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The Impact of Cross-Channel Integration on the Profitability of Apparel Retailers

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Abstract

As the retail market transitioned from single-channel to the current omnichannel landscape, retailers were challenged to transform their businesses in order to conquer customers' preference while sustaining profit levels. Considering this scenario, this research aimed to investigate the extent to which cross-channel integration impacts firms' financial performance in the short and long run. Moreover, we also questioned which firm-level factors are more influential in this relationship. To answer these questions, we collected data from 27 leading companies in the fashion and apparel retail industry globally from the years 2012 to 2021. Then, we performed panel data models with time-fixed effects having the operating profit margin as dependent variable, the level of cross-channel integration as main independent variable and three moderators, namely: number owned physical stores, usage of mobile apps or social media as sales channels, and investment in emerging technologies. The model results revealed that cross-channel integration positively impacts firms' profitability in the short- and long-term, however this effect is negatively influenced by the intensity of firms' physical presence. These findings have significant implications for academy and business. In addition to fulfilling research gaps from the literature, we provided empirical evidence that performing cross-channel integration activities is rewarding for companies in terms of profit margins, therefore, they should continue investing to become omnichannel.

Keywords: Cross-channel integration, omnichannel marketing, operating profit

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It is with immeasurable joy that I write these last words in my thesis.

Coming to the Netherlands to pursue a Master's in Data Science and Marketing Analytics was the fulfillment of a long-planned dream. Now, as I look back on this year, I am proud of what I achieved and humbled by the long knowledge road that lies ahead of me.

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I hope that you, the reader, can enjoy going through the next pages as much as I enjoyed going through this learning path.

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Tamires Beltrão

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1. Introduction

For a long time, traditional retail businesses grew and succeeded in operating basically with brick-and-mortar stores. Leading companies, such as Walmart, Nike and many others initiated their business in this setting. Everything started to change with the dissemination of the internet (Verhoef et al., 2015). First, online-only companies such as Amazon and eBay were created, shaking the retail market. Then, incumbent firms began to incorporate online channels, kicking off the era of multichannel strategies. At the time, these different channels had little or no integration among themselves (Timoumi et al., 2022).

These market movements became a focus of study since there were many unanswered questions regarding the business impacts of multichannel management. Being the changes in the direction of bricks to clicks (adding online channels) or clicks to bricks (adding physical stores), most researchers found that they led to positive results for companies in terms of sales, market share or profit (Dholakia et al, 2005, Min & Wolfinbarger, 2005, Venkatesan et al, 2007, Pauwels & Neslin, 2015). Nevertheless, potential caveats were also frequently mentioned, such as the cannibalization between channels (Avery et al., 2012, Pauwels & Neslin, 2015), the difficulty to sustaining customer loyalty (Coelho et al., 2003, Ansari et al. 2008, Melis et al. 2015), and lastly, the increase in costs and operational complexity (Ofek et al., 2011).

As the multichannel strategy became imperative, the discussion naturally evolved from the addition of channels to the relevance of coordination among channels. Several studies found evidence that greater channel integration has a positive influence on firms' performance (Liu et al., 2018), for instance, when evaluating the general perception of managers (Oh et al., 2012), the sales growth (Cao & Li, 2015), or the cost efficiency (Tagashira & Minami, 2019). One of the reasons for the positive results lies in customers' better perception of quality and reliability of firms that present higher cross-channel integration (Herhausen et al, 2015).

Conversely, the coordination of channels proved to be a complex and costly challenge for companies. As explained by Verhoef et al. (2015), with the advance of digitalization, multichannel management expanded beyond the original concept of route-to-market to an integrated view of distribution and communication channels that all became touchpoints in the customer journey. In this context, customers started to demand not only many options to interact and purchase, but an omnichannel customer experience, in which they can navigate through channels in a seamless way along the phases of the purchase process (Verhoef, 2021). As a reaction, retail companies were pulled to expand the number of touchpoints and the complexity of their operations, which resulted in margin reduction in retail markets around the globe (KPMG, 2021).

In face of this scenario, one important question is if more cross-channel coordination is always better for the company, especially when considering not only customer satisfaction reflected in sales but also profitability and return to investors in the short and long terms. On the one hand, customers are responding to external evidence of the integration efforts, such as connected stores or integrated customer care services, with feedback, purchases, and in the last instance, loyalty (Neslin, 2022). On the other hand, shareholders are assessing the consequences of channel decisions in the bottom line, which is affected not only by revenues but by investments and operational costs from the company (Homburg et al., 2014). In this respect, the integration of channels may act as a double-edged sword. While it can improve customer experience and internal synergies, it might also represent less strategic flexibility, expensive investments and increasing operational workload (Neslin et al., 2006).

The investigation of the nuances in outcomes of cross-channel coordination has been mentioned by diverse authors as an emerging topic and research gap in the current literature (Liu et al., 2018, Timoumi et al., 2022, Neslin, 2022). Thus, the goal of this study is to contribute to the omnichannel marketing management literature by addressing the following research question:

To what extent does cross-channel integration impact retailers' financial performance in the short and long run?

Additionally, the literature mentions several moderators influencing the relationship between channel management and business results, such as the number of physical stores, the experience of the retailer with e-commerce (Cao & Li, 2015, Tagashira & Minami, 2019), the product category, and the market environment (Oh et al., 2012, Liu et al., 2018). Moreover, there are some trends in the retail market that have been playing an important part in the conversion of omnichannel efforts into commercial success. Such trends can also be seen as moderators, for instance, the investment in new technologies, and the use of digital sales channels varied considerably among firms and was closely related to their financial performance in the last years (Mckinsey & Company, 2021, Verhoef, 2021). Hence, the following sub-question arises:

Which firm-level factors are more influential in the relationship between cross-channel integration and retailers' financial performance in the short and long terms?

By answering these questions, this study intends to contribute to the literature in several ways. The first is by using the operating profit margin as a measure of performance. This is intended to address a recurring concern of researchers regarding the impact of marketing actions on profitability, which has been little explored so far (Cao & Li, 2015, Neslin, 2022). More research on this is needed because sales can be a deceiving indicator of the real outcomes of channel integration efforts since the costs of these initiatives are not taken into consideration (Herhausen et al., 2015). The second contribution refers to the timeframe of analysis. In previous studies, researchers usually focused on short-term effects due to data availability and practical constraints (Cao & Li, 2015, Liu et al., 2018). By expanding the timeframe to ten years, this research will not only have sufficient data to measure these long-term effects but will also cover a period of intense strategic focus and investment in the transformation towards omnichannel marketing (Timoumi et al., 2022). The third contribution will come from the consideration of little-explored moderators that have been central in retail companies' strategies in the last few years, such as the investment in emerging technologies and the aggregation of mobile apps and social media as a sales channel (Liu et al., 2018, Verhoef, 2021).

Furthermore, the findings from this research will hold significant value to business decision-makers. Companies are constantly pressured by external (competitors, customers) and internal stakeholders (employees, investors) regarding impactful decisions such as those related to channel management (Homburg et al., 2014). Thus, managers can leverage insights from this study to decide upon the most suitable level of channel integration considering the current profit pressure scenario (Cordon, 2021, Mckinsey & Company, 2021). Additionally, our conclusions will support companies in prioritizing their actions towards becoming omnichannel by providing a deeper understanding of which specific strategies have been more rewarding in terms of profitability for the firms under investigation.

To achieve its objectives, this thesis is organized into five chapters. Following this introduction, Chapter 2 presents the literature review, which defines relevant concepts, explores previous studies' insights, and proposes our research hypotheses. Chapter 3 outlines the data collection process and methodological procedures. Next, Chapter 4 deep dives into our data analyses, presenting the descriptive statistics, data modeling, robustness tests, and interpretation of results. Finally, in Chapter 5, we summarize the findings of this paper and discuss implications to academia and business domains. Moreover, we conclude with a reflection over limitations and potential directions for future exploration within this field.

2. Literature Review

Chapter 2 aims to present the conceptual foundation and current knowledge regarding multi-channel strategies and their influence on firms' performance. Based on this, we elucidate the research gaps that this paper intends to address, and also introduce the conceptual framework underlying the research design implemented in the subsequent chapters. This literature review is, therefore, organized into three main parts. The first explores, with a conceptual and historical bias, the nuances of channel management from single channel to the current omnichannel scenario. The second part focuses on the impacts of channel integration decisions on firms' performances by presenting what recent studies found and the main drivers of their conclusions. Building upon this understanding, in the third part, we develop the rationale for the expected relationship between cross-channel integration and firm performance as well as the anticipated effects of the chosen moderators on this relationship.

2.1. Nuances of channel management from single-channel to the current omnichannel scenario

Traditionally, marketing channels are seen as the downstream part of a company's supply chain, i.e. the value network that makes viable the distribution of commercial products from the manufacturer to the final consumer (Harker et al., 2015). These structures can have different layers, which determine how they are classified (Tsay & Agrawal, 2004). A direct marketing channel is established when the manufacturer sells to the final customer without intermediates. Alternatively, if there are wholesalers and retailers (3 layers) or only retailers (2 layers) intermediating the distribution flow, it is considered an indirect marketing channel. According to Harker et al. (2015), the decision for which distribution channels to operate is very important for companies because it affects different marketing areas, such as pricing, communication, and sales force management. Moreover, in opposition to other marketing domains, these decisions usually involve long-term commitments to investments and partners involved in the operation, therefore, they require careful consideration of long-term trends and consequences (Homburg et al., 2014, Chu et al., 2007).

