2015).

Bearing in mind that purchases nowadays follow a very different process depending on whether they are done in physical stores or online, we have adapted the previous mentioned repurchase model to an omnichannel process that represents the combination between both worlds, online and offline. Since the initial online visit to the website can help to build trust through the online navigation experience (Koufaris, 2004) , it is impossible to tell whether the online trust formed is due to the online navigation experience or through the customer's interactions with the offline presence (physical stores) (Kuan & Bock, 2007). While an offline retail presence may reassure customers purchasing from an online channel, poor service online may negatively influence customer usage of an offline channel (Piercy, 2012). The increasing use of customer supportive technologies and applications within the physical retail store in the context of the omnichannel retailing era has enhanced shopping experience and store atmosphere (Lazaris et al., 2015).

Feeling the right personal experience at a certain retail store can be a very important evaluative factor and lead the customer to repeat a purchase to feel the experience again (Deloitte, 2017a) . In the same way, a web atmospheric cue is comparable to a brick-and-mortar atmospheric cue and can be defined as any web interface component that stimulates one's senses (Dailey, 2004). Some studies (Eisenberg et al., 2016; Nelson & Leon, 2012; PWC, 2017) indicate that online shopping is not going to be the trend in the near future as it does not provide with the shopping experience of the brick and mortar shop. Omnichannel retailers work by exploiting synergies between their offline and online presence to provide better customer service, especially through the transfer of customers' trust of the offline to the online presence (Stewart, 2003). It is very likely that a substantial proportion of customers have already formed offline trust before they visit the retailers' website (Kuan & Bock, 2007). The retail industry is getting reinvented (Evans & Schmalensee, 2016) and retailers need a clear guide of what to do and a deep knowledge of customer behaviour.

Retail reinvention is not a simple battle to the death between bricks and clicks (Evans & Schmalensee, 2016) but a peaceful integration. When considering the purchase process under an omnichannel model, we will consider that customers act in different ways and from different departure points and combining both worlds, online and offline:

- **Traditional shopping**: Either the research for information, alternative evaluation and purchase are made in the store.
- **Webrooming**: combines online channels and brick-and-mortar retail opportunities. But instead of viewing products in-store and purchasing them online, webrooming consumers research products online before visiting a brick-and-mortar store for final evaluation and purchase (Edwards, 2014). The opposite of showrooming, consumers mainly use for convenience, especially if they need a product immediately. This should become more common as in-store inventory visibility increases on e-Commerce sites. Also common for consumers who want to avoid shipping costs (Worldpay, 2015).

- **Instant webrooming**: similar to webrooming but consumers search online while in store and buy in store.
- **Showrooming**: visiting a store before making a purchase online (Pricewaterhouse Coopers, 2017)
- **Instant Showrooming**: is a practice whereby consumers visit a brick-and-mortar retail store to (1) evaluate products/services first hand and (2) use mobile technology while in-store to compare products for potential purchase via any number of channels (Rapp, Baker, Bachrach, Ogilvie, & Beitelspacher, 2015). The threat to retail chains posed by showrooming and mobile commerce generally is overstated to the extent that in many cases the retailer will capture sales online that they previously might have transacted in a store assuming they are price-competitive (Nelson & Leon, 2012).
- **BOPS**: With this functionality, the retailer shows online viewers the locations at which the items are available and gives customers the option to close the transaction online and then pick up the products at one of the retailer's locations shortly after closing the purchase (Galino & Moreno, 2014).
- **Desktop only**: the purchase process starts and ends online from a desktop or a tablet.
- **Mobile only**: the purchase process starts and ends on a mobile device.

In recent years, a growing number of customers use multiple channels during their shopping journey (Juaneda-Ayensa, 2016). With an explosion of mobile technologies and social media, multi-channel shopping has become a journey in which customers choose the route they take and which needs to be mapped to be understood (Wolny & Charoensuksai, 2014). In order to understand how showrooming and webrooming shape this journey, the interaction of customers across multiple channels needs to be examined (Wolny & Charoensuksai, 2014). By clearly understanding customer touchpoints, senior management can work with cross-functional team member to employ tactics that foster service innovation to improve customer experience associated with each touchpoint (Rosenbaum, Otalora & Contreras Ramírez, 2016).

1.3 The repurchase process in an omnichannel environment

Retail is changing as technology is growing. The traditional way of shopping has evolved thanks to mobile devices, and retailers are struggling to avoid customers' attrition. The purchase process established as a model by Engel, Kollat and Blackwell (Kollat et al., 1970) that starts with the recognition of a necessity, continues with the search of information, evaluation of alternatives and an eventual purchase is becoming more and more complicated. Now, in the process, consumers have different online and offline channels available (Flavián et al.,2016) and choose which one to use according to different motivations. The stage of the information search is no longer made at a physical brick-and-mortar store only. The customer may initiate the process online, from a desktop or a mobile device, get the information required, go to the store to get additional information or to feel and touch the product and finish the purchase there or go back to his/her desktop or device and buy from there. Or they can start at a brick-and-mortar store, and due to the shortage of stock, for example, buy the product online. These many different possibilities force retailers to develop new ways of engaging the customers and create loyalty programs so as to make the most of their investments in the stores. Quality, price and convenience are not enough to compete in an omnichannel environment and customers seek for experiences all over the purchasing process.

Based on the conclusions of more than 30 reports made by consultancy companies, we have analysed every step of the repurchase process looking for the confirmation of our proposal and the

moderating variables that we have established as basic when deciding on a purchase: brand reputation, product range, complementary services, service quality, atmosphere, price and convenience. We will also summarize the conclusions of the reports. The study is narrowed to three of the five phases of the repurchase process, i.e. information search, alternative evaluation and the purchase moment itself.

1.3.1 Traditional shopping

Even in the current omnichannel environment, 20% of customers prefer to search and buy in store (UPS, 2016). It has been stated that 74% of consumers who start shopping in a store end their purchases in the same store (Ingenico, 2017). It is also important to note that 79% of US brand respondents use stores as sales generators (PWC, 2017) and that a 40% of shoppers prefer to bring merchandise home immediately (UPS, 2016). 59% of US customers want an inviting ambiance when in store (PWC, 2017). For the 60% of customers, going shopping to a store is a social experience with family and friends, and a 57% appreciate additional activities when in (Cap Gemini, 2017). Although 89% of Millennials want personalization, only 18% see it from retailers (PSFK Labs, 2016). 88% of brands do not have the ability to acknowledge customers as they enter the physical store (Glass & Haller, 2017). Some customers feel they are more recognised online than in brick-and-mortar retail shops. 21% of brands are unable to access customer account details and therefore limiting the capability to personalize their offers (Glass & Haller, 2017). The top reasons to shop at small retailers are because of their unique products (50%), for the community support (34%) , and because of sales associates help (23%) (UPS, 2016). Nevertheless, the need to touch and feel is, by far, the most repeated reason among consumers (70%).

- INFORMATION SEARCH AND ALTERNATIVE EVALUATION
  The search for information is made in store and with the help of shop associates mainly. When asked how important certain attributes are in relation to in-store shopping experience, 78% of sales executives respond that sales associates with a deep knowledge of the product range is the most important factor for consumers (PWC, 2017). 23% of online shoppers like the possibility to interact with sales associates in stores to ask for information (UPS, 2016). 33% of shoppers are satisfied with the help received in store (PWC, 2017) and 33% of European consumers like to ask store staff for advice before buying (Ivend, 2017). 47% of shoppers say that engaging with them in innovative a creative ways to provide a multisensory experience influences their overall feeling of loyalty toward a brand (Accenture, 2017) and therefore, their repurchase intention.

- PURCHASE
  The main problem during the purchase process is the queues at checkout (Glass & Haller, 2017). However, 84% of brands rely solely on opening additional checkout lanes for queue busting. Even online shoppers, like the thrill of hunting for and finding great deals, more precisely, a 45% (UPS, 2016). A 73% of customers expect same day delivery, or take the products with them immediately (Cap Gemini, 2017).

1.3.2 Desktop only

As more and more consumers are using desktops to shop online, 73% of us brand respondents use webs as main sales generators (PWC, 2017). Consumers prefer to buy consumer electronics and fashion in store rather than online (51% vs. 39% for electronics and 51% vs. 40% for fashion) (PWC, 2017). One of the most important conclusions issued from the reports is that 60% of consumers who start in web end in web (Ingenico, 2017).

- INFORMATION SEARCH AND ALTERNATIVE EVALUATION
  Only 50% of brands provide very good or excellent online shopping functionalities (orders, wish lists, review, videos) and only 32% provide customers with opportunities to co-create and collaborate (Glass & Haller, 2017) although those subjects are the most valued by internet users. Loyalty online is quite inexistent with 75% of consumers moving to a more expensive channel when online support fails. 90% of users consider chat as the most helpful tool (HP, 2014).

- PURCHASE
  The main reasons to buy online stated by consumers are convenience, time saving and money saving (IAB, 2016). Contrasting with in-store shoppers, 40% of desktop consumers prefer self-service to human contact for their future contact with companies (HP, 2014). Another important reason is stock availability and delivery but 64% of brands do not enable customers to choose their delivery day or timeslot and 44% do not offer express home delivery service (Glass & Haller, 2017). As regards personalisation, only 59% of shoppers are satisfied with the ability to receive product recommendations based on past browsing and buying behaviour (UPS, 2016)

1.3.3 Webrooming

Webrooming is the way in which consumers research products online before visiting a brick-and-mortar store for final evaluation and purchase (Edwards, 2014). In 2016, 38% of customers have purchased a product in store after checking it online (IAB, 2016). 26% of consumers who start in web end in store (Ingenico, 2017). Worldwide, 88% of consumers are seeking information online before buying in-store or in-app (Ingenico, 2017). Webrooming is becoming more and more popular as shows that in Spain, 53% of shoppers used the web to look for information prior to a purchase in 2015 and 65% did so in 2016 (Ivend, 2017). Even if webrooming is mainly used to look for information 41% of consumers in the UK would like to use new technologies to experience how products would look in their homes or in themselves (Westfield, 2017). Web search is important for retailers as 23% of customers who start mobile end in store (Ingenico, 2017).

- INFORMATION SEARCH AND ALTERNATIVE EVALUATION
  75% of customers like the possibility to check product availability prior to their visit to a store (Cap Gemini, 2017). One of the factors considered important by retail executives is the ability to check other store or online stock quickly. 68% of executives think this is important (PWC, 2017). The main reasons given by customers for searching online are: to get inspiration from social networks (39%), to look at the retailer's website (37%) and to compare prices (35%) (PWC, 2017). Nevertheless, 67% of brands do not support product comparisons (Glass & Haller, 2017).

- PURCHASE
  One of the main reasons why "webroomers" shop in stores is because of the immediate availability of the product, stock availability and personal interaction with shop associates. The same reasons as traditional shoppers, mainly.

1.3.4 Instant webrooming

We call "instant webrooming" to the fact of searching online while in store and buy in store. The reason for doing so is mainly because consumers find it important the ability to see or order an extended range of products on screen in-store.

- INFORMATION SEARCH AND ALTERNATIVE EVALUATION
  Consumers use their mobile devices while in store, prior to purchasing for looking for a better price (49%), looking for more information (43%), looking for reviews (36%) or look for advice from family or friends (21%) (IAB, 2016). Even if 68% of customers want the ability to check other store or online store quickly (PWC, 2017), there is still a 17% of brands that are not able to guarantee against missing inventory data cross channels (Glass & Haller, 2017).

- PURCHASE
  Purchase follows the same reasons as normal webroomers we have mentioned above.

1.3.5 Showrooming

Showrooming occurs when consumers use stores to evaluate goods in person, and then go online to purchase for a better price. With the advent of smartphones, shoppers increasingly buy online while still in a store (Nelson & Leon, 2012). Another reason for showrooming is to get inspiration for future purchases online (UPS, 2016). Today, 19% of consumers who start in store end in web (Ingenico, 2017) but 69% of brands think showrooming will grow (UPS, 2016).

- INFORMATION SEARCH AND ALTERNATIVE EVALUATION
  60% of customers research products or prices on a mobile device while in store (UPS, 2016)

- PURCHASE
  Purchase is the same as for desktop only customers.
  The purchase is made under the same conditions as mentioned for desktop only shoppers.

1.3.6 Instant showrooming

The difference with showrooming is that the search is made in store and the purchase is also made there, in the same moment, to the same online brand or to another brand. 44% of mobile purchasers have purchased a product on their mobile device after checking it out in store (IAB, 2016). 31% of shoppers say they are always "on the go" with mobile devices (UPS, 2016). The most important figure is that 80% of smartphone shoppers use their mobile in store to help with shopping (Worldpay, 2015).

- INFORMATION SEARCH AND ALTERNATIVE EVALUATION
  One of the tools brands have are beacons. Beacons are miniature, store-based transmitters that communicate with a retailer's mobile app. They are a great way to enhance the in-store experience with online immediacy (UPS, 2016). Customers while in store want to know if a wider rage is available online but 50% of British brands do not offer technology in store (Practicology, 2017).

- PURCHASE
  28% of customers are fine with visiting the physical store and placing an order while there.

1.3.7 BOPS

Buy Online Pick up in Store. It combines both environments, online for purchases (see desktop consumers) and store. It is important to state that although 46% of BOPS customers have made additional purchases in store (UPS, 2016), still 39% of brands do not offer a click and collect service.

1.3.8 Mobile only

More than half of google searches in 2016 were made from a mobile device. (Ditrendia, 2016). Mobile commerce is increasing by 200% more than online commerce (Ditrendia, 2016). In 2016, a 47% of online shops that had mobile responsive webs say they have increased their sales from 10 to 25% thanks to mobile transactions (Ditrendia, 2016). Nevertheless, only 21% of retailers have a mobile purchasing channel (Deloitte, 2017b). The reasons mobile users state for using a smartphone to shop are: convenience, price, immediate purchase, and because of advertising prompting (IAB, 2016). The sectors that Spanish consumers research the most are fashion (with an increase of 405% in the year 2017) and consumer electronics (Ditrendia, 2016). Companies are still behind and 74% of brands do not offer any personalization on the mobile app (Glass & Haller, 2017)

- INFORMATION SEARCH AND ALTERNATIVE EVALUATION
  78% of mobile shoppers use it to compare prices, 68% to search for opinions, 20% to look for deals and 50% to search for product reviews (Ditrendia, 2016).