Historically, many companies were able to run their business successfully in a single-channel format (Moriarty & Moran, 1990, Cui et al., 2021). For example, Goodyear used to sell reposition tires only through retailers, Apple started its business selling computers via proprietary retail stores, and Amazon, a company founded already in 1994, initiated its books-selling business with a unique e-commerce website. However, as technology evolved affecting companies' and customers' behaviors and capabilities, these firms and almost all others moved from single-channel to multichannel configurations (Zhang et al., 2010). In addition to brick-and-mortar, catalogs, call-centers and sales representatives, companies incorporated websites, mobile apps and lastly social media platforms as means to interact and sell their products (Verhoef et al., 2015). Rangaswamy & Bruggen (2005) highlight that multichannel marketing goes beyond what they call "multiple-channel" marketing. They explain that, in the latter, the company decides to use different channels to interact with different segments of customers, while in the former it is the customer that decides how he wants to interact with the company along his purchase journey.

It is interesting to notice how these changes led to a different role for the customer in decisions concerning marketing channels. In the past, customers were mostly present only at the end of a linear selling flow (Venkatesan et al., 2018). As a result, companies' attention was more dedicated to the distribution process and the management of conflicts among the independent firms involved in the distribution chain (Frazier, 1999). As the customer gained the power to navigate between channels in a non-linear way, the view of supply channel management became more holistic and customer-centric (Lemon & Verhoef, 2016). In line with this, Neslin et al. (2006), developed an extensively accepted new interpretation for multichannel customer management as "the design, deployment, coordination, and evaluation of channels to enhance customer value through effective customer acquisition, retention, and development". In this approach, the customer takes the central position and firms need to take input from his past behaviors to define and adapt their multichannel strategy.

Considering the new necessities and opportunities from multichannel customer management, companies started to review their previous decisions on how to access the market (Tsay & Agrawal, 2004). The historical preference of manufacturers for indirect channels used to be justified by efficiency gains, mainly coming from scale and specialization, that were beneficial for all parts involved (Harker et al., 2015). Nevertheless, producers from multiple segments begin to see the addition of direct channels as an opportunity to reach new customers and achieve greater control of customer experience and marketing mix strategies (Tahirov & Glock, 2022). With this movement, while the customer gains more options to go through the marketing funnel, the supply-side players must manage an increasingly complex and competitive retail market (Tsay & Agrawal, 2004, Ailawadi & Farris, 2017).

In face of this general context, not only has the view of channel management changed but also how channels are conceptualized. The widespread digitalization transforms all points of contact between companies and customers into potential sales channels (Verhoef et al., 2021). As a result, the separation between communication and commercialization channels is not so clear anymore, in such a way that all touchpoints with the customer become relevant for an integrated channel management (Ailawadi & Farris, 2017). Verhoef et al. (2015) synthetized this development as a change of paradigm from multichannel to omnichannel marketing. In the new paradigm, customers go beyond accessing the companies through different channels, in fact, they seamlessly navigate through different channels along the steps of their purchase journeys.

In light of this, the initial concept of multichannel management (Neslin et al., 2006) was updated to incorporate the optimization of both cross-channel customer experience and firm performance by the synergic management of channels and customer touchpoints (Verhoef et al., 2015). This update not only reinforces the relevance of coordination among channels but also broadens the former concept to consider that both firms and customers must obtain value from the multichannel marketing management. Aligned with this vision, Cao & Li (2015) defined cross-channel integration as “the degree to which a firm coordinates the objectives, design, and deployment of its channels to create synergies for the firm and offer particular benefits to its consumers”. In practice, firms are experiencing omnichannel marketing management by taking a myriad of actions towards the seamless coordination of their channels. As stated by the aforementioned researchers, their main goal with this is to build customer loyalty on the one hand and gain operational synergies on the other to, ultimately, leverage financial results (Bendoly et al., 2005, Tagashira & Minami, 2019). The following section focuses on summarizing findings from the literature in this respect, while situating how this thesis intends to contribute to this research stream.

2.2. Impacts of channel integration decisions on firms’ performances

In face of the increasing adoption of multichannel, and lastly, omnichannel strategies, several researchers directed their focus to the impact of cross-channel integration on firms’ performances. Some studies approached this topic from the customer point-of-view, unveiling that customers prefer to have multiple channels to flexibly interact with companies (Liu et al., 2018), and that a greater level of cross-channel integration positively affects customers’ perceptions that are associated with more satisfaction, sales, and loyalty (Timoumi et al., 2022, Neslin, 2022). Other studies examined the theme from the firm side and found evidence of performance improvements derived from general cross-channel integration (Cao & Li, 2015, Oh et al., 2012) or coordination of specific aspects, such as logistics, assortment, or communication (Timoumi et al., 2022). Therefore, the general impression is that cross-channel integration has a positive net return for both customers and companies. However, more recent studies have been noticing that the benefits from integration are not the same for all firms in all markets, in other words, they are moderated by aspects such as product type, channel margin (Neslin, 2022), customer segments (Verhoef. 2021), firm differentiation and level market competition (Ofek et al., 2011).

Fortunately, there is a vast literature on the channel integration topic, ranging from conceptual frameworks to mathematical models and empirical studies with survey or factual data. Following the empirical approach of this thesis, Table 1 lists papers that used factual or survey data to study the impact of channel integration on customers and firms in the retail multichannel environment. The table presents three studies focused on the customer perspective of channel integration, three studies discussing the effects of specific integration measures on the performance of one firm, and three studies that investigate the impacts of channel integration across firms from different retail industries. In the following paragraphs, we will contrast the findings of these studies and the position of this research compared to them and to the broader literature.

Starting with the studies focused on the customer point of view, Bendoly et al. (2005), in a survey-based research, found that customers who perceive a higher level of online-offline (OI) integration in the retailer present higher loyalty behavior. According to the authors, the integration of channels reinforces the transparency of purchase options and reduces the perceived risk. In contrast, Herhausen et al. (2015) found, with experiments, that channel integration indirectly increases customers' search intentions, purchase intentions and willingness to pay in both online and offline channels. Unlike Bendoly et al. (2005), the authors verified that, instead of the perceived risk, it is the perceived service quality of the online store that mediates the effects of channel integration on customers' behaviors. Interestingly, the extent to which online-offline integration affects this perception is negatively influenced by the customer's level of online shopping experience. Moreover, Herhausen et al. (2015) stated that channel integration does not cannibalize physical stores because it mainly brings new customers with online-channel preferences. Venkatesan et al. (2007) added to this understanding by using factual data to show that customers who purchase in many channels are more profitable for firms. The authors suggest that multichannel customers develop a deeper relationship with firms

Table 1
Overview of related empirical studies

Study	Research focus	Data	Methods	Main findings	Time frame	Level of analysis
Bendoly et al. (2005)	The influence of customer perception of integration on customer loyalty	1598 customers of three multichannel retailers in the U.S.	Logistic regression	- The customer perception of integration positively influences customer loyalty; - The integration perception reduces the risk perception from unavailable products and the likelihood of switching firms.	Short-term	Customer level data from three firms
Venkatesan et al. (2007)	Drivers of multichannel shopping and multichannel impacts on customer profitability	Historical data of a apparel retailer in the U.S. from 2000 to 2003	Generalized linear model; Shared-frailty hazard model with panel data	- Customers that shop in multiple channels generate more profit; - The frequency of purchases and marketing communication and the easiness of returns are the most influential factors in customer multichannel behavior; - There is an optimal level of marketing communication frequency to incentivize multichannel behavior (U-shaped relation).	Short-term; Long-term	Customer level data from one firm
Herhausen et al. (2015)	Customer behaviors resulting from online-offline integration	Experiments with 107 German participants, 129 undergraduate Swiss participants and 715 customers from two German and Swiss retailers	Experiments; Regression analysis, bootstrapping, multinomial logistic regression	- Online-offline integration increases customer's search intention, purchase intention and willingness to pay in physical and online stores; - The perception of service quality from internet stores mediate the effects of the OI integration on customer behaviors; - Customer's online shopping experience negatively moderates the integration effects; - Internet channels complement physical channels - no cannibalization of channels.	Not specified	Customer level data from two firms
Gallino & Moreno (2014)	The effects of BOPS implementation on online and physical sales	Historical data of all stores of a big retailer in Canada and the U.S. from April 2011 to April 2012	Quasi-experimental; DiD estimated via panel data models	- BOPS implementation increases sales in general; - Sales and traffic in physical stores increases while online sales decrease; - BOPS generate a positive spillover effect on physical sales (cross selling effect) and ROPO behavior towards online sales.	Short-term	Zip code level data from one firm
Akturk et al. (2018)	Impact of ship-to-store introduction on sales and returns	Historical data of a jewelry retailer in the U.S. from September 2010 to September 2012	Quasi-experimental; DiD estimated via panel data models	- STS implementation increases sales in general; - Sales online decrease, sales offline grow and store returns reduce. Also, cross channel returns increase; - STS brings new online customers that purchase physically and increases the shift from online to offline.	Short-term	Zip code level data from one firm

Kumar et al. (2019)	The effects of store openings on the online sales and returns	Historical data of six retail stores from a multichannel retailer in the U.S from 2001 to 2005	Quasi-experimental; DiD estimated via panel data models	- Adding physical stores increase online purchases of existing customers; - The effect of a store openings on online purchases is positively moderated by the customer's proximity to the store; - Buy online, return in store is one of the main drivers of synergy among the channels.	Long-term	Customer level data from one firm
Oh et al. (2012)	The effects of channel integration through IT on firms' performance (perceived)	Survey with 125 multichannel retailers in Singapore	Partial least squares model	- The integration of organizational resources positively affects firms' performance; - IT-enabled cross-channel capabilities and HR capabilities are complementary; - Efficiency and innovation competences mediate the influence of IT-enable cross channel capabilities on firms' performance; - The influence of innovation competences on firms' performance is positively moderated by the environmental dynamism.	Not specified	Firms from different industries
Cao & Li (2015)	The effects of cross channel integration on firms' revenue	Historical data of 71 multichannel retailers in the U.S. from 2008 to 2011	Grounded theory; Random effects panel model	- There are four levels of cross-channel integration from silo mode to full integration; - Cross channel integration positively affects firms' revenues; - The effect of CCI on firms' performance is negatively moderated by firms' online experience and number of physical stores.	Short-term	Firms from different industries
Tagashira & Minami (2019)	The effects of cross channel integration on firms' cost efficiency	Historical data of 123 multichannel retailers in Japan from 2012 to 2015	Dynamic panel model with GMM estimation	- Cross channel integration positively affects cost efficiency; - The effect of CCI on firms' performance is negatively moderated by firms' online experience and the level of face-to-face services; - Integration of communication aspects have higher effect on cost efficiency than transactional and organizational aspects.	Short-term	Firms from different industries
This study	The effects of cross channel integration on firms' profit	Historical data of 30 multichannel fashion & apparel retailers in various countries from 2012 to 2021	Fixed and random effects panel models	- Cross channel integration positively affects the operating profit margin in the short- and long-terms; - The effect of CCI on firms' performance is negatively moderated by firms' number of physical stores in the short- and long-terms.	Short-term; Long-term	Firms from one industry

when they are exposed to more services in different channels, which leads to a preference in customers' allocation of purchases (higher share of wallet). They also argue that, aware of this, firms should pay careful attention to the most influential factors in the adoption of multiple channels by customers, which are returns management and purchase and marketing communication frequencies.

The results of customer-level studies are insightful in the sense that they shed light on the demand-side drivers of the effects of cross-channel integration on firms' results. Naturally, there are some caveats with the generalization of these findings coming mainly from the possibility of self-selection of a priori loyal customers into using multiple channels (Verhoef, 2021) and the number of moderators to infer causality between cross-channel integration and profits (Neslin, 2022).

Moving the focus from the customer to the firm, the next three studies in the table used quasi-experimental research designs to investigate the impact of multichannel retailers' strategic actions on sales and returns. Gallino & Moreno (2014) concluded that the implementation of the "buy online, pick up in store" (BOPS) functionality generated gains in total sales, despite the reduction in the online revenue. Similarly, Akturk et al. (2018) found that sales grew after the implementation of the "ship-to-store" (STS) feature, also with reduction in the online channel and a more than compensating increase in store sales. Both studies explained this as a channel-shift effect triggered by a "research online, purchase in store" (ROPO) behavior. Additionally, Gallino & Moreno (2014) further justify the growth in store sales as a cross-selling effect, i.e. when online customers pick up their online purchases in store, they opportunistically buy additional items. Akturk et al. (2018) argue that the same happens when customers go to the stores to return items purchased online. Kumar et al. (2019) reinforces Akturk et al. (2018) argument explaining that the facilitation of returns affects customers' perception of control over online transactions, increasing their purchase intentions. In their study about the effects of store openings on sales and returns from a multichannel retailer, they found that opening new physical stores resulted in expanded online purchases from existing customers. They also claim that the increased proximity of a physical store positively influences customer engagement, especially during the product evaluation phase.

These firm-focused studies provided robust evidence in favor of the implementation of actions towards the integration of channels. It is curious to notice that Kumar et al. (2019) research was not directly related to cross-channel integration measures, but in a multichannel context, unveils how the customer takes advantage of physical stores to improve their purchase process in all channels, which ends up being beneficial for the firm. Certainly, these studies are not exhaustive, however, they are representative of the general perception of more positive than negative outcomes from the implementation of cross-channel integration features in the literature (Timoumi et al., 2022). Nonetheless, a recurring limitation is that many researchers use data from a unique player in one retail industry. For example, all three studies presented here draw conclusions from retailers with predominantly non-digital product portfolios (e.g. apparel, jewelry). Therefore, the extent and direction of cross-channel effects, such as synergy or cannibalization, can vary according to differences in product or market characteristics (Gallino & Moreno, 2014, Akturk et al., 2018, Kumar et al., 2019).

Expanding on the individual firm' analyses, Oh et al. (2012) used a survey-based approach to investigate retailers' perception of cross-channel integration. They found that IT-enabled channel integration capabilities increase firms' performance via efficiency and innovation competences. The authors further explain that the positive effects can be boosted when the company operates in a dynamic environment and has strong cross-channel human resources capabilities. Cao & Li (2015) and Tagashira & Minami (2019) confirmed the main finding from Oh et al., (2012) by performing studies using factual data. First, Cao & Li (2015) developed a framework to evaluate firms' level of cross-channel integration and then, implemented this framework in a sample of U.S. retailers to measure the impact of channel integration on sales growth. They found positive significant results, negatively moderated by the firms' physical presence and online experience. Applying the same framework to Japanese companies, Tagashira & Minami (2019) demonstrated that higher levels of cross-channel integration positively affect cost efficiency. Differently from Cao & Li (2015), the firms' physical presence was not significant as a moderator in this case, but the online experience as well as the level of face-to-face services. Moreover, the authors verified that the integration of communication features (level 2) had a higher impact on cost efficiency than the more advanced levels of integration, indicating a non-linear relationship between cross-channel integration and cost efficiency.

As intended, these last three studies complemented the set of evidence brought by the other papers with a less granular but expanded view of the effects of cross-channel integration measures on firms' performance. From this point of view, we strengthen the perception that channel integration strategies are relevant for multichannel retailers since they positively impact both revenue and cost measures (Cao & Li, 2015, Tagashira & Minami, 2019). Furthermore, we learned about the importance of firms' competences and capabilities as enablers to a successful integration of channels as well as considering market conditions (Oh et al., 2012). Overall, these results are aligned with the discussion from previous papers in this literature review.

The last row in Table 1 presents the characteristics of this research, by which we intend to contribute to fulfill relevant gaps from the cross-channel integration literature. First, we will expand on the work of Cao & Li (2015) by using their framework to assess the effects of cross-channel integration on firms' profit in the short- and long-term. The change from sales to operating profit will address a recurring concern regarding the costs of implementation and maintenance of cross-channel integration measures that are not considered in studies with sales and returns as dependent variables (Cao & Li, 2015, Gallino & Moreno, 2014, Bendoly et al., 2005). Moreover, the extended period of analysis (10 years) will allow us to capture long-term effects, which were little explored in this research stream (Liu et al., 2018), and are important to account for the maturation time of firms' actions (Cao & Li, 2015) and the respective customers' reactions in the long run (Neslin & Shankar, 2009). Secondly, we will draw upon a multilevel theoretical foundation to investigate the influence of retailers' trending strategies on the cross-channel integration and profits relationship. This approach answers the call for considering a resource-based view of the firm in studies on omnichannel strategies (Neslin, 2022) and for further exploring the impact of new technologies usage on retailers' performance (Verhoef, 2021). And thirdly, we will deep dive into one of the most studied retail industries, namely, fashion and apparel, analyzing the global market leaders' transition to omnichannel marketing management and the short- and long-term financial consequences of it. Studying this industry will be interesting to support a broader generalization of conclusions regarding the apparel market (with extension to non-digital products industries and markets outside the U.S.) and to expand the discussion from pure retailers to manufacturers advancing to retail, which is a growing movement with deep implications for all players in retail markets (Tahirov & Glock, 2022).

2.3. Conceptual framework

The primary objective of this study is to investigate the impact of cross-channel integration on the profitability of retail companies in both the short and long term. Moreover, we are also interested in exploring secondary factors that moderate this relationship. In this section, we build the reasoning that supports our conceptual framework and underlies the expected modeling results translated into the research hypotheses. Figure 1 visually summarizes this conceptual model.