- PURCHASE
  73% of mobile customers are satisfied (UPS, 2016) and spend an average of 79€ on smartphones for every 100€ spent on desktop per transaction, a 7% year over year increase (Criteo, 2017). Satisfied mobile consumers report being 40% more likely to buy from other channels at the same merchant (Ingenico, 2017). 77% of smartphone users say that receiving surprise points or rewards, exclusive content and special birthday messages would have a positive impact on their loyalty (Vibes, 2015).

Brick-and-mortar retail is not dying as some may think. In fact, according to a report issued by Interbrand (Interbrand, 2014): "While e-commerce sales continue to grow 10 percent each year, questions about the role of brick and mortar seem to be largely resolved. The store is now a brand experience that drives revenues across all channels".

1.4 Personal and profesional motivation

My final goal with this thesis is to provide retailers with some knowledge of the omnichannel purchase process and some tools to react to a new purchase process in an omnichannel environment. I have worked for many years in the franchise sector and I know how difficult and costly is to run a business and to engage customers so as to make it profitable.

Firstly, I wanted to know what are the factors that lead customers towards choosing a certain purchase path. After that, I searched for an optimization of brick and mortar stores. The main objective

is to demonstrate that brick and mortar retail is not disappearing but adapting to a new environment. I also wanted to give some advice to retailers in such a way that they get the most of their stores in terms of stock, product mix and product typology. The description of the factors that motivate this seamless experience across all channels will provide brands with knowledge about how to improve their strategic approach to engagement, belonging and retention of customers.

From an academic point of view, as omnichannel is a quite new subject, I wanted to review the literature regarding it and provide future researchers with a starting point for their work.

Effective product recommendation has become one of the key selling strategies employed everywhere, from brick-and-mortar stores to omnichannel retail, in order to increase sales and revenues. With the goal of maximizing the total attractiveness value for the visiting customers, and considering a multi-period time horizon, this thesis studies how to determine an assortment of products to be included in display tables at retail stores. In order to define a realistic scenario, a number of constraints are also considered, e.g.: diversification of price and product categories, achievement of an acceptable profit margin, etc. Solving this multi-period product attractiveness problem enables brick-and-mortar stores to provide an exciting experience to their customers. As a consequence, an increase in sales revenue should be expected. In order to deal with the underlying optimization problem, a biased-randomized heuristic is proposed. In a first stage, it constructs an initial feasible solution. In a second stage, this initial solution is improved by employing a local search mechanism. A set of instances has been generated to test our approach. Different product-selection methodologies have been tested to illustrate the potential benefits of the proposed algorithm.

The methodology of the research combines an exhaustive revision of academic literature as well as reports regarding omnichannel shopping in the apparel sector. We have chosen reports from the main consultancy companies in the world and extracted conclusions from them. Then, based on reports regarding Spanish trends in omnichannel shopping, we have refined these conclusions and adapted them to the Spanish market. On a second stage, an algorithm to optimize the stock to be shown at retail stores is developed and tested.

1.5 PhD Thesis structure

This thesis has been structured in three main chapters. The first one corresponds to the general introduction to the purchase and repurchase intention of customers in an omnichannel environment and their implications with retail stores. Chapter 2 is an analysis of the trigger factors that affect every shopping path in the purchase process, especially on the stages of information search and purchase itself. We discuss about the difference between the concepts of multichannel, cross-channel and omnichannel strategies. The third chapter establishes an algorithm to determine the best mix of recommended stock for brick and mortar stores. Each of these two chapters includes an explanation of the methodology used and the results corresponding to every subject.

To end with, the fourth chapter highlights the main conclusions issued from the research and gives advice to retailers about how possibly maximize their performance in an omnichannel environment. Together with this, we mention the limitations of the research together with possible gaps and future lines of research.

CHAPTER 2

TRIGGER FACTORS IN BRICK AND CLICK SHOPPING

Traditionally, customers made their purchases in brick-and-mortar stores with the help of salespeople to find what they wanted or needed and within a certain atmosphere. With the growth of technology and on-the-go devices, different shopping channels have appeared and have attracted the attention of customers. E-commerce gave customers the possibility to browse through different stores in an online environment and get information, opinions and a vast available stock. Although some experts predicted that online shops would kill the physical ones, the truth is that they coexist and have transformed the way customers shop nowadays (Galino & Moreno, 2014). Customers entered in a multichannel environment using different channels to shop (Mosquera, Olarte & Juaneda Ayensa, 2017). Companies set then an omnichannel strategy so as to blur the borders among the different channels and offer the customer a seamless experience (Heitz-Spahn, 2013). Customers switch between channels, between retailers and between devices in a very natural way for different reasons and valuing different factors: brand perception, atmosphere, price, availability of stock, convenience or personalisation (Agnihotri 2015; Cap Gemini 2017; Kibo 2017; UPS 2015; Willmott 2014; Zimmerman 2012). Knowing how customers move from one channel to another and how they combine them in a seamless experience is key for retailers so as to increase sales, retain them and enhance loyalty (Sands et al. ,2016). The blending of bricks (the physical store) with clicks (the online environment) is boosting a whole new way of shopping. The seamless experience offered by brands across different shopping channels is key because a connected shopper spends 30% more than an unconnected shopper (PSFK Labs, 2016).

This research was developed in three stages. First, we revised the existing literature to identify the purchase process theories and define the basic factors that affect each one. After that, we defined the different omnichannel purchase processes based on the EKB Model (Kollat et al., 1970) so as to determine if the purchase process in an omnichannel environment is somehow different from a process in a physical retail environment. Lastly, we made a comparison of the different channels and the purchase process so as to have a clear view of the trigger factors that affect every channel and every stage of the process. We have classified the phases of the classical consumer behaviour model (need recognition, information search, alternative evaluation, purchase and postpurchase) (Kollat et al. 1970) under an omnichannel approach in all possible combinations, i.e. shopping in the store, webrooming, showrooming, BOPS (Buy Online Pick up In Store), online shopping and mobile shopping. We consider the omnichannel shopping process as an integrated sales experience that melds the advantages of physical stores with the information-rich experience of online shopping (Rigby, 2011). More precisely, omniretailing is considered by Levy et al. (2013, p.67) as a coordinated multichannel offering that provides a seamless experience when using all the retailer's shopping channels.

Understanding customers' decision-making process to predict their future purchase intentions and behaviour has been the goal of many psychology, marketing and consumer-behaviour theories (Ryu & Han, 2011). In order to maximize customers' purchase intentions, managers need to know the success factors influencing purchase intent and their relative importance (Frank et al., 2014). The description of the factors that motivate this seamless experience across all channels will provide brands with knowledge about how to improve their strategic approach to engagement, belonging and retention of customers.

2.1 Literature Review

2.1.1 Multichannel and omnichannel shopping

Customers shop around to get the best deal (Rajamma et al., 2007) but nowadays they are changing where, how and even why they shop (Nelson & Leon, 2012). Depending on whether the purchases are made in physical stores or online, they follow a very different process (Brynjolfsson, Hu, & Rahman, 2013). Traditionally, shopping took place only in physical stores and in a limited geographical region or city. They were the only channel that customers had to buy and therefore transactions where based on face-to-face personal relationships (Kim, Ferrin, & Rao, 2008). With the rise of internet another way of shopping was possible and customers started to shop online from their desktops (Sands et al., 2016). With the explosion of mobile technologies and social media, multichannel shopping has become a journey in which customers choose the route they take and which needs to be mapped to be understood (Wolny & Charoensuksai, 2014). As a result, new shopping ways have emerged, for example webrooming, where consumers research products online before visiting a brick-and-mortar store for final evaluation and purchase (Edwards, 2014) and the opposite, known as showrooming, where consumers visit retailers' stores to "touch and feel" a product, but they consummate their eventual purchase online (Fulgoni, 2014).

Multichannel shopping involves the use of basically online and offline channels one at a time. It implies a division between both environments (Juaneda-Ayensa et al., 2016). The increasing use of customer supportive technologies and applications within the physical retail store in the context of the multichannel retailing era enhanced shopping experience and store atmosphere (Lazaris et al., 2015). But multichannel fails in the integration of different shopping channels and appears unconnected and offers multiple shopping channels but focused on the process itself and not on the customer (Burke, 2002). Multichannel means that the customer has different shopping channels from which to choose the purchase but companies use also different strategies depending on one or another channel (Lazaris & Vrechopoulos, 2013). For example, if a customer receives a coupon in an online channel, he may not

exchange it on a physical store. With the increase of new technologies and their availability to the customer, a new way of shopping has appeared. With the rise of technology and on-the-go devices customers look for a seamless experience among channels and companies are focusing their strategies to coordinate them in a way that if offers the possibility to interact in all channels for a single purchase offering a shopping process without boundaries between the different channels.

Omnis is a Latin word meaning "all" or "universal," so omnichannel means "all channels together"(Lazaris & Vrechopoulos, 2013). Because the channels are managed together, the perceived interaction is not with the channel, but rather with the brand (Piotrowicz & Cuthbertson, 2014). Multichannel emphasizes the individual channel while omnichannel gives importance to customers' experience. Therefore, the difference between multichannel and omnichannel strategies relies on the approach and the management strategy used in every channel. In multichannel shopping all channels are available to the consumer but they are not integrated. Omnichannel shopping offers an integrated strategy and therefore the sense of connection and relationship with the brand no matter the channel the customer uses (Verhoef, Kannan, & Inman, 2015).

An omnichannel strategy understands the purchase as a process in which different channels participate. It is important to understand what drives customers to every channel so that companies can offer them a satisfactory purchase experience. No matter how the shoppers swap across channels and devices, the use of various channels and touchpoints are able to be consistent, concurrent and compatible (Melero, Sese, & Verhoef, 2016).

2.1.2 Purchase process

Several researchers (e.g. Howard & Shethe 1969; Ajzen 2011; Kollat et al. 1970; Schiffman & Wisenblit 1995) have written about the purchase process. The EKB Model (Kollat et al., 1970) is one of the most spread theories and has been the base to subsequent transformations and new ideas. According to this theory, in a purchase process, a customer identifies a need, looks for information, evaluates alternatives, makes a decision and evaluates the purchase (Kollat et al., 1970).

Nowadays, the search for information and evaluation of alternatives can be done online or offline. In both cases, external sources like marketing efforts made by the brands, peers and family opinions and word-of-mouth can be determinant of a decision made by a customer (Khan et al., 2015). Online channel loyalty has been observed to be more toward products that belong to a "search category" rather than to an "experience category"(Kim & Forsythe, 2007). In the same way, purchases can be made at brick-and-mortar stores or online and this fact makes it difficult to control the path that the customer makes towards a product or a service. A customer can start looking for information at a physical brick-and-mortar store and end the purchase there, which would be what traditional customers have always done. With the growth of technology, a new shopping scenario appeared, the online world gave the possibility to start and end the process there, or to start the process physically and end virtually, or vice versa. Moreover, the increasing use of mobile devices, opens another new way of shopping (Gao & Yang, 2016). Looking at where the customer starts the search for information and where the purchase takes place, we enumerate the following classification of the path that the customer takes to complete a purchase:

- **Traditional shopping path:** start at brick-and-mortar stores and purchase at brick-and-mortar stores.
- **Desktop path**: start online, from a desktop or tablet at home and end the purchase at the same place.

- **Showrooming path**: start the purchase process at a brick-and-mortar store, where the customer gathers information and end online from a desktop or a tablet at the same brand or at a competing retailer (Gensler, Neslin, & Verhoef, 2017).
- **Reverse showrooming path:** so as to prevent the customer from switching brands, a new purchase path has appeared, the so called reverse showrooming, wherein retailers encourage bricks-and-mortar consumers to search their products online through kiosks or mobile apps, thereby increasing the likelihood of keeping the sale (Parise, Guinan, & Kafka, 2016).
- **Webrooming path:** the customer researches products online at home before visiting a brick-and-mortar store for final evaluation and purchase (Edwards, 2014).
- **BOPS path:** The customer buys online and picks up in physical store (Bell, Gallino, & Moreno, 2014).
- **Mobile only path:** the customer starts on a mobile device and ends his purchase on the same device (Beck & Rygl, 2015).

All these shopping paths involve the use of one channel at a time and the physical transfer of the customer from one place to another to use those channels. As mentioned, in showrooming for example, the customer searches for information at the brick-and-mortar store and then goes to another place to buy online (Verhoef et al., 2015). Nevertheless, there is a possibility to use a mobile device at the same physical place to complete the purchase on site after looking for information (F. Gao & Su, 2016). This is what we call "instant showrooming". Another situation is that of the customer who looks for information through a mobile device while in the store and completes the purchase at the store. We name this situation as "instant webrooming". Therefore, the above mentioned list, should be completed with two other paths:

- **Instant showrooming path**: the purchase process starts at a brick-and-mortar store and the purchase is made online but from a mobile device in the same store.
- **Instant webrooming path:** the customer looks for information online from his mobile device while in the store and buys at the same brick-and-mortar store.

There are two ways to group these different shopping paths. From the retailer's perspective, there are three different strategies: (1) single channel strategy by which the brand or retailer has only one shopping channel where to offer their products or services, either physical or on the web, (2) multichannel strategy which refers to the integration of various channels, not connected, in the consumer decision-making process (Wolny & Charoensuksai, 2014) and omnichannel strategy, a holistic shopping experience through the integration of online and offline channels offering the customer a seamless experience (Mosquera et al., 2017). From the customer's perspective, the above explained paths can also be single channel (traditional brick-and-mortar physical stores, online shopping and mobile only), multichannel (showrooming and webrooming) and omnichannel (instant showrooming, instant webrooming, reverse showrooming and BOPS). The classification shown in Table 1 takes into account the starting point, where the customer searches for information and the end point where the actual purchase is made.