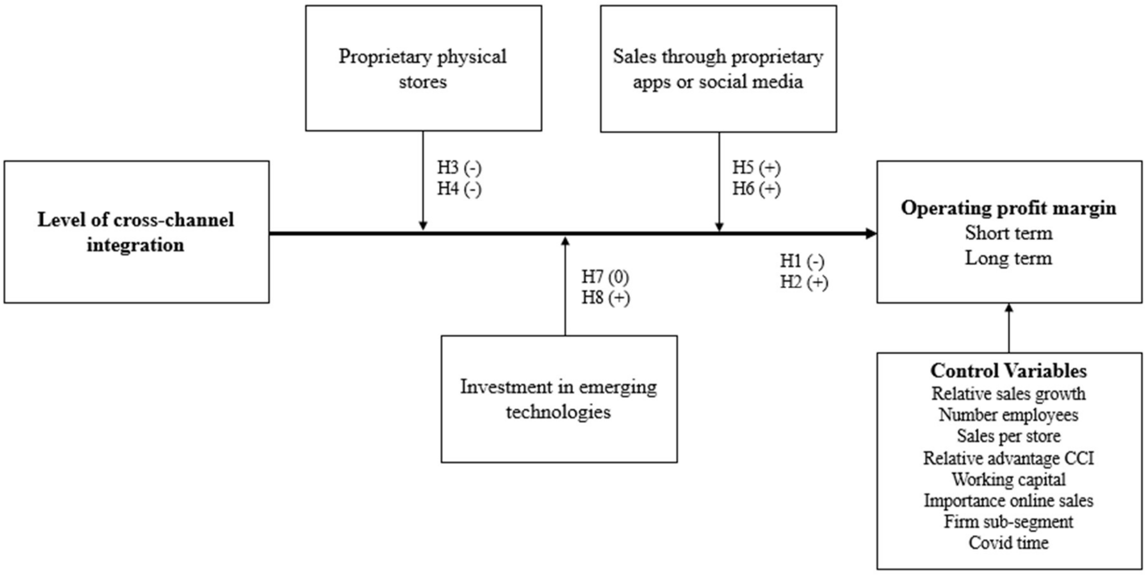

Figure 1. Conceptual Framework

2.3.1. Effects of cross channel integration on profitability

To begin with, it is possible to see our first research question through two general dichotomies: regarding the time frame, we can differentiate short-term and long-term effects; and considering outcome drivers, we can ponder impacts in sales and impacts in costs. To better elucidate, one can imagine a simplified continuum scenario - derived from Cao & Li (2015) and Neslin (2022) views of the cross-channel integration as an evolutive process - of a retailer in the omnichannel context implementing channel integration measures. These measures imply immediate and persisting cost changes for the firm and trigger customer and competition reactions in the short and long term, which in turn, affects firm sales, that summed up with the costs define the resulting profits.

This framework is helpful to investigate step-by-step the multiple conflicting effects influencing our research problem. To begin with the revenue perspective in the short term, it is valuable to consider customers' perception of the integration of channels. We saw in the literature review that customers present higher satisfaction, loyalty, and willingness to pay (WTP) when companies make channel integration actions transparent to them (Bendoly et al. 2005, Herhausen et al., 2015). In addition, customers purchase more when they can integrate their transactional experience between online and offline channels (Gallino & Moreno, 2014), and multichannel customers have higher engagement with brands, which makes them more profitable than single-channel customers (Venkatesan et al., 2007). All these positive effects are related to the revenue side of the profit equation. One of the only drawbacks of cross-channel integration when it comes to sales concerns the cannibalization among channels. As customers face fewer switching costs, they will use channels according to their convenience, which sometimes leads to sales reduction in some channels in favor of others (Lemon & Verhoef, 2016, Van Baal, 2014). As we transition from the short-term to the long-term analysis, there is evidence that as customers get more experienced with omnichannel initiatives, they tend to value less companies' efforts and expect a high-quality seamless experience by default (Neslin, 2022). In this sense, Herhausen et al. (2015) showed that customers' online experience negatively moderates positive cross-channel integration effects and Bilgicer et al. (2015) found that extraordinary profits from multichannel customers tend to grow in the short-term and come back to the initial level in the long-term. However, these fading effects can be overcome by the reinforcement of customers' engagement with the brand, for example, by strengthening the company's physical presence (Kumar et al., 2019).

When it comes to the cost perspective, there are both positive and negative aspects to consider. From a positive point of view, cross-channel integration comprises not only measures that are seen by the customer but also internal changes that can be beneficial for a company managing multiple channels. Tagashira & Minami (2019) found evidence that channel integration creates cost efficiencies, which can be explained by gains with joint optimization, economies of scale and economies of scope. In essence, if the company is able to integrate its organizational structure, take advantage of scale growth and increase the sharing of inputs and assets, it will be able to gather the benefits of improved operational efficiency. Nevertheless, many companies find difficulties implementing the necessary internal changes to achieve this efficient state. At this point, it is interesting to draw upon a resource-based view of the firm (Barney, 1991), by which we can understand that the development of internal capabilities is essential to achieve differentiation and competitive advantage. Oh et al. (2012) demonstrated that information technology and cross-channel human resources are important enablers of the competences that allow firms to see performance gains from cross-channel integration. Neslin (2022) mentions that the path towards the complete integration of channels depends on the firm's capabilities, which will determine how costly it is. Moreover, Cao & Li (2018) argue that cross-channel integration measures are heavily dependent on the development and adoption of innovations, which incur in taking risks and investing first to obtain advantages in the future.

These arguments lead us to expect high implementation costs and organizational entropy related to cross-channel integration in the short-term, followed by a stabilization phase with operational improvement and the addition of desirable omnichannel features in the long-run.

In light of these positive and negative mechanisms, we expect to find different effects of cross-channel integration on profits in the short and long term. Thus, we propose the following first two hypotheses:

H1: Cross-channel integration has a negative effect on operating profit margin in the short term.

H2: Cross-channel integration has a positive effect on operating profit margin in the long term.

2.3.2. Moderating factors

We will consider three moderators to support the investigation of the second research question, which is focused on firm-level factors that influence the impact of cross-channel integration on profit. The first moderator is the number of proprietary physical stores. The second is sales through proprietary apps or social media. And the third is the investment in emerging technologies, such as machine learning for customer insights, AI (Artificial Intelligence), VR (Virtual Reality), AR (Augmented Reality), robotics, web3 technologies and IoT (Internet of Things).

The chosen moderators are representative of the most frequent strategies that firms have been adopting to be present at each step of the customer journey (KPMG, 2022, Mckinsey & Company, 2022). All of them can be beneficial or damaging for the operational profit in the extent to which these companies are able to convert investments into more sales. Also, they can make the cross-channel integration efforts more or less impactful in triggering customers' desired behavior (trust, preference, advocacy, etc.) or in generating cost efficiency. For instance, if the company automatizes and integrates warehouse management, it can serve all channels with more efficiency (beneficial for the company) and reduce delivery time (beneficial for the customer).

2.3.3. Cross-channel integration and proprietary physical stores

The first moderator refers to the number of proprietary physical stores under the company's operation. It is widely accepted that physical presence is essential for retail companies once it increases customer engagement by facilitating the interaction of the customer with the firm, which is converted into more sales and profitability at the customer level (Avery et al., 2012, Akturk et al., 2018, Kumar et al., 2019). Conversely, studies have been questioning the optimal size of companies' physical representation in omnichannel marketing (Feng & Fay, 2020). A large store chain means more market coverage and sales, but less tactical flexibility and high operational costs (Srinivasan et al., 2013). As online sales grow, customers gain digital maturity, and companies develop technology-boosted omnichannel capabilities, the differentiation previously offered by physical stores reduces considerably (Kumar et al., 2017).

This discussion gets more complex when considering markets with highly differentiated products in which independent retailers and manufacturers compete directly for customers' preferences, as observed in the fashion & apparel industry. In this scenario of manufacturer encroachment (Arya et al., 2007), it is important for manufacturers to access the customers directly to increase market coverage, strengthen brand recognition and gain more control of marketing mix strategies, even if they are less efficient than independent retailers (Cao et al., 2010). However, in this case, manufacturers need to be even more mindful of costs with physical stores. As manufacturers develop retail expertise and proximity with customers enabled by omnichannel capabilities, i.e. increased cross-channel integration, an extensive and overlapping chain of physical branches could be seen more as a source of costs than a driver of sales.

Given this discussion, we propose the following two hypotheses:

H3: Proprietary physical stores negatively moderate the effect of cross-channel integration on operating profit margin in the short term.

H4: Proprietary physical stores negatively moderate the effect of cross-channel integration on operating profit margin in the long term.

2.3.4. Cross-channel integration and sales through proprietary apps or social media

Sales via mobile applications (apps) or social media have been an important marketing strategy in the last few years. They can be seen as an evolution from original online sales channels. Initially, companies developed websites, subsequently adapting them for mobiles, then, mobile apps (independent or connected with the websites) were launched, and lastly, companies incorporated digital stores inside social media platforms. Despite the cannibalization of the website channel (Liu et al., 2018), the literature presents positive sales outcomes from the addition of apps by multichannel retailers in the short-term (Narang & Shankar, 2019) and long-term (Zhang et al., 2019). Van Heerde et al., 2019 found evidence that the app fulfills specific needs from offline-only customers that were not covered by website and physical channels, increasing customer loyalty. From the firm point-of-view, proprietary apps have two main points of synergy with cross-integration initiatives: the first is the reduced operational cost due to the widespread access to app development technology and the easiness to integrate the operational tasks triggered through the app with the online sales structure (Cao et al., 2018); the second is that the app enables the implementation of many omni-channel capabilities that can increase customer experience (Lemon & Verhoef, 2016) and operational efficiency in the point-of-sales. Naturally, as an additional channel, the app will demand an implementation effort and ongoing maintenance over time, however, the main long-term concern with an app is the decay of audience engagement in a way that costs start to overcome the benefits from it (Liu et al., 2018). Finally, regarding social media, we expect this channel to have a similar influence as the app, with the addition of a trade-off between more operational simplicity and less control over the user experience. Thus, we hypothesize that:

H5: Sales through proprietary apps or social media positively moderate the effect of cross-channel integration on operating profit margin in the short term.