Table 1: Classification of purchase paths

	Path	Information search		Purchase
Single channel	Brick-and-mortar only	Brick-and-mortar	→	Brick-and-mortar
	Desktop only	Desktop	→	Desktop
	Mobile only	Mobile device	→	Mobile device
Multichannel	Showrooming	Brick-and-mortar	→	Desktop (home)
	Webrooming	Desktop (home)	→	Brick-and-mortar
Omnichannel	Instant showrooming	Brick-and-mortar	→	Mobile device
	Instant webrooming	Mobile device	→	Brick-and-mortar
	Reverse showrooming	Brick-and-mortar	→	Retailer's desktop
	BOPS	Desktop	→	Desktop (pick up brick-and-mortar)

2.1.3 Trigger factors for channel choice

As we can see in Table 1, customers move around different channels starting at one channel and ending at the same or at another one. To know the reasons why customers choose these different paths to purchase is key and that is why we made research so as to determine what moves customers towards one or another of the mentioned paths. There are several trigger factors that push the customer toward the decision of shopping through one certain channel only (traditional brick-and-mortar shops or online stores) or through a multichannel experience. The most highlighted trigger factors are stock availability (Beck & Rygl, 2015; Gensler et al., 2017; Lazaris et al., 2015; Willmott, 2014), personalisation (Burke, 2002; Karimi, Papamichail, & Holland, 2015; Nelson & Leon, 2012; Rajamma et al., 2007), atmosphere (Andajani, 2015; Lazaris et al., 2015; Piotrowicz & Cuthbertson, 2014; Ryu & Han, 2011), price (Hagberg, Sundstrom, & Egels-Zandén, 2016; Pawar & Sarmah, 2015; Picot-Coupey, Huré, & Piveteau, 2016; Zeithaml et al., 1996) and convenience (Gensler et al., 2017; Lemon & Verhoef, 2016; Rigby et al.,2014).

The fundamental reason for shopping is to buy the product or the service, and this is guided by factors such as availability, quality and variety of merchandise (Rajamma et al., 2007). Research (Nelson & Leon, 2012) has shown that one of the reasons for preferring online purchases is the variety of offer that cannot be found in physical stores. Store traffic and assortment may also influence the online and offline retailers' pricing strategies (Li et al., 2014). Customers do not make a second attempt if their first choice is out of stock (Li et al., 2014).

Another trigger factor is personalisation. Applying this point to the omnichannel model, if the product can be delivered quickly at a relatively low cost, the online channel is preferred whereas if the delivery cost is high and customers are impatient, the traditional channel is better (Li et al., 2014). The increasing use of customer supportive technologies and applications within the physical retail store in the context of the omnichannel retailing era has enhanced shopping experience and store atmosphere (Lazaris et al., 2015). Feeling the right personal experience at a certain retail store can be a very important evaluative factor and lead the customer to repeat a purchase to feel the experience again. In the same way, a web atmospheric cue is comparable to a brick-and-mortar atmospheric cue and can be defined as any web interface component that stimulates one's senses (Dailey, 2004). For example, 35% of UK shoppers would be interested in attending a lifestyle lessor or club at their favourite store (Westfield,

2015),. This means that face-to-face relationships and personalisation are still important during the purchase process.

Nowadays, the increasing availability of comparative price information online make customers more price-sensitive (Degeratu et al., 2000). Price seems to be one of the most important criteria to evaluate a purchase but it can be less taken into account if the other factors we have mentioned (stock availability, personalisation and convenience) are important for the customer (Gensler et al., 2017). Even if the online population becomes comparable to the general population, the combined effects of price and promotion seem to be stronger in brick-and-mortar stores than in online stores (Degeratu et al., 2000). Price comparison-oriented consumers move across channels to maximize their chances of finding the best deal (Heitz-Spahn, 2013). In showrooming specially, shoppers search for information in the store and simultaneously search on their mobile device to get more information about offers and may find more attractive prices (Rapp et al., 2015).

The literature, e.g. (Evanschitzky et al., 2004) identifies the convenience dimension as a key motivator for selecting a retail type. Convenience means that the customer seeks to purchase a product with a minimum investment of time, physical effort and mental effort (Schröder & Zaharia, 2008). Multichannel retailing can be a strategy to attract and retain customers that value convenience and flexibility (Sands et al., 2016). Mobile technology is bringing internet to consumers 24 hours a day and convenience for them is an important factor to choose this channel (Brynjolfsson et al., 2013).

2.2 Methodology

With the purpose of conducting an in-depth analysis of what were the important factors for consumers during their purchase process in different channels, we designed an explorative approach through primarily qualitative data and therefore gathered over 30 reports from some of the most important consulting firms and a number of academic papers. The analysis of all the material was done in three phases. First, we gathered reports and academic papers. The search was made using the keywords "omnichannel" and "purchase process" and we chose only those reports produced during the past three years and signed by important consultancy companies in the marketing sector. The search in google resulted in 30 reports. The search in Web of Science, Scopus and Mendeley resulted in many academic papers that were the base of our next steps. All those reports older than 2014 and not mentioning any of our keywords were discarded. Secondly, we read and analysed the documents to find references about our proposed trigger factors (product range or variety of stock, personalisation, price and convenience) and we coded all the reports with numbers from 1 to 30. We listed the main conclusions and results from every report. Based on our initial list of trigger factors, we extracted them from the reports and we made a list in which we noted the percentages of customers that considered a certain factor as a trigger for his choice of shopping channel. We took percentages over 55% into account to consider them as a trend for our research.

Thirdly we constructed a table to summarize the results of our findings. On the vertical axis, we placed all the phases of the purchase process (need recognition, information search, alternative evaluation, purchase and post purchase) and on the horizontal axis we placed the omnichannel purchase paths (traditional shopping, webrooming, instant webrooming, showrooming, instant showrooming, Buy Online Pick up In Store, online only, mobile only). We read all the reports again and filled in the corresponding space in the table with conclusions extracted and with the code of the report. For example, if we were reading a report by Criteo (code number 9) concluding that 63% of the customers find the ability to check inventory on a retailer's app prior to the visit to the store, then we wrote this fact in the corresponding space (information search, webrooming).

Although the reports are diverse and from different countries, results show common trends that affect consumers and shopping in general.

2.3 Results and discussion

Results suggest that there are common trigger factors for every shopping channel and for every stage of the purchase path.

2.3.1 Traditional Shopping

In the traditional way of shopping, the customer goes to a brick-and-mortar store so as to get information from sales associates mainly (Ivend, 2017; PWC, 2017; UPS, 2016). Customers expect sales associates to have a deep knowledge of product specifications and range. 89% of Millennials, that is, young consumers born between approximately 1985 and 1999 (Kotler & Keller, 2009) want personalization (Kibo, 2017) when shopping at a brick-and-mortar store. Another reason to shop in store is the atmosphere and the sense of touch and feel that cannot be found in other channels (Willmott, 2014). The way to reach customer satisfaction and engagement would be offering unique products and immediate availability (UPS, 2016). Even though it is not possible to discern if behavioural loyalty derives from a solid affective link or simply stems from greater convenience or accessibility, retailers aim to foster attitudinal and affective links with customers to the extent that it leads to desirable behaviours that contribute to their profit in the long run (Martos-Partal & Gonzalez-Benito, 2013).

Another reason why customers prefer to buy at a brick-and-mortar store is the fact that they can take the products with them immediately (Cap Gemini, 2017). When consumers face time pressures, they benefit more from quicker service, fast access, quick payment and so forth. Their switching costs also are higher, which should make them more store loyal (Martos-Partal & Gonzalez-Benito, 2013). Offering time savings solutions to customers in store should be one of the main objectives for retailers if they want to keep customers and attract new ones. The top reasons to shop at small retailers are because of their unique products (50%), for the community support (34%) , and because of sales associates' help (23%) (UPS, 2016). Nevertheless, the need to touch and feel is, by far, the most repeated reason among consumers (70%).

These results match with academic research and demonstrate that the one aspect that can provide advantages to traditional retailers of good repute is their outstanding capability to blend their unique resources such as reputation and physical presence with threshold resources like technology and product variety (Agnihotri, 2015). Almost half of shoppers say that engaging with them in innovative a creative ways to provide a multisensory experience influences their overall feeling of loyalty toward a brand (Accenture, 2017) and therefore, their purchase intention. Retailers should explore how to best use technology to move consumers through each of the stages in the purchase process (Burke, 2002).

2.3.2 Desktop only

As regards purchases that start and end on a desktop, one of the conclusions is that one of the most valued factors when shopping from a desktop is the ability to compare products and shops (Nelson & Leon, 2012). The ability to get discounts or compare prices is also important for half or more of shoppers. Price is also a determinant factor for shopping online only as well as convenience (time saving and delivery) (IAB, 2016). The main reasons to buy online stated by consumers are convenience, time saving and money saving (IAB, 2016). Contrasting with in-store shoppers, 40% of desktop consumers prefer self-service to human contact for their future contact with companies (HP, 2014). Another important reason is stock availability and delivery. One of the most important conclusions issued from the reports

is that 60% of consumers who start in web end in web (Ingenico, 2017). These conclusions are widely supported by academic literature (Degeratu et al., 2000; Demirkan & Spohrer, 2014; Picot-Coupey et al., 2016; Tsai & Huang, 2007).

2.3.3 Mobile Shopping

Mobile commerce is increasing by 200% more than online commerce (Ditrendia, 2016). In 2016, a 47% of online shops that had mobile responsive webs say they have increased their sales from 10 to 25% thanks to mobile transactions (Ditrendia, 2016). The reasons mobile users state for using a smartphone to shop are: convenience, price, immediate purchase, and mainly because of advertising prompting (IAB, 2016). Mobile shopping experiences have very strong emotional significance for customers (Thakur, 2016) and is becoming a trend among millennials and a threat for physical stores. Although several forecasts show the enormous future potential of mobile shopping, there is insufficient adequate literature which attempts to investigate all relevant aspects of this shopping path (Groß, 2015). 78% of mobile shoppers use it to compare prices and 68% to search for opinions (Ditrendia, 2016). In this case, convenience and time saving are the main reasons why customers choose this way of shopping. According to different reports (Ditrendia, 2016; Glass & Haller, 2017) mobile commerce is increasing drastically and will grow by almost 50% in the next years. 33% of consumers who start mobile end mobile (Deloitte, 2017b) and that means that it is one of the most important shopping channels to be aware of. Mobile technologies are crucial due to the gap between offline and online channels (Mosquera et al., 2017) and therefore, a key purchase path for omnichannel retailing as it integrates and offers the seamless experience that the customer is looking for.

2.3.4 Showrooming

Showrooming occurs when consumers use brick-and-mortar stores to evaluate goods in person, and then go online to purchase for a better price. Whereas in the multichannel phase research shopping gained some attention (Gensler et al., 2017), in the omnichannel phase instant showrooming is becoming an important issue (Verhoef et al., 2015). Shoppers now frequently search for information in the store (60% according to UPS, 2016) and simultaneously search on their mobile device to get more information about offers and may find more attractive prices (Rapp et al., 2015). In showrooming, consumers visit retailers' stores to "touch and feel" a product, but they consummate their eventual purchase online. In fact, about one-third of consumers say they have showroomed at some time (Fulgoni, 2014). The product and price transparency afforded by mobile technologies puts even more pricing pressures on physical retailers: either beat (or at least match) the online price or the shopper will walk out of the store empty-handed (Nelson & Leon, 2012). When asked why they showroomed, 73 percent said it was because the price was lower online (Fulgoni, 2014) Consumer showrooming behaviour has been critiqued widely because showroomers often end up buying from a competitor's website (Zimmerman, 2012). Showrooming is dangerous for retailers as real purchases may end up in another channel and even to another retailer. Nevertheless, it may still be beneficial to the retailer if consumers facing stockouts can be persuaded to make the purchase on the retailer's own online channel (Gao & Su, 2016). Showrooming works best for differentiated goods (Pricewaterhouse Coopers, 2017) and this allows retailers to create a competitive advantage over the competitors, either in the same shopping path or in a different one. Complementary services such as retailers' associates' help are important for the customer but price is still a very important factor. Searches and future purchases online are made based on price mainly. The threat to retail chains posed by showrooming and mobile commerce generally is overstated to the extent that in many cases the retailer will capture sales online that they previously might have transacted in a store (Nelson & Leon, 2012).

2.3.5 Webrooming

Webrooming is the way in which consumers research products online before visiting a brick-and-mortar store for final evaluation and purchase (Edwards, 2014). Consumers mainly use it for convenience, especially if they need a product immediately. This should become more common as in-store inventory visibility increases on e-Commerce sites. Also common for consumers who want to avoid shipping costs (Worldpay, 2015). Worldwide, 88% of consumers are seeking information online before buying in-store or in-app (Ingenico, 2017). Webrooming is becoming more and more popular as shows that in Spain, 53% of shoppers used the web to look for information prior to a purchase in 2015 and 65% did so in 2016 (Ivend, 2017). In product categories where the touch-and-feel of the new product is crucial for consumers and the benefits of online shopping are relatively small (e.g., apparel and accessories), this positive surplus of switch consumers is an increasing function of product quality (Luo & Sun, 2016). One of the main reasons why "webroomers" shop in stores is because of the immediate availability of the product, stock availability and personal interaction with shop associates. The same reasons as traditional shoppers, mainly. The need of touch and feel is important for most customers as well as immediate availability. Technology has changed the game when it comes to immediacy and reach of customer feedback, and it is also equipping retailers with better tools to listen and respond to those conversations (Rigby et al., 2014). Listening to customers should be a common practice among retailers. Even if customers research online prior to purchases, the need of "touch and feel" is more and more important. Thus, the atmosphere in the store plays an important role in the purchase process. Availability of stock and price are also key factors. Because the customer looks for information in the store and buys online, comparison tools and technology to experience how products would look in their homes is key for 41% of customers (Westfield, 2017).

2.3.6 Instant showrooming

When it comes to omnichannel paths, one of the main shopping practices is instant showrooming. The difference with showrooming is that the search is made in store and the purchase is also made there, at the same moment but through a different shopping channel. An important figure issued from our research is that 80% of smartphone shoppers use their mobile in store to help with shopping (Worldpay, 2015). Rather than simply providing web access in the store, retailers should optimize the interface for the in-store shopping environment (Burke, 2002). Customers while in store want to know if a wider rage is available online (Practicology, 2017) and also the price of a certain product. Customers acquired via showrooms (rather than stores) appear "conditioned" to accept online fulfilment and are therefore highly receptive to performing second and subsequent purchases directly online, at a cost greatly below that of serving repeat customers via stores (Bell et al., 2014).

The reason why customers follow an instant webrooming path is mainly because consumers find it important the ability to see or order an extended range of products on screen in-store. Availability of stock in the store is key to be able to offer the customer the sense of touch and feel they look for in a physical store (Neslin et al., 2006). Price is another reason why customers purchase online while in store. The fact that customers may buy not only from the same brand but also from other brands and stores is a key point for retailers. Consequently, retailers are starting to practice reverse showrooming, wherein they encourage bricks-and-mortar consumers to search their products online through kiosks or mobile apps, thereby increasing the likelihood of keeping the sale (Parise et al., 2016).

2.3.7 BOPS

The BOPS (Buy Online Pick up In Store) path combines both environments, online for purchases (see desktop consumers) and brick-and-mortar store. It is important to state that although 46% of BOPS customers have made additional purchases in store (UPS, 2016), still 39% of brands do not offer a click and collect service. With this functionality, the retailer shows online viewers the locations at which the items are available and gives customers the option to close the transaction online and then pick up the products at one of the retailer's locations shortly after closing the purchase (Galino & Moreno, 2014). Results from a study made by Galino & Moreno (2014) can be explained by two simultaneous phenomena: (1) additional store sales from customers who use the BOPS functionality and buy additional products in the stores (cross-selling effect) and (2) the shift of some customers from the online to the brick-and-mortar channel and the conversion of noncustomers into store customers (channel-shift effect) (Galino & Moreno, 2014). Convenience is the most valued factor among BOPS customers. They take the best of both worlds, online to search for information, and buy and the physical store to pick up and get the sense of touch and feel. The key point would be to attract more purchases from the customers who pick up in store and provide them with the convenience they expect not having to wait at queues.

Table 2 shows a summary of the different trigger factors according to the stages of the purchase process (information search, alternative evaluation and purchase) in every shopping path.

Table 2 Why do consumers use the different channels?

TS[1]	DO	MO	WR	IWR	SR	ISR	RS	BOPS
Personalisation	Price	Convenience	Stock	Price	Personalisation	Stock	Convenience	Price
Stock	Stock	Price	Price	Stock	Price	Price	Stock	Stock
Convenience	Convenience		Convenience		Stock			Convenience

2.4 Conclusions

2.4.1 Understanding purchase reasons

Understanding the customers purchase process and the reasons why they purchase again from the same brand is critical for firms. Customers now face multiple channels when looking for information, evaluating alternatives and purchasing. In an attempt to describe how important is every channel, we examined the different trigger factors of each channel and we have reached to the conclusion that the shopping experience is one only and that customers look forward to a seamless multichannel experience.

Each channel has positive and negative aspects and retailers need to be aware of what is perceived by customers as key factors in every channel so as to rearrange the offer through the different channels. Customers look for the best of all offerings: stock availability, convenience, price, service quality, atmosphere, personalisation and complementary services and use different channels to make their purchases. If a customer can use different channels from the same brand to complete a purchase, then it is more likely that they complete the purchase within the same brand. It is at the retailer's hands to provide customers with an omnichannel experience so as to reach the desired engagement and loyalty, that is, repeat purchases and to lower attrition rates when moving from one channel to another one.

[1] TS=Traditional Shopping, DO=Desktop only, MO=Mobile only, WR=Webrooming, SR=Showrooming, IWR=Instant Webrooming, ISR=Instant Showrooming, RS=Reverse showrooming

Customers expect a seamless experience across the physical and digital worlds because they have the ability to use mobile technology to easily find the information needed to support their buying decisions wherever and whenever they choose (Fulgoni, 2014). Looking at results, we can observe that brand reputation is not considered as an important factor by customers. This can be due to the fact that when choosing a certain brand, customers expect other additional benefits rather than the brand itself or due to the fact that the choice of the brand is made before the information search stage.

2.4.2 Foundation of the omnichannel concept

While traditional multichannel & E-Commerce literature contributed to the foundation of the omnichannel concept, additional literature in other areas provided useful knowledge regarding the simultaneous use of channels, which is the ultimate form of omnichannel and constitutes the prevalent behaviour of "omnishoppers" (consumers that use all channels simultaneously) (Lazaris et al., 2015). A truly omnichannel strategy means that firms must deliver consistent experiences, messages, content and processes to their customers across the available channels (Melero et al., 2016). Therefore, a conclusion that can arise from our research is that channels are more than channels and that they can be typologies of customers: the traditional customer, the "webroomer", the "showroomer", "the online shopper", the "m-shopper", etc.. Knowing the purchase process of these typologies of customers will lead to a deep knowledge of how they behave and what are the key touchpoints with brands.

Despite the introduction of new channels by firms and the importance that customers attach to obtain a satisfactory and personalized experience through all the interactions in any of the available channels, most companies continue to manage their channels individually and separately (Melero et al., 2016). Brands are starting to offer their customers solutions that combine the best of both online and offline shopping (Glass & Haller, 2017). Retailers are redefining the brand experience through new formats such as "click- and-collect", "delivery in 24 hours", "in-store ordering, home delivery", "order online, return to store", "click in store" and other combinations of online and traditional retail activities that facilitate and improve the shopping process and the customer experience (Bell et al., 2014). The consumer experience is determined by a mix of touchpoints to the brand, and how the retailer engages with each user in terms of providing immediate, personalized and emotional content will determine its success (Parise et al., 2016). The relationship between the brand and the customer goes beyond channels and in a seamless experience, channels interact and interfere one another. Omnichannel is moving towards a complete interaction of what could be defined as "interchannel", that is the total interaction of channels at every stage of the purchase process.

2.4.3 Final conclusions: Implications of omnichannel shopping

Omnichannel shopping has implications for all the actors in the purchase process. First the retailers because they need to avoid customers' attrition. Then the shop associates because they need to close deals after giving personal information and interacting with the customer. And finally, the customers themselves because they want the best of all worlds: the stock availability from online shops, the sense of touch and feel of physical stores and the convenience of BOPS. Giving customers what they want and guiding them through an omnichannel path should be the aim of retailers: allow the shift from one channel to another without losing the customer is key for acquiring new loyal customers. According to research made by Aberdeen Group companies that use an omnichannel strategy retain 89% of their clients and companies that do not use it, retain only a 33%.

As we have mentioned before, a process of reverse showrooming would help retailers keep customers loyal and therefore, help them to repurchase products or services from the same brand. In none of the reports we have studied is brand reputation a variable that customers take into account when repeating purchases. This must lead companies to rethink their communication strategies and give more importance to what is really valued so as to define a correct omnichannel strategy. Traditional shopping is not dying as some may think. It is only being transformed and fed with technological innovations that help customers make decisions. Immediacy and the need to touch and feel are vital for consumers. It is true that they come to the store much better informed but also with a higher disposition to purchase (Parise et al., 2016). They want to be treated personally and need to find a sales associate that answers precise questions (Worldpay, 2015). Training the sales force is key for retail stores as well as adapting to the last technology so that customers can complete their purchases on site and therefore, retain them. Knowing the factors that the customers value in different channels will help companies increase the client's life-time value and also increase the customers' interactions with the brand so as to build a brand engagement.

CHAPTER 3

USING HEURISTICS TO ATTRACT CUSTOMERS TO RETAIL STORES

As discussed in (Verhoef et al., 2017), customers today are changing the way they decide where, how, and even when to buy. With the rise of Internet-based technologies and mobile devices, different shopping channels have appeared and attracted the customers' attention. Hence, e-commerce not only offers customers the possibility of browsing through different stores in an online environment, but also the ability to get information, opinions, and a vast availability of stock. Omnichannel commerce is a fully-integrated approach to e-commerce that provides customers with a unified experience across different shopping platforms, e.g.: a personal computer, a physical retail centre, or a mobile device. In an omnichannel environment, retailers at brick-and-mortar stores have to compete with other channels, and especially with the showrooming behaviour of customers. Showrooming occurs when customers go to a brick-and-mortar store to `touch and feel' the product, but then complete the purchase online. Even when customers are now in the position of choosing where and when to buy, most brands still generate a noticeable part of their sales revenue at brick-and-mortar stores, so they play a relevant role in capturing customers' attention.

One of the strategies used by brick-and-mortar retailers to engage more customers is to offer them a variety of attractive products during a multi-period time horizon, which typically covers several weeks. As pointed out by (Galino & Moreno, 2014) ,in order to achieve this goal the retailer needs to decide which combination of products has to be shown at the store, so that their combined attractiveness is maximized. (Caro, Martínez-de-Albéniz, & Rusmevichientong, 2014) studied in detail the concept of product attractiveness in retail stores. According to their work, a product displayed for the first time attracts the customer's attention and, therefore, increases the probability of being bought. As time goes

by, the attractiveness of any product decays, and the retailer must release new products. Similarly, if customers see the same products exposed in a store during several consecutive time periods (days or weeks), their willingness to visit that store will decrease. That is why some popular retailers introduce new products into their stores almost on a daily basis. Attractiveness can also be measured by visual properties, and this is directly related to the existence of correlation between pairs of products (e.g., products that are complementary or substitutive). That is why retailers have to take into account customers' purchases that take place in channels different from brick-and-mortar stores. A large amount of data can be obtained from customers' behaviour and preferences in an omnichannel environment.

These data can provide retailers with vital information, such as which products raise a higher attraction level among customers of a certain retail store. Hence, identifying the best assortment of products to display has to be made considering customers' preferences (Honhon, Gaur, & Seshadri, 2010). Selling strategies for retail stores should have the ability to offer customers a set of different surprising experiences. Using display tables to recommend a set of correlated articles on retail stores is one way to achieve the aforementioned goal. In the apparel sector, for example, a yellow sweater may be positively correlated with a white pair of jeans but negatively correlated with orange trousers (since yellow and orange are not colours that match according to certain fashion trends). Likewise, a skirt might be positively correlated with a top and negatively correlated with a pair of jeans, since both cloth pieces are bottom parts. Again, data gathered in an omnichannel database could be one of the most efficient ways to determine these correlation values between pairs of products.

In order to recommend an attractive assortment of products to their customers, retailers have to deal with the so-called product recommendation problem (PRP), which was introduced by (Karlgren, 1990). Figure 3 shows a schematic representation of a PRP solution with 50 items, 3 display tables with a capacity of 5 items each, and a 2-period time horizon.

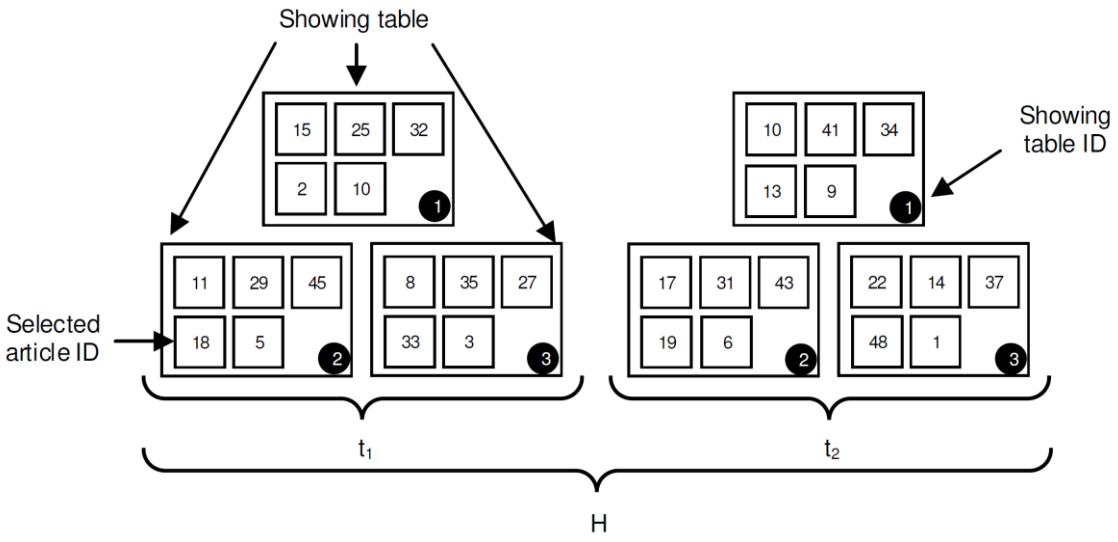

Figure 3: A solution representation for a simple PRP example

An effective product recommendation system should always consider the customers' preferences and willingness (Choi, Kang, & Jeon, 2006). Current recommendation systems in online shops provide a list of products which are either based on the user's past behaviour or on decisions made by `similar' users. This recommendation strategy has been widely applied in e-commerce, where it has been able to generate benefits in raising both sales as well as customers' satisfaction (Kaminskas et al., 2017). Companies such as Amazon, for example, use a method called collaborative filtering. Here, ratings and purchases made by similar users are considered to recommend products to online customers (Ahn, 2008). The PRP is also an important problem for brick-and-mortar stores, since they might clearly benefit from an optimal selection of products to be allocated on display tables over time.

The main contributions of this research are described next:

(i) a novel mathematical formulation for the multi-period PRP is proposed with the purpose of clearly define the problem under consideration;

(ii) in order to solve this optimization problem in the context of a retail store with several display tables, an original biased-randomized algorithm is proposed;

(iii) a set of novel benchmark instances, considering realistic constraints and different product characteristics, is proposed to test the quality of our approach; and

(iv) from the experimental results, some managerial insights are derived. A recent review on biased randomization of heuristics can be found in Grasas et al. (2017). Regarding the constraints considered in this work, they include diversity of fashion collections, selling-price categories, and marginal-profit categories. The rest of the paper is arranged as follows: Section 3.1 presents a brief literature review on related research; Section 3.2 describes the addressed problem in more detail and provides a mathematical formulation for it; Section 3. 3 introduces the proposed biased-randomized algorithm; Section 3.4 includes an explanation of the computational experiments carried out to test the quality of our approach, while Section 3.5 contains an analysis of the results; finally, Section 3.6 highlights the main conclusions of this work and proposes some lines for future research.