H6: Sales through proprietary apps or social media positively moderate the effect of cross-channel integration on operating profit margin in the long term.

2.3.5. Cross-channel integration and investment in emerging technologies

As previously stated, we consider as emerging technologies a wide range of technological advances that have been applied by companies in several areas. Examples of these technologies include machine learning, robotics, internet of things, augmented reality, etc. As expected, the literature on the consequences of the incorporation of these technologies in retail is still scarce, however, scholars have been pointing out the transforming potential they offer for the overall retail experience and the core business of incumbent and entrant firms (Verhoef et al., 2021). Once more, this discussion can be supported by RBV (Barney, 1991) and innovation theories (Schumpeter, 1950, Christensen, 1997). If we assume the market under investigation in this thesis as highly competitive and dominated by mostly traditional companies (e.g. LVMH, Skechers), we can expect many challenges and barriers for a broad incorporation of the emerging technologies (Verhoef et al., 2021). In the short-term, companies must perform extensive investments in terms of capabilities development, organizational transformation, and cash flow burn (Verhoef & Bijmolt, 2019). If they are successful in overcoming these initial challenges, they are expected to achieve differentiation and competitive advantage in the long run. In order to balance the initial investments, incumbent firms usually perform gradual implementation plans in a way that they can test and learn and also obtain business benefits throughout the process. For instance, firms can implement warehouse automation only in a few regions or pilot a new ML-enabled customer segmentation with a small part of the customer database. As a result of likewise features implementation, companies can boost sales through improved capacity to meet customers' expectations in a personalized manner and reduce costs by the increase in organizational productivity and operational efficiency (Kumar et al., 2017, Kumar et al., 2021).

In light of this, we see the investment in emerging technologies as one of the main enablers of advanced omnichannel capabilities. Because of the extent of financial investments and learning it demands in the short term, we only expect a positive moderating effect from the cross-channel integration effect on profits in the long term. Thus, we present the last two hypotheses:

H7: The investment in emerging technologies has a neutral influence on the effect of cross-channel integration on operating profit margin in the short term.

H8: The investment in emerging technologies positively moderates the effect of cross-channel integration on operating profit margin in the long term.

3. Methodology

In Chapter 3, we present the data and methods used to address the research questions. In the first section, we provide a detailed explanation of the data sampling and data preparation steps, considering dependent, independent, moderating and control variables. In the second section, we provide a succinct overview of the methods employed in this paper and the models' specifications to empirically test the proposed hypotheses. First and foremost, this chapter aims to offer a lucid description of the research design implemented and further elaborate on the rationale behind each methodological choice.

3.1. Data sample and measures

To examine the impact of cross-channel integration on profit margins, we used a sample of 30 leading companies from the fashion and apparel retail sector listed in the stock exchange for the past 12 years. The decision to focus on this sector was motivated by its relevance in the retail market, accounting for 1.7 trillion dollars market size in 2021 (Euromonitor International, 2022), and by specific characteristics of this segment that are interesting in the context of cross-channel integration analysis, such as: the high levels of competition and dynamism in the industry (Euromonitor International, 2021); the vertical integration of supply chain, meaning that, each time more manufacturers and independent retailers compete in the same markets (Richardson, 1996, Mckinsey & Company, 2022); and the heterogeneity of firms' characteristics (e.g. ages, origins, portfolios) and strategies (e.g. high-end versus low-end positioning, different channel mix compositions).

To select the companies for the sample, first, we consulted global rankings of public corporations in market value, filtering the fashion and apparel industry (Fashion United, 2023, Deloitte, 2022). From the initial list, we removed companies that were not traded on the stock exchange between 2012 and 2022 and companies that did not operate multiple channels, then we retained the top 30 companies from which we could obtain the publicly published annual reports in the English language for the years of analysis. We opted to focus on the top companies from the segment for two reasons: the first was to take advantage of the availability of reliable free-of-charge data from the company and third-party sources, and the second was to attempt capturing the general strategic and behavioral trends being developed on a large scale in the industry.

After defining our sample, we downloaded the annual reports from companies' Investor Relations webpages. These reports were the only source from which we processed the cross-channel integration and investment in emerging technologies variables. Additionally, we collected financial and company data (e.g. number of stores) from Eikon Datastream and market data from Euromonitor. Any missing data was completed with information from the annual reports or online sources. After coding the annual reports, three companies from the original selection were removed from the final data set because of their low disclosure regarding marketing actions, namely: Nike, Puma and Under Armour. We decided to remove the companies instead of searching online (e.g. in news, articles or press releases) for the cross-channel integration information to safeguard consistency and fairness in the evaluation of this aspect for all companies. Therefore, our final data set is composed of 27 companies from the fashion and apparel industry, with global operations, and ranked among the top companies for this segment in market value. These companies are analyzed over 10 years, from 2012 to 2021, constituting a balanced panel data set with 270 firm-year observations.

3.*1.1. Main independent variable: Cross-channel integration*

The main independent variable of this study is the firm's level of cross-channel integration. This measure is derived from a framework developed by Cao & Li (2015) to account for front-end and back-end aspects of a firm's journey towards the full integration of channels (or omnichannel integration in up-to-date terms). As a result of their thorough qualitative analysis using grounded theory, Cao & Li (2015) proposed that companies' level of cross-channel integration should be evaluated considering 27 empirical codes. These codes are aggregated into eight sub-categories and four general categories that represent the cross-channel integration evolutionary stages, namely: silo mode, minimal integration, moderate integration, and full integration.

For this thesis, the coding of the annual reports according to Cao & Li's framework was predominantly an artisanal job. Initially, we used the Atlas.ti software to analyze all reports from the years 2012 and 2021 having only the initial codes and example excerpts shared in the original article (Cao & Li, 2015) as a reference. Based on this initial analysis, we developed a system of keywords related to each of the cross-channel integration codes. For example, to find excerpts related to the code "buy online and return in-store", we proposed the keywords "return* *and* *store*". Likewise, we employed each code's keywords to analyze the remaining reports from years 2013 to 2020. By using this system, we ensured that, first, all relevant information contained in the vast volumes of text was retrieved and, secondly and most importantly, the 300 reports were evaluated according to a standard procedure and criteria. The codes and categories from Cao & Li (2015) paper, and the keywords and sample excerpts from the application of the framework in our data set are available in the Appendix.

After analyzing the annual reports, we processed the resulting codes to obtain the level of cross-channel maturity for each firm-year. Following Cao & Li (2015), we assumed that cross-channel integration activities mentioned in one year continued happening in the following years, even if the company does not mention it anymore. Another implicit assumption was that every activity mentioned in the reports was implemented for the company as a whole (i.e. not only a unit or region or number of stores). However, we propose a different calculation to measure the final firm's level of cross-channel maturity in each year. Whereas Cao & Li (2015) used the firm's highest level of integration activity as the measure of a given year, we calculated the weighted average of all firm activities in the year, as presented in Equation 1. This change was a necessary update to the original article's methodology to account for market changes that compelled the vast majority of retail companies to implement numerous actions towards omnichannel marketing management (Verhoef, 2021). According to Neslin (2022), "omnichannel marketing is de rigueur today", but the level of omnichannel integration effectively presented by retailers is still highly irregular. Based on this understanding, having a measure that ponders the number of cross-channel integration activities each year instead of giving full weight for the most advanced activity seems to be a more appropriate way to evaluate firms' evolutionary process. Moreover, this approach balances the two optimistic assumptions of activities continuation through time and homogeneity in the extent of actions' implementation across companies with a more conservative aggregated measure. To illustrate the results of the coding with the new methodology, an example of the final cross-channel integration measures year-by-year for one firm is available in the Appendix.

$$CCI\ weighted\ average_{it} = \frac{\sum_{j=1}^{4} CCI\ level_{itj} \times CCI\ number\ of\ activities_{itj}}{\sum_{j=1}^{4} CCI\ number\ of\ activities_{itj}} \tag{1}$$

Where *CCI weighted average* is the cross-channel integration final calculation for each firm-year, *CCI level* is the cross-channel integration level *j* (ranging from 1: silo model to 4: full integration) for the firm-year, *CCI number of activities* is the sum of activities of the level *j* for the firm-year.

3.1.2. Dependent variable: Operating profit margin

To represent the profitability of the company, we selected the operating profit margin as the dependent variable in this research (*Operating Margin*). This financial measure is also known as operating income margin and is calculated as the operating profit values divided by the sales values (Welch, 2009). The operating profit, in turn, is a line in the Income Statement of companies calculated as sales minus cost of goods sold (COGS), selling, general and administrative expenses (SG&A) and depreciation and amortization expenses (usually already included in COGS and SG&A lines) (Welch, 2009). Also commonly referred to as EBIT (earnings before interests and taxes), the operating profit is an important performance measure because it informs about the financial health of the company's operational activities, which makes it a focus of investor analysis and a recurring KPI (key performance indicator) in short and long-term executives' incentive programs (Baeten & Van Hove, 2021).