3.1 Related Work

Product recommendation and stock optimization have been widely studied in the academic literature from different perspectives, e.g.:stockout-based substitution (where customers choose the products that are available at the time of their visit to the physical store) (Honhon et al., 2010), management of multi-item retail inventory systems with demand substitution (Smith & Agrawal, 2000), or dynamic assortment planning with demand learning (Sauré & Assaf, 2013). (Sherman, Mathur, & Smith, 1997) concluded that profitability depends on incorporating substitution effects in the inventory management. This increases the demand for other items and affects the optimal stock levels. (Sauré & Assaf, 2013) stated that it is vital for retailers to select what products to offer due to the limited display capacity in the physical stores. They described different stock assortment policies and introduced a model for dynamic assortment planning. (Honhon et al., 2010) also presented a dynamic programming algorithm to determine the optimal assortment in a single-period problem with stock out-based substitution. (Rajamma et al., 2007) described a method for resolving inventory depth and variety breadth and the mix between basic and seasonal pieces of clothing in fashion retail. Strategic decisions on the right variety and depth of in-the-shop stock have been developed by (Mantrala et al., 2009). These authors provided reviews about how to customize the retail assortment at the store level, rather than simply using a centrally planned assortment for all stores. A complete review on stock assortment is provided by Kök, Fisher, & Vaidyanathan (2009).

As identified by Mantrala et al. (2009), product assortment not only has the constraints of physical space and retailers' budget, but also an attractiveness factor -as perceived by customers- should

be taken into account too. In Caro et al.(2014), the authors consider a problem in which the attractiveness of products decays over time once they are introduced in the selected assortment. In the presented formulation, there is a need to decide in advance the timing when each product is introduced in the selected assortment. A related study on space and store operations can be found in Mou, Robb, & DeHoratius (2017) . These authors also consider how attractiveness decreases with time, and the need for retailers to gather information from different channels in order to better plan their stock assortment.

The product recommendation problem has received increasing attention in recent years. According to Liu & Shih (2005), "recommender systems rely on customer purchase history to determine customer preferences and to identify products that customers may purchase''. Figure 4 shows the time and evolution in the number of Scopus-indexed articles which include in its title the terms "product" and "recommendation". Notice that the initial documents on this topic go back to 1973, but it is only in the late 90s when they show a nearly-exponential growth. Figure 5 illustrates the subject areas where product recommendation problems have been analysed. These include, in order of influence: computer science, engineering, medicine, and business management.

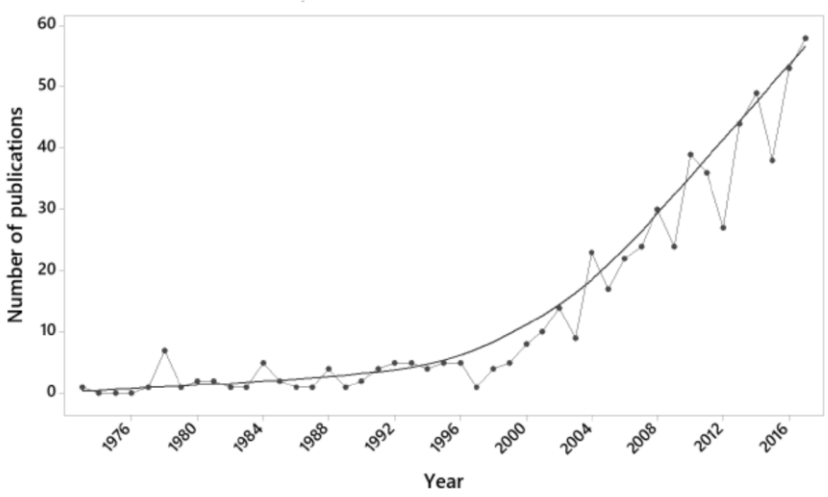

Figure 4 Evolution of Scopus-indexed publications including in its title the words "product" and "recommendation".

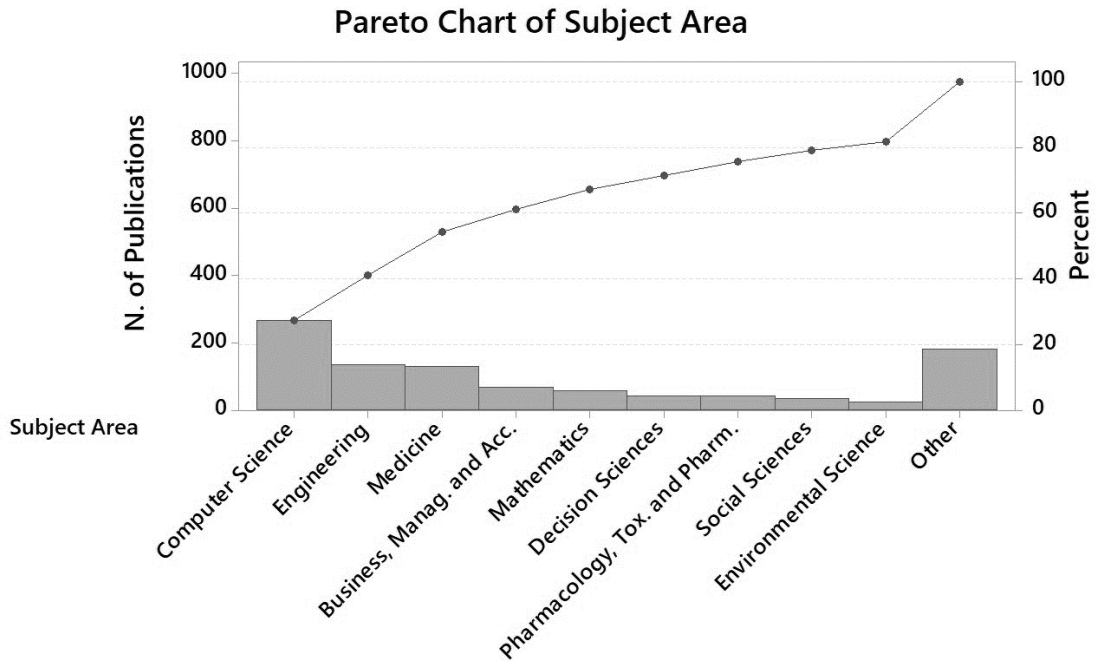

Figure 5 Subject area of publications which include the words "product" and "recommendation

Regarding the product recommendation problem, (Li et al., 2014) proposed a framework for a localized product recommendation system associated with automatic vending machines. Their system offers suitable recommendations of localized products to customers in different locations. They developed a hybrid technique using a metaheuristic approach, a clustering technique, as well as classification and statistical methods. The importance of product recommendation in today's omnichannel retailing world is also mentioned by Balakrishnan, Cheng, Wong & Woo (2018). These authors adopted an intuitive co-clustering algorithm for locating useful patterns in a *0-1 matrix*, which studies buying behaviour of customers using historical data on past purchases. In order to handle the product recommendation problem for e-commerce applications, (Baykal, Alhajj, & Polat, 2005) proposed a co-operation framework for multiple role-based reasoning agents. (Choi & Cho, 2004) presented a similar product-finding algorithm for the collaborative business companies that share the product taxonomy table and have exchangeable products information. The proposed algorithm computes the aggregated utility ranges over specification values of products in the same product class, and finds similar ones between the products.

Choi et al. (2012) proposed an online product recommendation system, which combines implicit rating-based collaborative filtering (CF) and sequential pattern analysis (SPA). The proposed system derives implicit ratings by applying CF to online transaction data (even when no explicit rating information is available), and integrates CF and SPA for improving the recommendation quality.

Zhao et al. (2014) developed a novel product recommender system called METIS. This system identifies, almost in real time, users' purchase trials from their microblogs. Then, it makes product recommendations based on matching the users' demographic information --extracted from their public profiles-- with product demographics learned from these microblogs and additional online reviews. Zhao et al. (2016) proposed a novel solution for `cross-site' and `cold-start' product recommendation, which aims at recommending products from e-commerce websites to users at social networking sites in cold-start situations. They proposed learning both users' and products feature representations via collected data from e-commerce websites, using recurrent neural networks, and then applying a

modified gradient boosting trees method to transform users' social networking features into user embeds. More recently, Kaminskas et al., (2017) addressed a particular product recommendation problem regarding small-scale retail websites, where the small amount of returning customers makes traditional user-centric personalization techniques inapplicable. Hence, these authors applied an item-centric product recommendation strategy that combines two well-known methods --association rules and text-based similarity-- for generating recommendations based on a single `seed' product. Furthermore, their approach is also used to recommend products based on a set of seed products in a user's shopping basket. The effectiveness of their recommendation approach is demonstrated, in the product-seeded and basket-seeded scenarios, through a series of experiments employing real customer data.

Product recommendation systems are related to the product assortment problem: a set of correlated products must be selected to be exposed (or recommended) in an exposition area with limited capacity. This selection of products should help to improve the experience of customers when visiting a store. In effect, by exposing an appropriate set of items at the showing tables it is possible to increase the level of attraction of customers to the store, which directly influences the customers' experience and, hence, the sales revenue. Although this Section shows that research has been done on both product recommendation systems and the product assortment problem, there is still a lack of works regarding how to combine different products in retail display tables at brick-and-mortar stores, especially when considering a multi-period time horizon.

3.2 A formal description of the Multi-Period PRP

Consider a warehouse hosting a set of products or items. This warehouse has to supply a retail store at different time periods. Each item belongs to a certain collection (e.g., shirts, jeans, etc. in the case of clothes), has a selling price, and a marginal profit which is typically given as a percentage of the selling price. Depending on its selling price, an item is classified as 'expensive' or not. A planning horizon is defined by a set of time periods, and at any given period, the retail store contains a set of tables, each of them displaying a subset of non-repeated items. Each item has an initial attractiveness value, which is estimated from historical observations in an omnichannel environment. The attractiveness value can also depend upon other items currently being displayed in the table, since correlations between pairs of products might need to be considered.

Among all the available products in the warehouse, a subset of different items should be selected to be exposed at the retail display tables. The dependency between each pair of items is registered in a dependencies matrix. The attractiveness value of each item is reduced by a known quantity (typically expressed as a percentage) every time the product is repeatedly shown in two (or more) consecutive periods. In other words, if an item is repeatedly exposed during several consecutive periods of time, its novelty disappears and, and as consequence, its attractiveness value is reduced. On the other hand, whenever an item has not been shown in the previous period, its attractiveness value is increased due to the novelty effect.

The goal is then to solve a multi-period PRP in which a subset of items has to be selected to be displayed at each table-period combination in order to maximize the aggregated attractiveness level over all periods.

A number of additional constraints are also considered in this study in order to make the problem more realistic:

- *Collection constraint:* the subset of items assigned to each table should cover at least a given percentage of goods from each collection or category.
- *Price constraint:* a minimum number of products at each table should belong to a given price category (e.g. expensive or not).
- *Profit constraint:* the profit margin of each table should be greater than a manager-defined threshold.

3.2.1 Mathematical Formulation

Let it I be a finite set of items, which are hosted in a warehouse. Each item $i \in I$ is associated with a manufacturing price $p_i > 0$, a marginal benefit $m_i \geq 0$, and an initial attractiveness value $v_{i0} > 0$. A final selling price of each item $i \in I$ is given by $p'i > 0$, in which the marginal benefit is included.
The subset of expensive items is given by $I_p = \{i \in I / p_i \geq p_0\}$, where p_0 is a minimum price value defined by the user.

A subset of items should be exposed at a set of homogeneous tables T, during a set of time periods H. The decision variable x_{ith} is equal to 1 if item i is selected for table t in period h, and to 0, otherwise. Thus, the set of non-repeated selected items for each table $t \in T$ in period $h \in H$ is given by $S_{th} = \{i \in I / x_{ith} = 1\}$. The complete set of non-repeated items in period $h \in H$ is represented by $S_h = \bigcup_{t \in T} S_{th}$.
To represent the dependency level between any pair of items, we consider a dependencies matrix $D = [d_{ij}]_{i,j \in I}$. The attractiveness value of item i in period h is a function f of its attractiveness value in the previous period and the composition of the table in that previous period, i.e., $v_{ih} = f(v_{i(h-1)}, S_{h-1})$.

With this notation, the addressed problem can be formulated as follows:

$$Max \sum_{h \in H} \sum_{t \in T} \sum_{i \in I} v_{ih} x_{ith} + \sum_{h \in H} \sum_{t \in T} \sum_{i \in I} \sum_{j \in I / i<j} D_{ij} x_{ith} x_{jth} \quad (1)$$

Subject to:

$$\sum_{t \in T} x_{ith} \leq 1 \qquad \forall i \in I, \forall h \in H \quad (2)$$

$$\sum_{i \in C_k} x_{ith} \geq l_c \qquad \forall c_k \in C, \forall t \in T, \forall h \in H \quad (3)$$

$$\sum_{i \in I_p} x_{ith} \geq l_p \qquad \forall t \in T, \forall h \in H \quad (4)$$

$$\sum_{i \in I} (p'_i - p_i) x_{ith} \geq l_m \qquad \forall t \in T, \forall h \in H \quad (5)$$

$$x_{ith} \in \{0, 1\} \qquad \forall i \in I, t \in T, h \in H \quad (6)$$

The objective function (1) maximizes the total attractiveness of the planning horizon by considering individual attractiveness of the items and the relation among the selected items at each showing table. Equation (2) guarantees that each item i at each period h cannot be selected more than once. Equation (3) confirms that each table covers at least l_c items from each collection c_k. Equation (4) guarantees that each table consists of at least l_p expensive items. Equation (6) ensures that the profit margin of each table should be greater than l_m. The values of l_c, l_p, and l_m are previously defined by the user.