We considered the operating profit margin a preferred measure over operating profit for the following reasons. First, the operating profit values are very sensitive to sales variations (Welch, 2009), which means that they move up and down according to sales changes if the cost structure remains the same. Secondly, when comparing different companies, the operating profit alone is more informative of companies' relative sizes than relative performances, whilst the operating profit margin facilitates the contrast of core business' financial health and strategic positioning across firms. Reinforcing this point, Fairfield & Yohn (2001) argue that the profit margin is closely related to firms' operating strategies and measures their capacity to generate sales while keeping costs under control, which translates to the firms' operating efficiency. Thus, as we are interested in investigating the impact of the cross-integration actions on firms' profitability with a holistic view of sales and costs consequences, the operating profit margin offers a more informative and comparable measure to take as our dependent variable.

3.1.3. Moderating variables

This thesis considers three firm level moderating variables. The number of proprietary physical stores (*Number Stores*) was obtained from Eikon Datastream and complemented with information from the annual reports in case of missing data. Following Cao & Li (2015), in the models, this variable was used in the natural logarithm form. The usage of mobile apps or social media as sales channels (*Sales App.SM*) was incorporated in the model as a dummy that turned 1 in the years in which the company had at least one of the two sales channels active. To obtain this information, we analyzed the annual reports using the same keyword system developed for the cross-channel integration coding. When the information was not available, we consulted public online sources, such as news articles and press releases. Finally, the investment in emerging technologies (*Invest Tech*) was included in the models as the number of different emerging technologies employed by the firm in a given year. To produce this measure, we also used information from companies' annual reports coded according to a list of keywords. After coding all excerpts related to emerging technologies, we aggregated similar terms. For example, mentions of "machine learning", "big data" and "data models" were aggregated as "advanced analytics". Then, we counted the number of technologies for each firm-year considering the same continuity and completeness premises that were used for cross integration activities. The table with the keywords used to code the moderating variables and an example of the *Invest Tech* calculation for one company are available in the Appendix.

3.1.4. Control variables

Considering that this study uses factual data to investigate the possible causal effects between the level of cross-channel integration and firms' profitability, we added control variables to account for alternative explanations. The selection of control variables mainly followed the literature related to multichannel retailers' performance measurement, which we adapted due to differences in our research design or data limitations. In total, we added eight control variables, five in the firm-year level, two in the firm level (with no variation through time), and one in the year level (with no variation across firms). Starting with the firm-year level variables, we controlled for: the firm size, using the natural logarithm of number employees (Tagashira & Minami, 2019, Oh et al., 2012); the availability of cash to support operational activities, using the natural logarithm of firms' working capital (Cao & Li, 2015); the efficiency of sales in relation to the size of the physical stores network, using the total sales divided by the number of stores (derived from Tagashira & Minami, 2019); the relative growth of the firm versus the competitors in the same sub-segment, measured as the average year-over-year firm sales growth for the past 3 years minus the average year-over-year market sales growth for the past 3 years (adapted from Lamey et al., 2021, Homburg et al., 2014); and, the relative advantage of a competitor in moving toward cross-channel integration, which was calculated as -1 if the sub-segment median cross-channel integration is lower than the focal firm's same measure, 1 if the sub-segment median is comparative higher, and 0 if it both have equal values (Cao & Li, 2015).

Then, we introduced a time-variant dummy to control for the extreme market conditions during the COVID-19 pandemic years. This dummy assumed a value of 1 in the years 2019 and 2020 (considering that we model the dependent variable one year advanced from the explanatory variables), and 0 in the remaining years. Lastly, we added two firm-level variables to control for: the firm sub-segment in the fashion and apparel market using a categorical variable adapted from the GICS sub-industry and ICB subsector classifications (following Cao & Li (2015) and Oh et al. (2012) but controlling for differences in sub-segments within one industry instead of differences between industries); and the importance of online sales for the firm, creating a categorical variable that attributed a “low” label for companies in which online sales represented less than 15% of the total sales in 2021, “medium” for representativeness between 15% and 30%, and “high” for representativeness higher than 30% (adapted from Cao & Li, 2015, Tagashira & Minami, 2019).

3.1.5. Summary of variables

In short, we assembled a data set compounded by 13 variables and 270 firm-year observations related to 27 firms from the years 2012 to 2021. Table 2 presents a summary with the description, type, level, and source for each of the variables. The descriptive statistics will be explored in Chapter 4.

Table 2
Summary of variables

Variable	Description	Type	Level	Source
Operating Margin	Operating profit margin (in percentage)	dependent	firm-year	Eikon / Annual reports
CCI	Cross-channel integration measured as the weighted average of the accumulated scores from CCI actions according to Cao & Li (2015) framework	independent	firm-year	Annual reports
Number Store	Natural logarithm of the number of stores	moderator	firm-year	Annual reports
Sales App SM	Sales through apps or social media. If true for this firm in this year = 1, if false = 0	moderator	firm-year	Annual reports / Public information online
Invest Tech	Accumulated number of emerging technologies employed by the firm (e.g. AI, NFT)	moderator	firm-year	Annual reports
Rel. Sales Growth	Average year-over-year firm sales growth for the past 3 years - Average year-over-year market sales growth for the past 3 years. Market considering the sub-segments in which the firm operates.	control	firm-year	Eikon / Euromonitor

Rel. Adv. Integration	Competitor relative advantage in moving towards CCI. If the market sub-segment median CCI is lower than the focal firm, coded as -1, if it is higher, code as 1, if it is equal, coded as 0.	control	firm-year	Annual reports
Sales Store	Total of sales (in USD) / total number of proprietary physical stores	control	firm-year	Eikon / Annual reports
Working Capital	Natural logarithm of the working capital	control	firm-year	Eikon / Annual reports
Number Employees	Natural logarithm of the number of full-time employees	control	firm-year	Eikon / Annual reports
Covid Time	Dummy for the covid years. Considering that the dependent variable is analyzed in t+1, this dummy assumed 1 for 2019 and 2020 and 0 for other years.	control	year	-
Imp. Online Sales	Importance of online sales for the firm in 2021 divided in three categories: if <= 15%, low; if > 15% and <= 30%, medium; if > 30%, high.	control	firm	Annual reports / Public information online
Firm Segment	Firm sub-segment in the Apparel & Fashion industry (adapted by the author)	control	firm	Annual reports / Public information online

3.2 Data analysis

Due to the longitudinal nature of our data sample, i.e. a data set constituted of information from the same firms observed through time, we employed panel data models to test our hypotheses. Panel data models are particularly valuable for studies focused on using statistics to explain a given phenomenon instead of predicting future results, as is the case with this thesis. According to Croissant & Millo (2019), the main goal of using longitudinal models is to manage unobserved heterogeneity that comes from absent variables. Hsiao (2003) adds that the use of controls for individual and/or time effects enables not only gains in explanation power but the capacity to model dynamic and complex conditional relationships from the real world. Moreover, from a statistical perspective, the control for individual heterogeneity adds variability in the observations, which is helpful to reduce multicollinearity problems and increase the reliability of estimations (Hsiao, 2003).

Considering the eight hypotheses derived from our research questions presented in Chapter 2, we proposed two different panel models to account for short- and long-term differences. The complete short-term model for the firm *i* in the year *t* is represented as follows:

$$
\begin{aligned}
Operating\ Margin_{it+1} \\
= \beta_0 + \beta_1 CCI_{it} + \beta_2 Sales\ App.SM_{it} + \beta_3 Invest\ Tech_{it} + \beta_4 Number\ Stores_{it} \\
+ \beta_5 CCI_{it} \times Sales\ App.SM_{it} + \beta_6 CCI_{it} \times Invest\ Tech_{it} \\
+ \beta_7 CCI_{it} \times Number\ Stores_{it} + \beta_8 Rel.Sales\ Growth_{it} \\
+ \beta_9 Rel.Adv.Integration_{it} + \beta_{10} Sales\ Store_{it} + \beta_{11} Working\ Capital_{it} \\
+ \beta_{12} Number\ Employees_{it} + \beta_{13} Firm\ Segment_i + \beta_{14} Imp.Online\ Sales_i \\
+ \beta_{15} Covid\ Time_t + \varepsilon
\end{aligned} \tag{2}
$$

Where $Operating\ Margin_{it+1}$ is the operating profit margin for the year t+1, *CCI* is the level of cross-channel integration, *Sales App.SM* the dummy of sales through mobile apps or social media, *Invest Tech* the investment in emerging technologies, *Number Stores* the number of physical stores operated by the firm, *Rel.Sales Growth* the measure of relative firm sales growth in the past three years compared to the market sales growth, *Rel.Adv Integration* the measure of relative advantage of competitors in integrating their channels, *Sales Store* the firm's total sales divided by the firm's number of stores, *Working Capital* the working capital values, *Number Employees* the firm's total number of employees, *Firm Segment* is the categorical variable to control for industry sub-segments, *Imp.Online Sales* is the categorical variable for the firm's level of online sales and *Covid Time* is the time dummy to control for the covid years. Following the literature best practices (e.g. Cao & Li, 2015, Feng & Fay, 2020), all explaining variables are measured in the year *t,* and the dependent variable is measured in the year *t+1*. This adjustment is relevant to avoiding reverse causality problems (Feng & Fay, 2020).

For the long-term model, we used the same independent variables and advanced the operating profit margin to three years ahead of the time *t*. This long-term time horizon was defined considering business and academic references. On the one hand, mainstream corporate practice refers to the long term as at least three ahead in time (Pessoa de Araujo & Robbins, 2019, KPMG, 2019). On the other hand, retail researchers evaluate long-term effects from the second year after a given measure was implemented onwards (e.g. Venkatesan et al., 2007, Kumar et al., 2019). Pondering both perspectives, we evaluate that measuring long-term outcomes with the profit margins advanced three years provides a good balance between maturation time of the actions under investigation and optimized use of our limited data set. Therefore, the complete long-term has the following specification:

$$
\begin{aligned}
Operating\ Margin_{it+3} \\
= \beta_0 + \ \beta_1 CCI_{it} + \ \beta_2 Sales\ App.SM_{it} + \beta_3 Invest\ Tech_{it} + \beta_4 Number\ Stores_{it} \\
+ \beta_5 CCI_{it} \times Sales\ App.SM_{it} + \beta_6 CCI_{it} \times Invest\ Tech_{it} \\
+ \beta_7 CCI_{it} \times Number\ Stores_{it} + \ \beta_8 Rel.Sales\ Growth_{it} \\
+ \ \beta_9 Rel.Adv.Integration_{it} + \ \beta_{10} Sales\ Store_{it} + \ \beta_{11} Working\ Capital_{it} \\
+ \beta_{12} Number\ Employees_{it} + \beta_{13} Firm\ Segment_i + \beta_{14} Imp.Online\ Sales_i + \ \varepsilon
\end{aligned}
\tag{3}
$$

Where $operating\ margin_{it+3}$ is the operating profit margin for year *t+3*, and the right-side variables are the same as in the short-term model, except for the *Covid Time* that is not relevant in this case. In both models, we assessed the impact of cross-channel integration on the operating profit margin by analyzing the directions and statistical significance of the *CCI* coefficients. Likewise, the influence of the moderators on the cross-channel integration-operating profit margin relationship is determined by the same analysis considering the interaction terms' coefficients.

We implemented these models in R using the PLM package. After running initial descriptive analyses with the data, we performed fixed effects and random effects methods and then selected the most suitable specification for our data set and variables by executing the Hausman test. In general terms, the fixed effects model has its name because it uses fixed individual or time effects to control for the unobserved heterogeneity of the model. The results of the fixed effects model are equivalent to adding individual or time dummies to a linear regression but estimated more efficiently with the use of an entity-demeaning OLS (ordinary least squares) estimator (Croissant & Millo, 2019). In turn, the random effects model assumes the unobserved heterogeneity as random samples from a specific distribution. Based on this assumption, it uses the GLS (generalized least squares) estimator to find the parameters of this distribution, which are, then, used to estimate the individual effects' slopes (Croissant & Millo, 2019). Given these methodological differences, the choice between the two models must consider the characteristics of the sample, the nature of the covariates (since the time/individual fixed-effects model cannot estimate individual/time-invariant variables), and primarily, the correlation of the covariates with the individual effects. If this correlation exists, the random effects estimates are not consistent since the independence between the covariates and the individual effects is one of the premises of the model. On the other hand, if the correlation does not exist, the random effects model must be chosen because its GLS estimator is more efficient than the fixed effects estimator. This is precisely what is assessed by the Hausman test, which states in the H0 (null hypothesis) that both models are consistent, but one is more efficient, and in the H1 (alternative hypothesis) that only one model is consistent. Therefore, if we do not reject the Hausman test, we select the random effects model; alternatively, if we do reject it, we choose the fixed effects model.

To ensure the statistical consistency of the results, we also tested for possible problems with the models and their residuals, among others: multicollinearity, heteroscedasticity, serial correlation, and cross-sectional dependence (Croissant & Millo, 2019). Encountering some of these problems when dealing with factual data is not uncommon, however, several corrective measures can be applied to proceed with the interpretation of the results, such as the model re-specification, variables transformation and use of robust estimators (Baltagi, 2021). The complete modeling process and estimation results considering all these steps will be explored in the following chapter.

4. Results

In Chapter 4 we delve into the data analyses and models developed to test the hypotheses proposed in this study. We begin our investigation with an overview of the descriptive statistics, followed by model-free analyses, which collectively provide valuable initial insights from our data. Afterwards, we examine the results of the short-term and long-term models and discuss the contribution of the robustness tests to the reliability of our estimates. Finally, based on the gathered evidence, we conclude with a summary of the answers to the research hypotheses.

4.1. Descriptive statistics

As mentioned earlier, we compiled a balanced panel data set with 270 firm-year observations, which refers to 27 fashion and apparel firms over 10 years of activity. Table 3 presents the descriptive statistics for the quantitative variables. From the table, we note that cross-channel integration (*CCI*) presents an expressive variability, ranging from 0 to 3.5 (when it could vary from 0 to 4). Moreover, the mean sits at 2.7 and the median at 2.9, indicating a bias towards more advanced levels of cross-channel integration. Regarding the operating profit margin (*Operating Margin*), we also observe a substantial dispersion, evidenced not only by the 55p.p. (percentual points) between the minimum and maximum values, but by the standard deviation of 9% versus average and median values of 13% and 12%, respectively. In fact, elevated dispersion rates are present in most of the variables, which can be a concern for the modeling because of skewness and outliers. Given the relatively small sample size, to address this issue and work with better distributed variables (closer to normal distribution), we applied logarithm transformation in the scalar variables (Wooldridge, 2010, Gelman & Hill, 2007), namely Number Stores, Working Capital, and Number Employees.

Table 3
Descriptive statistics for quantitative variables in the short-term models

	Mean	Median	Sd	Min	Max
CCI	2.70	2.90	0.70	0.00	3.50
Operating Margin (t+1)	0.13	0.12	0.09	-0.15	0.40
Invest Tech	1.60	1.00	2.40	0.00	12.00
Rel. Sales Growth	0.08	0.05	0.14	-0.32	1.20
Rel. Adv. Integration	-0.01	0.00	0.91	-1.00	1.00
Sales Store	8.60	6.10	8.50	0.13	50.00
Number Stores	2,260	1,155	2,811	63	17,921
Working Capital	2,426	1,346	3,047	-681	17,898
Number Employees	45,035	18,800	58,299	2,468	340,000

Notes: Sample size = 270. Original values are used when calculating summary statistics.

For the long-term model, as we advanced the dependent variable in three years, we could only use data from 2012 to 2019 (with *Operating Margin* from 2015 to 2022). Consequently, the long-term data set is composed of 216 firm-year observations. In terms of descriptive statistics, there are small differences compared to the short-term data set. For example, the mean and the median values of the cross-channel integration (*CCI*) reduced to 2.6 and 2.8, respectively, and the mean number of technologies implemented by companies (*Invest Tech*) reduced from 1.6 to 1.2. These differences make sense considering the acceleration of companies' digitalization during the last few years, mainly pushed by the COVID-19 peak in 2020. The complete descriptive statistics for the long-term data set is available in the Appendix.

Continuing with the descriptive statistics, Table 4 displays the frequency distributions for the categorical variables in our data set. From the table, we recognize "Luxury fashion" as the industry sub-segment (*Firm Segment*) with more observations, comprising 11 companies, whereas the "Off-price" and "Eyewear" sub-segments have only one company each. Additionally, we notice that almost half of the firm-years did not have sales through apps or social media (*Sales App.SM* = 0). To put this into perspective, in 2012, only 5 companies had apps or social media as sales channels, whereas in 2016, this number increased to 16, and, in 2019, it reached its peak with 21 companies. Thus, this statistic reflects the diversity of firms' strategies with respect to these digital channels. Next, regarding the importance of online sales (*Imp. Online Sales*), the majority of companies (52%) obtained between 15% and 30% of their revenues from online channels in the year 2021, representing a medium level according to our scale. Taking into account that we are dealing with leading companies in the global apparel industry, the concentration of companies at the medium and high levels is sound evidence of the market transformation discussed throughout this paper.

Table 4
Descriptive statistics for categorical variables in the short-term models

Variable	Obs.	%
Firm Segment	270	
Off-price	10	4%
Casualwear	40	15%
Eyewear	10	4%
Fast fashion	20	7%
Footwear	20	7%
Luxury fashion	110	41%
Retail	20	7%
Sportswear	40	15%

Variable	Obs.	%
Sales App.SM	270	
0	117	43%
1	153	57%

Variable	Obs.	%
Imp. Online Sales	270	
low	50	19%
medium	140	52%
high	80	30%

Variable	Obs.	%
Covid Time	270	
0	216	80%
1	54	20%

The Pearson correlation results in Table 5 indicate that the cross-channel integration level (*CCI*) is positively correlated with *Invest Tech* and *Sales Store,* and negatively correlated with all other variables. However, only the correlations with *Invest Tech* and *Rel. Adv. Integration* are statistically significant. Overall, the correlations are below 0.5, indicating low risk of multicollinearity issues. The only exception is the correlation between *Number Employees* and *Number Stores*. Given the importance of these covariates, we will proceed with them and pay special attention to multicollinearity assessment after running the models.