3.3 Heuristic-based Solving Approaches

In this study, three different heuristic-based algorithms are proposed to solve the multi-period PRP. Each of these algorithms consist of two stages: (i) a construction stage, in which a feasible initial solution is built taking into account the constraints; and (ii) an improvement stage, in which a local search is applied to the initial solution in order to enhance its quality. During the first stage, three alternative strategies to select the items are taken into consideration: uniform random, completely greedy, and biased (non-uniform) random. The improvement stage is based on a relatively simple local search procedure that is applied to the initial solution until some stopping criterion is reached. This two-stage procedure is applied repeatedly for each time period until all periods are considered.

In the heuristic-random (HR) strategy, each article is randomly chosen following a uniform probability distribution, i.e.: each item has the same probability of being chosen during the solution-construction process. In the heuristic-greedy (HGs) strategy, the item with the highest individual attractiveness value is selected at each selection step during the solution-construction process. In the heuristic with a biased-randomized (HBRs) strategy, products are sorted into a list according to their individual attractiveness level and then different probabilities of being selected are assigned to them, i.e.: the higher the attractiveness value, the higher the probability of being selected. In our case, this biased-randomization strategy is induced by a Geometric probability distribution, as proposed in Juan et al., 2013) . The three heuristics described can be considered as `static' in the sense that they do not consider the correlation matrix among items in the table. Since these dependencies might generate important changes in the total attractiveness value of the display table, two `dynamic' variants of the greedy and the biased-randomized heuristics are considered: HGd and HBRd. Thus, unlike HGs and HBRs, which only consider the individual attractiveness value at each selection step, the HGd and HBRd consider the total cost effect, including attractiveness and dependency when adding each item to the current solution.

We will assume that the showing tables at the retail store are empty at the beginning of the first period of the planning horizon. Also, each product is assumed to have a given initial attractiveness value, which is based on historical observations and, possibly, some expert judgment. Then, for each of the aforementioned selection strategies a subset of products to show is selected from the available ones. At each period of the planning horizon, the attractiveness value of each item is updated according to whether or not it has been included in the display table during the previous period. Additional details on each of the two stages are given below.

3.3.1 Construction of the initial solution stage

Following one of the alternative selection processes, an initial solution is built by adding products to the display tables. In order to guarantee the feasibility of the solutions, some 'repairing' rules are considered to convert infeasible solutions into feasible ones.

For each period, a subset of items is assigned to a given display table. First, a subset S_{th} is built by selecting n products according to one of the three rules (uniform-random, greedy, or biased-randomized) for table t at period h. At this point, the collection constraint (constraint 1) is incorporated into the construction procedure by selecting a (manager-defined) minimum number of items from each collection. This procedure guarantees the feasibility of the first constraint. Next, the satisfaction of the price (constraint 2) and profit (constraint 3) constraints is checked for S_{th} subset. If all the constraints are

satisfied, the next table is considered; otherwise, the solution is repaired. The repair process selects an item from S_{th} and replaces it by another one selected among those that, by their characteristics, can help to satisfy the price and / or profit constraints. In the HR, both items are randomly chosen, while in HGs and HGd, the less attractive and less expensive items currently displayed at the table are replaced by the most attractive and costly ones, respectively. The repair in HBRs and HBRd works in a similar way, but considering the biased-randomization strategy when selecting the replacing items. Therefore, in the case of the price constraint, the selection process is based on the replacement of items from one price category (e.g., non-expensive ones) by products belonging to another one (e.g., expensive ones). In the case of the profit constraint, the selection process is based on the replacement of items with a low profit margin by products with a higher profit margin. The selected product is then added to the S_{th} subset and the constraint satisfaction condition is checked again. This process is repeated until a feasible partial solution is eventually achieved.

When a feasible subset is obtained for a given display table, the corresponding configuration is saved and the process is re-started from scratch to generate a new subset of products for the next table. Figure 6 illustrates the construction process

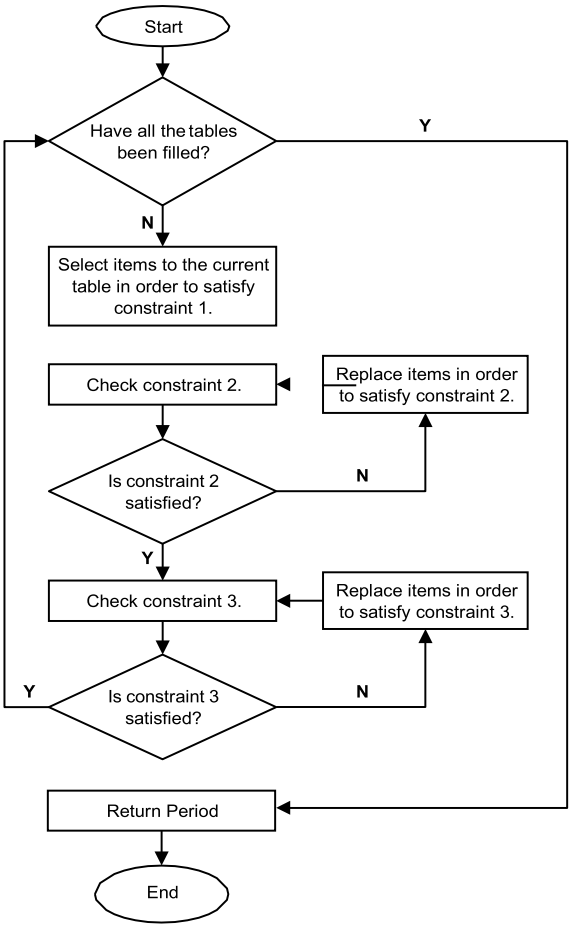

Figure 6 Constructing an initial solution for a given period

The next stage is the improvement of the initial solution using a local search procedure, which is based on the random improvement method described next.

3.3.2 Improvement stage

The local search procedure is applied to the items assigned to each display table, and works as follows (Pseudocode 1): starting from the first table t and the first period h, a randomly-selected item a is removed from S_{th} and replaced by a non-selected (available) product b from I, that can be inserted without violating any constraints. As a result, a new table t' is generated. The attractiveness value of t' is updated taking into account the dependency between pairs of items. If its attractiveness value (*table Attractiveness*$_{t'}$) is greater than that one in t (*table Attractiveness*$_{t}$), then table t' is accepted as the new t, and the search restarts with this new table. Otherwise, another item is randomly chosen from S_{th} and replaced by a randomly chosen available product from I. This process is repeated for table t until a certain number of replacements is executed without obtaining any improvement. The same process is applied to the remaining tables of the period and repeated until all the periods have been considered.

Algorithm 1: Improvement Algorithm

Data: period h, maximum number of iterations with no improvement MAX

Result: best obtained period h^*

```
articleToRemove ← null;
articleToInsert ← null;
for each table t ∈ T of h do
    counter ← 0;
    while counter < MAX do
        t' ← t;
        itemToRemove ← random item a ∈ S_{t'h} from t';
        itemToInsert ← random non-selected article b ∈ I that keeps the feasibility of t';
        Remove itemToRemove from t';
        Insert itemToInsert into t';
        Update total attractiveness and correlation of t';
        if tableAttractiveness_{t'} > tableAttractiveness_t then
            t ← t';
            counter ← 0;
        else
            counter ← counter + 1;
        end
    end
end
```

Algorithm 1 Improvement Algorithm

3.4 Computational experiments

This section describes the experimental setup to evaluate the performance of the five proposed heuristics (HR, HGs, HBRs, HGd and HBRd). As explained before, these heuristics use the selection strategies of uniform-random, greedy, and biased-random. To the best of our knowledge, this is the first work employing heuristics to maximize the attractiveness of products assigned to display tables in a

multi-period horizon. Hence, we had to generate a complete set of benchmarks with different characteristics to comprehensively evaluate and test the proposed heuristics. These characteristics are: number of articles ($|I|$), number of showing tables ($|T|$), number of collections ($|C|$), and number of items per display table (n). More specifically, we set $|I| \in \{500, 1000, 1500, 2000\}$, $|T| \in \{5, 10\}$, $|C| = 4$ (basic-top, basic-bottom, fashion-top, and fashion-bottom), and $n = 10$. Therefore, the total number of instance combinations is $4 \times 2 \times 1 \times 1 = 8$. For each combination, 5 different instances were generated, thus resulting in a total of 40 test instances. Each of these instances was named according to these specifications. Thus, for example, instance *a500m5i1* consists of 500 products and 5 tables. The last index represents different instances using the same combination. In order to facilitate reproducibility of the experiments, all the generated instances are publicly available at https://osf.io/wfqnt.

The final selling price of each product is generated according to a uniform distribution in the range [10, 150]. The profit margin percentage for each product follows a uniform distribution in the range [10%, 35%]. The price and profit margin are considered to generate the absolute profit, which is used to check if the respective constraints are satisfied. The initial attractiveness value for each item and the correlation value between any pair of items are generated according to a uniform distribution in ranges [10, 100] and [−35, 35], respectively. The planning horizon of the problem considers one season, which is divided into 12 weeks, i.e.: $h = 12$.

Regarding the considered constraints, the subset of selected products at each table should cover at least 20% of each collection. The products, respect to their price, are categorized into two different categories: those products which cost less than 60 monetary units are considered as non-expensive; otherwise, they are considered as expensive. In our experiments, it was requested that the selected subset at each table should include at least 50% of expensive products. Finally, for each table, the marginal profit that each subset of selected products should provide is requested to be 100 monetary units or more.

To account for the `novelty factor', when a product is displayed on a table during a given period, its attractiveness value is decreased by a 10\% for the next period (always considering that the minimum attractiveness value that a product can reach is 0). Conversely, if a product is not displayed at a given period, its attractiveness value increases by the same percentage for the next period (also considering that the maximum attractiveness value that a product can reach is 100).

After some initial tests, a Geometric probability distribution with a parameter β randomly chosen in the interval (0.80, 0.99) has been used for the biased-randomization process during the solution-construction stage. Regarding the improvement stage carried out by the local search, the stopping criterion is set to 1000 iterations without observing any improvement. Our proposed heuristics are coded in Java. In order to perform all tests, a standard PC with an Intel Core i5 CPU at 2.7 GHz and 8 GB RAM has been employed.

3.5 Analysis of results

For each of the 40 instances, a total of 5 runs are executed (each run using a different seed for the pseudo-random number generator). This results in 40 x 5 = 200 executions per heuristic. In order to evaluate the performance of each heuristic, we consider the percentage gap between the best solution found using that heuristic (i.e., the one with the highest attractiveness value) and the best-known solution (BKS) obtained with any heuristic. Thus, the lower this gap is, the better the performance of the heuristic will be.

Table 3 provides the summarized results of the best-found solutions for each instance and heuristic. The following data is provided: attractiveness value associated with the best solution found by the corresponding heuristic, gap with respect to the BKS, and CPU time requested to find the corresponding solution. The best-found solution for each instance is presented in bold. The RPD

represents the distance (in terms of value) between a specific solution and the best-found solution, both from the same instance and test specifications. The higher the RPD is, more distant a solution is from the best-known solution.

Notice that HBRd performs better than the other heuristics, providing the BKS for all instances. As mentioned before, during the selection strategy, HGd and HBRd consider both the individual attractiveness value as well as the correlation effect, while the rest of the heuristics just focus on the attractiveness value during that constructive stage. Also, the CPU time employed by each approach is summarized in Table 3. As results show, the heuristics which use a greedy selection strategy execute extremely fast, while the biased-randomized heuristics consume some more CPU time although they still in the order of seconds.

Best Solution (attractiveness)						Gap (%) w.r.t. BKS					AVg. CPU Time (s)				
Instance	HR	HGs	HBRs	HGd	HBRd	HR	HGs	HBRs	HGd	HBRd	HR	HGs	HBRs	HGd	HBRd
a500m5i1	120,590.77	119,142.09	122,345.82	121,039.31	**122,402.64**	1.48	2.66	0.05	1.11	**0.00**	0.82	0.68	6.41	0.51	6.36
a500m5i2	120,894.57	121,051.35	122,838.66	121,681.37	**123,815.08**	2.36	2.23	0.79	1.72	**0.00**	0.73	0.71	6.46	0.52	6.38
a500m5i3	120,627.40	120,130.66	122,228.00	121,563.79	**122,797.19**	1.77	2.17	0.46	1.00	**0.00**	0.74	0.73	6.38	0.52	6.41
a500m5i4	120,497.17	119,978.98	122,270.61	121,554.69	**123,537.01**	2.46	2.88	1.03	1.60	**0.00**	0.70	0.69	6.43	0.60	6.43
a500m5i5	120,696.11	120,205.90	122,356.09	122,078.86	**123,573.06**	2.33	2.72	0.98	1.21	**0.00**	0.73	0.80	6.42	0.52	6.32
a500m10i1	216,149.47	214,622.88	217,737.49	217,251.51	**219,876.93**	1.70	2.39	0.97	1.19	**0.00**	1.35	1.36	6.76	0.99	6.78
a500m10i2	216,364.27	215,684.43	218,487.15	218,535.66	**220,515.96**	1.88	2.19	0.92	0.90	**0.00**	1.32	1.35	6.90	1.01	6.73
a500m10i3	214,736.11	213,362.90	215,687.05	215,827.33	**217,711.69**	1.37	2.00	0.93	0.87	**0.00**	1.34	1.28	6.88	1.09	6.78
a500m10i4	215,322.60	213,690.51	216,841.91	217,089.80	**219,574.05**	1.94	2.68	1.24	1.13	**0.00**	1.52	1.26	6.85	1.02	6.76
a500m10i5	211,591.00	211,335.47	213,671.98	213,985.00	**216,096.03**	2.08	2.20	1.12	0.98	**0.00**	1.44	1.36	6.86	1.03	6.77
a1000m5i1	133,369.98	132,357.15	135,454.45	135,805.84	**137,835.60**	3.24	3.97	1.73	1.47	**0.00**	1.07	1.09	12.51	0.68	12.41
a1000m5i2	134,138.63	133,377.50	135,781.31	136,786.37	**138,615.12**	3.23	3.78	2.04	1.32	**0.00**	1.09	1.00	12.60	0.71	12.40
a1000m5i3	132,895.41	132,115.56	134,996.12	135,719.43	**137,129.82**	3.09	3.66	1.56	1.03	**0.00**	1.10	1.04	12.51	0.70	12.43
a1000m5i4	132,575.78	133,207.75	134,835.08	134,994.26	**137,250.28**	3.41	2.95	1.76	1.64	**0.00**	1.08	1.07	12.62	0.72	12.46
a1000m5i5	133,828.45	133,169.56	135,431.85	136,079.06	**137,850.15**	2.92	3.40	1.75	1.28	**0.00**	1.08	1.04	12.56	0.71	12.37
a1000m10i1	246,595.17	246,351.63	249,194.24	252,375.41	**254,533.47**	3.12	3.21	2.10	0.85	**0.00**	2.19	2.00	13.23	1.32	12.91
a1000m10i2	243,657.12	242,788.15	245,701.29	249,079.17	**251,202.27**	3.00	3.35	2.19	0.85	**0.00**	1.97	2.04	13.30	1.42	12.96
a1000m10i3	245,604.12	244,336.73	246,822.37	251,151.06	**252,817.65**	2.85	3.35	2.37	0.66	**0.00**	2.03	1.93	13.15	1.40	12.94
a1000m10i4	245,638.65	243,430.06	246,149.55	250,389.43	**251,894.22**	2.48	3.36	2.28	0.60	**0.00**	2.22	1.89	13.14	1.39	12.88
a1000m10i5	247,401.81	245,424.83	248,445.64	251,555.98	**253,891.69**	2.56	3.33	2.15	0.92	**0.00**	2.01	1.85	13.25	1.39	12.91
a1500m5i1	138,056.84	137,917.79	140,069.13	141,859.93	**143,445.16**	3.76	3.85	2.35	1.11	**0.00**	1.48	1.41	18.80	0.92	18.56
a1500m5i2	139,967.30	139,694.49	141,952.97	144,373.60	**145,845.62**	4.03	4.22	2.67	1.01	**0.00**	1.61	1.44	18.75	0.87	18.53
a1500m5i3	139,526.03	137,919.37	140,679.93	142,519.64	**144,490.54**	3.44	4.55	2.64	1.36	**0.00**	1.63	1.41	18.73	0.86	18.54
a1500m5i4	138,459.79	137,130.84	140,425.95	142,193.86	**144,080.40**	3.90	4.82	2.54	1.31	**0.00**	1.53	1.28	18.71	0.99	18.50
a1500m5i5	138,779.24	137,638.32	139,652.47	141,783.12	**144,176.42**	3.74	4.53	3.14	1.66	**0.00**	1.55	1.34	18.78	0.85	18.56
a1500m10i1	261,118.98	259,486.86	262,728.13	269,106.02	**270,917.30**	3.62	4.22	3.02	0.67	**0.00**	2.99	2.64	19.71	1.64	19.12
a1500m10i2	259,822.00	258,872.52	261,620.95	268,609.28	**269,812.29**	3.70	4.05	3.04	0.45	**0.00**	2.71	2.56	19.65	1.65	19.23
a1500m10i3	260,226.71	258,365.65	261,996.35	267,418.43	**269,755.09**	3.53	4.22	2.88	0.87	**0.00**	2.75	2.62	19.51	1.57	19.19
a1500m10i4	261,021.15	259,544.65	262,843.74	268,989.30	**271,298.86**	3.79	4.33	3.12	0.85	**0.00**	2.79	2.63	19.54	1.67	19.04
a1500m10i5	258,895.08	259,612.90	261,414.76	266,737.45	**268,990.10**	3.75	3.49	2.82	0.84	**0.00**	2.78	2.68	19.55	1.80	19.14
a2000m5i1	141,111.13	141,235.80	143,453.06	146,961.64	**148,678.06**	5.09	5.01	3.51	1.15	**0.00**	1.88	1.70	24.92	1.09	24.60
a2000m5i2	140,832.82	141,150.06	143,323.51	146,675.20	**148,000.13**	4.84	4.63	3.16	0.90	**0.00**	1.87	1.74	24.85	1.03	24.58
a2000m5i3	141,802.91	142,272.53	144,375.44	148,157.39	**149,120.72**	4.91	4.59	3.18	0.65	**0.00**	1.80	1.78	24.88	0.97	24.63
a2000m5i4	142,141.22	142,589.71	145,060.40	148,905.45	**149,507.33**	4.93	4.63	2.97	0.40	**0.00**	1.85	1.66	24.95	1.01	24.62
a2000m5i5	142,187.31	141,921.72	144,795.92	148,434.00	**149,772.73**	5.06	5.24	3.32	0.89	**0.00**	1.81	1.71	25.03	1.03	24.60
a2000m10i1	269,426.70	268,127.07	271,648.59	280,739.35	**281,913.33**	4.43	4.89	3.64	0.42	**0.00**	3.65	3.38	26.03	2.05	25.22
a2000m10i2	270,141.55	269,185.17	271,856.39	279,775.80	**281,691.62**	4.10	4.44	3.49	0.68	**0.00**	3.58	3.38	25.86	1.99	25.20
a2000m10i3	270,586.32	269,205.51	273,288.89	280,236.34	**282,624.29**	4.26	4.75	3.30	0.84	**0.00**	3.49	3.16	25.84	2.11	25.26
a2000m10i4	270,043.76	268,257.41	270,841.94	279,120.77	**280,529.36**	3.74	4.37	3.45	0.50	**0.00**	3.58	3.29	26.06	2.00	25.31
a2000m10i5	269,765.15	268,208.43	271,563.35	279,919.68	**281,645.28**	4.22	4.77	3.58	0.61	**0.00**	3.60	3.42	25.82	2.01	25.36
Average	-	-	-	-	-	3.30	3.70	2.26	0.99	0.00	1.89	1.76	16.03	1.16	15.75

Table 3 Comparison of the results obtained using different heuristic approaches.

Figures 7 and 8 show, respectively, boxplots of the percentage gaps with respect to the BKS for the best-found and all-obtained solutions. As can be seen, the behaviour of the proposed heuristics in both figures is coherent. HGd and HBRd, which consider both individual attractiveness value and correlation effect, perform better than the other heuristics –which only consider individual attractiveness. Notice also that the performance of the two heuristics with same selection strategy changes when the correlation effect is considered: HGd and HBRd perform better than the HGs and HBRs, respectively. According to the results, the HR performs better than HGs. This observation indicates that the efficiency of the greedy selection strategy is reduced when the correlation is not considered during the selection process.

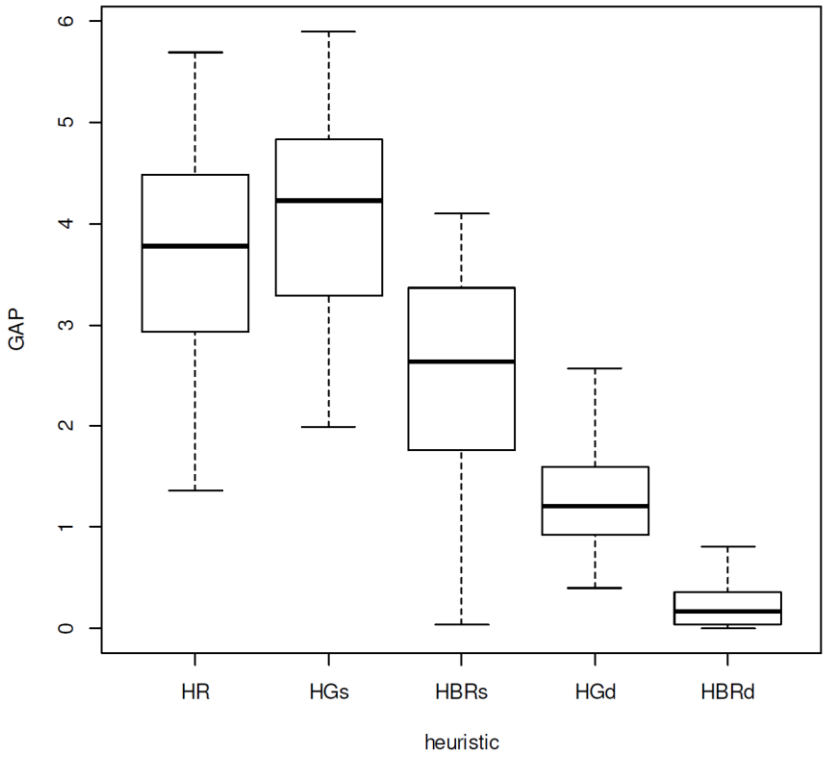

Figure 7 Boxplot representing the performance of each heuristic by analysing its best-found solutions

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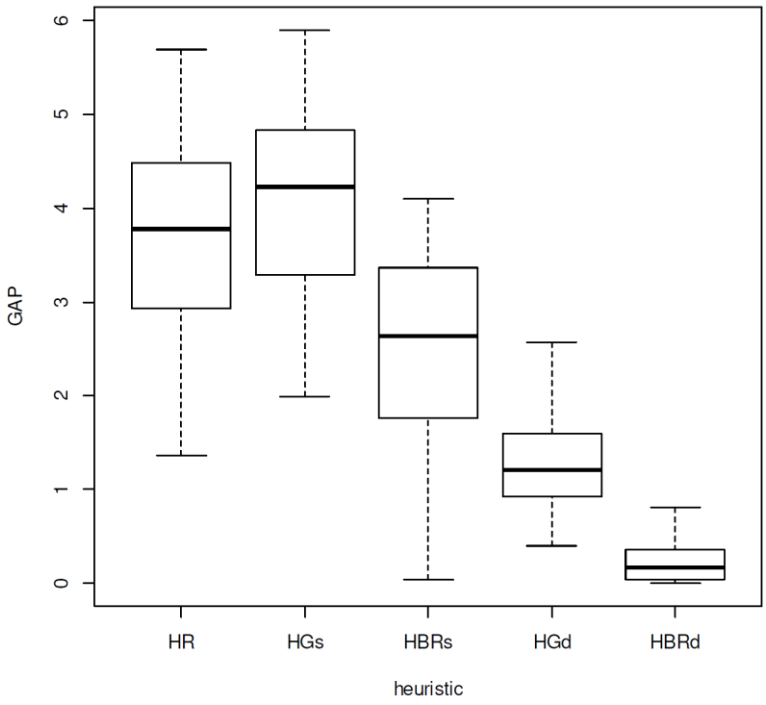

Figure 8 Boxplot representing the performance of each heuristic by analysing all the generated solutions

3.6 Conclusion

Increasing levels of competitiveness not only among brands but also among channels of the same brand make it difficult for retailers at brick-and-mortar stores to engage customers while in the shop. One of the ways to attract clients to the stores is to offer a different experience and a factor of surprise. Recommending a set of correlated and attractive products on retail display tables that vary often is a promising way to engage customers with such an attractive experience. From a managerial perspective, being able to know the best selection of products that best appeal to customers means a rationalization of the stock shown at every store. Moreover, the fact that the system can offer results in a very short lapse of time, increases productivity of the employees in charge of such stock decisions.

In this research, five different heuristics are proposed to solve the associated multi-period product recommendation problem, in which a set of correlated products has to be selected over multiple periods of time in order to maximize the total attractiveness level of the display tables in a retail store. A number of realistic constraints have been incorporated to the problem in order to increase its realism.

As solving approaches, five alternative heuristics -employing different selection criteria and a common local search- have been proposed. To test these methodologies, a complete set of instances was generated by considering realistic assumptions and different design factors. In this approach, it is assumed that the attractiveness value of each product can be estimated using historical data obtained from an omnichannel environment. The experimental results show that the heuristic using a biased-randomized selection strategy and considering the items-correlation effect during the selection process (HBRd) is able to provide, in just a few seconds, solutions that clearly outperform the random and greedy behaviours.

By increasing the attractiveness level of retail display tables during a time horizon, managers can be able to reduce customers' attrition and, as a consequence, increase sales revenue in their stores. Using a relatively simple-to-implement heuristic like the HBR, instead of solving these complex problems by hand, represents a clear enhancement over current real-life practices, which typically require many hours of a dedicated expert to generate even a feasible solution.

CHAPTER 4

FINAL CONCLUSIONS, RECOMMENDATIONS AND FUTURE RESEARCH

The increasing appearance of new shopping channels involve a deep change in the customers' behaviour and decision process (Galgey, Will; Pattinson, 2013). The retail landscape is changing rapidly and therefore customers' attitudes towards the shopping habits. Customers now choose among many possibilities in their journey towards a purchase and they combine different channels to complete it, even for cheap and unimportant products. The decision process is no longer a linear one nor within the same channel. Customers may look for information at one shopping channel, evaluate the alternatives at another one and complete the purchase at a third different one. This behaviour is considered a threat by retailers, especially those who own a small shop or those franchisees that have to compete not only with other brands but also with other channels within the same brand and have difficulties in retaining customers to their shops. That is why, obtaining customers' loyalty is decisive.

Loyalty is a "deeply held commitment to re-buy or to re-patronise a preferred product / service consistently in the future, thereby causing repetitive same-brand or same-brand set purchasing, despite situational influences and marketing efforts having the potential to cause switching behaviour" (Oliver, 1999). The idea of customer loyalty was initiated in the airline industry. Ever since, studies on customer expectations, service performance perception, satisfaction and loyalty have been restricted to service organisations like banks, insurance, hotels and other related settings (Hennig-Thurau & Klee, 1997). Loyal customers are important assets for brands. In an omnichannel environment, to adopt measures of retention and repurchasing intentions are basic for the survival of retailers.

Retailers struggle to survive because they have to face expenses of leasing the spaces and fill them with stock. They also fail in offering customers the personalisation they want. Out of the 89% of those who want personalisation in physical stores, only 18% see it from retailers today (SweetIQ, 2017).E-commerce has an impact (mostly perceived as negative) on brick-and-mortar stores and that is resulting in store closures, moves to smaller premises and new approaches in the physical store. Brick-and-mortar stores are not only places to show products and deal with clients but pickup centres for online orders, convenience stores for returns and exchanges and showrooms where to touch and feel the products before buying them online. Retailers must adapt their business models to the current omnichannel environment and offer

solutions to combine online and offline shopping. Other formats will appear pushed by the customer's convenience: "click- and-collect", "delivery in 24 hours", "in-store ordering & home delivery", "order online & return to store", "click in store", and other combinations of online and traditional retail activities that facilitate and improve the shopping process and the customer experience (Bell et al., 2014). Brick-and-mortar stores have to provide a unique experience and increase customer satisfaction and therefore loyalty (PWC, 2017). To do that, retailers need to know what factors customers value the most in every shopping channel and try to compete against these factors. After an exhaustive revision of the literature and specialised reports, we can conclude that there are four main factors that affect channel choice, e.g. personalization, stock availability, convenience and time saving. As regards brick-and-mortar stores, customers give importance to being treated in a personal way and to find the products they search for, that is stock availability. Consumers do not recognize channels; they only see the brand. An inconsistent, frustrating experience could cause customers to shop elsewhere, resulting in significant declines in sales and profits. (Glass & Haller, 2017). The first action to take is to engage with consumers.

Apart from finding excellent personal care at the retail store, customers want to see their expectations accomplished (Kotler & Keller, 2009). Finding different and renewed products every time that a customer steps in the store is a way to retain them and to rationalise the expenditure in stock that retailers are facing nowadays. The second part of this thesis was devoted to find a solution to this fact. The proposed algorithm will optimize the stock as well as reduce the amount of work made by visual merchants who are in charge of deciding what products to show, how and for how long.

Retailers and brands in general also have to realise that webrooming, showrooming and purchases through mobile devices are becoming the trend. The second main conclusion is that channels shape customers. Therefore, we can identify the traditional customer who buys in physical stores, the "webroomer" who looks for information online and ends the purchase at the store, the "showroomer" who does the opposite, "the online shopper" who uses a computer for shopping, the "m-shopper" who browses mobile devices and completes the transactions there. Knowing the purchase process of these typologies of customers will lead to a deep knowledge of how they behave and what their key touchpoints with brands are.

And last, but not least, another contribution of this thesis is providing retailers not only with pieces of advice by also with a tool to retain customers and, therefore, increase their revenues by selling more and more often. From data obtained in different channels about customers' behaviour and preferences, retailers can deal with the so called Product Recommendation Problem. In a store with limited capacity and limited stock, the heuristic proposed in chapter 3 shows that, by exposing an appropriate set of items, well combined and correlated, over a multi-period time horizon, it is possible to increase the store's attractiveness and therefore, sales revenue. Automatization of the process will save time and effort and will produce more accurate results. By increasing the attractiveness level of the retail display tables and the products shown in them, retailers can avoid customers' attrition and increase their future loyalty and retention.

4.1 Limitations and future research

There is a number of limitations in this research that should be addressed in future research. We have extracted most of the information about customers' preferred shopping channels and the trigger factors moving to them from updated reports issued by some of the most important consultancy companies who offered them on a free basis. Conclusions could be complemented with some private reports only available by paying a fee, but no significant changes are expected in the results.

A consideration to take into account in the future and in the use of results is that customer behaviour is changing as time goes by, and therefore results may vary year after year. Technology also evolves constantly and further shopping channels may appear in the future. Purchase paths then will become more complex and include many other shopping ways.

We have based our research in the apparel sector and therefore conclusions have been applied to this area. Another sector that operates mainly under an omnichannel environment is consumer electronics.

In this sector, the shopping channels are similar: traditional shopping, webrooming and showrooming. In the case of webrooming customers go to the shop with a great deal of information and seek for more detailed specifications of the product. The similarity with the apparel sector is that the retailer has to make efforts so that the customer finishes the purchase in the shop and not online. The difference is that purchases in this sector are not so frequent and customers cannot be attracted to the shop by showing them new products every short period of time. Another added aspect, especially when showrooming, is that price is the most important factor and customers can easily find, through their mobile phones, if the product is cheaper online and therefore, buy it there, even from the same shop.

According to the paths described, we have only considered one visit to every channel. For example, in the webrooming path, we have determined that the purchase starts on the web and finishes up in a physical store. Customers may repeat the journey, that is, browse the web again and go to the shop again (and maybe look for further information on a mobile device). It would be interesting to draw all the possible paths and establish the key touchpoints in the journey. An omnichannel Customer Journey Map (CJM) would offer the visual interpretation of the customer's relationship with the brand overtime and across channels. The CJM includes the description of the customer, his timeline, touchpoints, and the most important, the emotions felt at every stage of the journey. This would allow brands and retailers to know exactly how to act and understand the factors that are relevant at every stage of the journey. As mentioned before, the purchase path is no longer a linear one. Customers switch between channels in multiple occasions and make it difficult for retailers and brands to know exactly when they decide to complete the purchase, what is the real trigger factory and how can this factor be emphasized so as to retain the customer. In the paths described, it could also be interesting to note how many times the customer goes over a certain channel. As shown in Table 5, showrooming, for example, can start in the shop, then look for additional information on a desktop at home, go back to the shop and finish the purchase online finally.

Table 4 Multiple paths

Double Path	**Information search**	**Additional information**	**Additional touch and feel**	**Final Purchase**
Showrooming	Brick-and-mortar	Desktop (home)	Brick-and-mortar	Desktop (home)

The combination of different channels during the different stages of the purchase process can complicate the process and therefore provide a detailed Customer Journey. A customer can start looking for information online for example (in the case of webrooming), go to the store to touch and feel or look for additional, personalised information, then look for specifications on his mobile device, go home, compare the different options, use social media and word-of-mouth opinions to complete the decision and finally purchase at a brick-and-mortar store. These uncountable combinations could be a field to explore in detail and would probably shed light on the different aspects of the omnichannel customer behaviour.

As an immediate avenue of research, we suggest a study on how to measure the customer experience across the different channels in the Customer Journey. As described by Pine and Gilmore in their book The Experience Economy, "an experience occurs when a company intentionally uses services as the stage, and goods as props, to engage individual customers in a way that creates a memorable event" (Pine & Gilmore, 1998). The objective would be to study how the richness of the customer experience can be measured across multiple touchpoints and in different stages of the journey. Customer experience was first conceived in 1982 (Holbrook & Hirschman, 1982). From then on, many authors have developed theories and have explained consumer behaviour and customer experience. Nasermoadeli, Ling, & Maghnati (2013) made an exhaustive literature review on the concept. From there, a multidimensional research instrument could be developed and designed to measure customer experience by capturing the respondents' experience along the omnichannel customer journey. First it would be interesting to gather different views of what is considered as experience: perceptions, feelings and the interaction between the customer and the organization. Then, based on the research made by Verhoef et al. (2009), the way

customer experience is created, either based on convenience, value or quality could be developed. In their work, they differentiate between the direct contact (purchase, use, service) as aspects initiated by the customer and indirect contact (word-of-mouth, advertising, reviews, etc.). It is very important to determine the degree of customers' involvement in different dimensions : sensory experience, emotional experience and social experience (Popa, 2013). Similarly to the SERVQUAL tool (Parasuraman, Zeithaml, & Berry, 1988) that measures quality in services by taking into account perceptions and expectations, or the SERVPERF (Cronin et al., 2000) that measures reliability, efficiency, quality and service, the idea could be to approach the tool using some of the dimensions mentioned by Klaus & Maklan (2012): product experience, outcome focus, moments-of-truth and peace of mind. Halvorsrud, Kvale, & Følstad (2016) describe the Customer Journey based on touchpoints. The more the touchpoints, the worst because it means that the customer has needed more contacts. A good start point for this study could be to measure the quantity of touchpoints that are considered "ideal" in a Customer Journey, then identify the ones that are out of the path and allocate punctuations according to the type of deviation. The lesser the deviations, the best experience.

APPENDIX A

CHAPTER 2 SUMMARY OF REPORTS

The following table shows the main conclusions extracted from the different reports. The numbers in brackets correspond to the code given to identify the report.

	TRADITIONAL	WEBROOMING Search online buy store	INSTANT WEBROOMING Search online while in store buy store	SHOWROOMING Search in store buy desktop	INSTANT SHOWROOMING Search in store buy online while in store	BOPIS Buy online pick up in store	DESKTOP ONLY Search and buy online	MOBILE ONLY Search and buy mobile
	(7) 40% prefer to bring merchandise home (CONVENIENCE)	INFO SEARCH (31) 88% of consumers are seeking information online before buying in-store or in-app	**(31) 23% of consumers who start mobile end in store (40% end in web)**	**(7) 8%** 69% of brands think showrooming will grow (7) 17% of online shoppers have made a purchase in a showroom (24) 44% of mobile purchasers have purchased a product on their mobile device after checking it out in store (31) 19% of consumers who start in store end in web	(7) 28% are fine with visiting the physical store and placing an order while there (7) 31% say they are always "on the go" with mobile devices (31) 6% of consumers who start in store end in mobile	(3) 28% of Spanish brands have a pick up service in the store (7) 50% have shipped to sotre for pickup 46% of those have made additional purchases in store	(7) 42% (4) 73% of US brand respondents use webs as sales generator (5) Preference to buy online versus in-store: Consumer electronics 39% online 51% in store. Clothes 40% online, 51% in store (7) percent of shopping 32% desktop (7) online purchases made by millennials 54% vs. 49% of non millennials. (7) ChannelAdvisor estimates that Marketplace sales account for almost 25% of total online retail sales (31) 60% of consumers who start in web end in web. 13% end mobile	(3) Connected devices will grow by 23% every year until 2021 (3) more than half of google searches in 2016 were made from a mobile device (3) m-commerce is expected to grow by 48% in 2017 (4) (5) 33% of US respondents use their mobile devices for purchasing (5) shop org survey of retail executives when asked where most of their 2017 tech investments would be 39% chose mobile (just 6% said in store. (7) percent of shopping 25% smartphone (7) 22% of smartphone purchasers don't want to turn on other devices if their smartphone is already at hand (7) Mobile commerce reached 18% of total digital commerce during the 2015 holiday season (22)mobile accounts for 40% of all sales IMRG Cap Gemini (31) 33% of consumers who start mobile end mobile. (33) only 21 of retailers have a mobile purchasing channel
NEED RECOGNITION	Influenced by publicity Influenced by friends Influenced by experience (29) Consumers don't know what they want until they see it	Banners (pop ups) Influencers	Can be impulse shopping	Impulse shopping (29) Showrooms work best for differentiated goods			Banners (pop ups) Influencers 34% of shoppers are influenced by influencers, bloggers or vloggers	
INFORMATION SEARCH	In store Shop associates (5) when asked how important certain attributes are in relation to in-store shopping experience, 78% of sales executives respond that "sales associates with a deep knowledge of the product range" is the most important factor for consumers. 63% of consumers are satisfied (30) 33% of European consumers like to ask store staff for advice before buying	Desktop Mobile device Reviews % of research (5) Another factor considered important by retail executives is the ability to check other store or online stock quickly 68% (5) US customers, inspiration for purchases 39% social networks, 37% individual retailer websites, 35% price comparison websites, 32% multi-brand websites (30) In Spain 65% of customers researched online before buying in store compared to 53% in 2015	Quick Mobile device Mainly price seekers (5) shop org survey of retail executives: which online media sources inspire purchases? Social networks 47% (5) 59% of Consumers find it important the ability to see/order extended range of products on screen in-store (7) 43% of customers find the ability to check store inventory on a retailer's app important (24) What consumers do with their mobiles while in store: 49% look for better price 43% look for more info 36% look for reviews	WHERE? In store ASSISTANCE Shop associates WHAT IS IMPORTANT? Price Product specifications Adequacy to needs Personalisation (5) What is important for consumers? Ability to check other store or online stock quickly 68%. 58% are satisfied (7) 60% researched products on a mobile device while in store	36% of millennials are receptive to beacons (15) customers while in store want to know if a wider range is available online. Tech available in store 27% store kiosks, 17% staff with mobile devices 50% no technology in store (19) 80% of smartphone shoppers use their mobile in store to help with shopping		Deep research (2) 50% of brands provide very good or excellent online shopping functionality (orders, wish lists, review, videos) (2) 53% have functionalities that offer autocompletion and filtering (2) 61% do not provide online chat options (2) 18% do not respond to inquiries posed via social media or take more than 48 hours (2) 32% provide customers with opportunities to co-create and collaborate (6) 75% of consumers move to a more expensive channel when online support fails. 63% are more likely to return to a website that offers	Quicker research (2) With a projected 5 billion mobile phone users worldwide by 2019 mobile is becoming the "first screen". 37% of brands provide a poor mobile experience or no mobile. (3) 80% of Spanish consumers search for information about products in their mobile devices (3) 78% use it to compare prices. (3) 68% use it to search for opinions ((22) 20% use it to look for deals (7) 56%) (7) 64% researched products prior to visiting a store (7) 50% search for product reviews

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GIVEN CODES

1. (PSFK Labs, 2016)
2. (Glass & Haller, 2017)
3. (Ditrendia, 2016)
4. (Ibañez, G.; Liege, J.; Lostalé, E.; Casado, 2016)
5. (PwC, 2014)
6. (HP, 2014)
7. (UPS, 2016)
8. (PwC, 2015)
9. (Criteo, 2017)
10. (Criteo España, 2017)
11. (Deloitte, 2017a)
12. (Cap Gemini, 2017)
13. (Accenture, 2017)
14. (Rigby, 2011)
15. (Practicology, 2017)
16. (Apteco, 2017)
17. (SweetlQ, 2017)
18. (Bigcommerce, 2017)
19. (Worldpay, 2015)
20. (Pine & Gilmore, 1998)
21. (Landscape, 2017)
22. (JLL, 2016)
23. (Westfield, 2015)
24. (IAB, 2016)
25. (*European Ecommerce*, 2017)
26. (McKinsey, 2016)
27. (Harris, 2012)
28. (Reinartz, 2016)
29. (Willmott, 2014)
30. (Ivend, 2017)

CHAPTER 6

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