Table 5
Pearson correlation results

	1.	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**
1. CCI	1							
2. Operating Margin	-0.121	1						
3. Invest Tech	0.383***	0.054	1					
4. Rel. Sales Growth	-0.046	0.173	-0.038	1				
5. Rel. Adv. Integration	-0.436***	0.191**	-0.002	0.064	1			
6. Sales Store	0.153	0.066	-0.04	-0.052	-0.007	1		
7. Number Stores	-0.058	0.022	0.353***	0.032	-0.031	-0.493***	1	
8. Working Capital	-0.084	0.245***	0.168	0.07	0.078	-0.119	0.238***	1
9. Number Employees	-0.064	0.09	0.397***	-0.005	0.034	0.123	0.669***	0.233***

Notes: The correlation coefficients are calculated with the transformed variables as described in Table 2. 2. Operating Margin refers to the period (t+1). Stars indicate statistical significance: *** p < .01, ** p < .05, * p < .1.

We conclude this section with a visual investigation of our main variables. First, Figure 2 presents the histogram of cross-channel integration at the left side and operating profit margin (t+1) at the right side. By analyzing the left-side graph we reinforce the conclusions drawn from the mean and median analysis of the *CCI* levels. Most of the observations in this graph are between 2.5 and 3.5, which results in a left-skewed distribution. On the right-side graph, the *Operating Margin* histogram reveals a more centered and normal-like distribution, with most observations concentrated between 10% and 20% values.

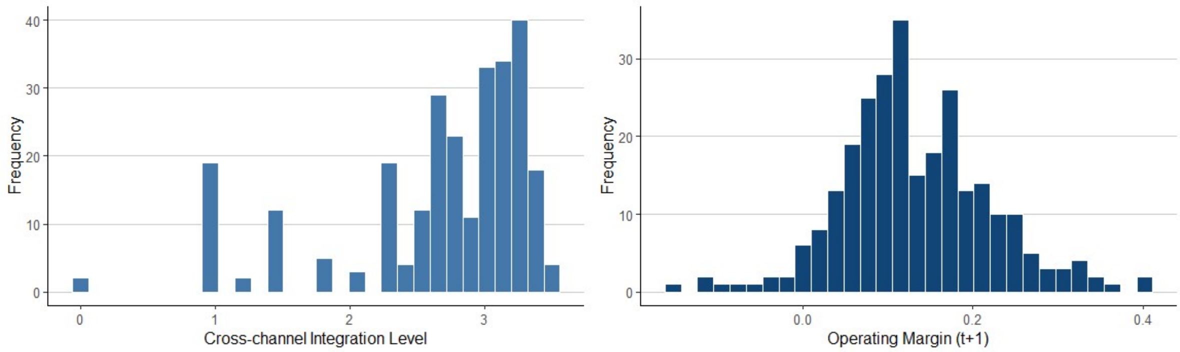

Figure 2. Histograms for Cross Channel Integration and Operating Margin (t+1)

Then, in Figure 3, we switch the focus from frequency distributions to average values over time. In this graph, while the *CCI* line (solid light blue) shows a sustained growth over the years, the *Operating Margin* (t+1) values (dashed dark blue) oscillate from a downward trend with a deep valley during COVID-19 peak year to a recovery period with accentuated growth in the subsequent year. A naïve analysis of these curves opposing behaviors would suggest a negative relationship between *CCI* and *Operating Margin*. Nevertheless, there are important external factors that must be controlled to unveil the real impact of cross-channel actions on firms' operating margins. This is what we will try to achieve with the econometric models performed in the following sections.

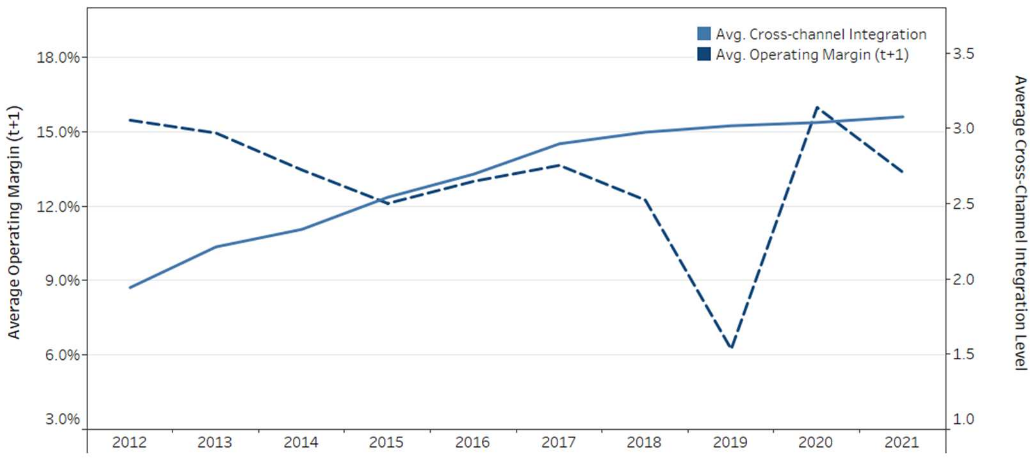

Figure 3. Development of Cross-channel Integration and Operating Margin (average per year)

4.2. Model-free analyses

Before proceeding to statistical models, this section aims to present insights from model-free analyses, which are helpful to gain a deeper understanding of the phenomenon under investigation in this paper. In section 4.2.1, we discuss findings from the coding of the annual reports that are relevant for the interpretation of the results, though not transparent in the aggregate *CCI* measure used in the models. In section 4.2.2 we inspect the differences among the industry sub-segments in our sample, shedding light on the importance of this variable to contemplate companies' heterogeneity in the statistical analyses.

4.2.1. Insights from the annual reports

Starting with a broader view, Figure 4 displays the evolution of omnichannel activities year-by-year in terms of the number of companies executing actions from each sub-category in the cross-channel integration framework. As expected, the graph shows a prominent growth of omnichannel actions across companies in all sub-categories over the years of analysis, going from an average of 5.7 firms per sub-category in 2012 to 21 in 2021 (from a total of 27 companies in the data set). Beyond the general trend, we can capture two more insights from this graph. First, we notice that the growth rate of the bars is much higher between 2012 and 2015 than in the following years. For example, the sub-category "integration of consumer information" goes from 3 to 13 companies in the first four years, and from 13 to 21 in the remaining six years of analysis, which represents half of the growth rate of the first years. Secondly, the growth between the sub-categories varies considerably from year to year. Comparing again the periods 2012-2015 and 2016-2021, we see that, in the first years, the categories experiencing stronger growth were those related to the integration of transactional aspects (numbers 3 and 4 in the graph), which comprise actions such as "Buy online and return in-store" and "Allowing online customers to browse the inventory in-store". Although these sub-categories continued to grow through the whole period, in the end, the sub-categories with the highest penetration among companies were "6: Centralization of back-end system", "7: Organization transformation" and "5: Alignment of fundamentals", respectively. This variation between sub-categories suggests that, in their quest to become omnichannel, companies had to mix their investments between actions more transparent to the customers (e.g. "Allowing online consumers to browse the inventory in-store") and actions related to internal organization and development of capabilities to support their transformation.

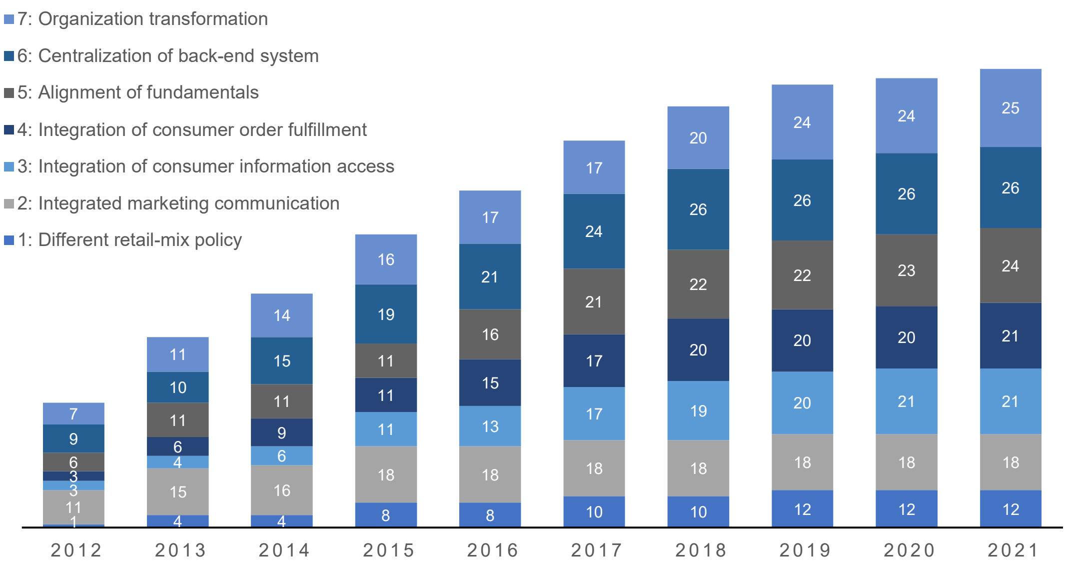

Figure 4. Evolution of Cross-channel Integration (number of companies per sub-category and year)

When we drill down from the sub-categories to the cross-channel integration indicators coded from the annual reports, we observe that, up to 2015, the most present code was the "Consistency of marketing message across channels". Indicating companies initial omnichannel efforts to give signs of cross-channel alignment to customers. In contrast, for all the remaining years, the code "Aligned services across channels" was the leader in penetration, being identified in the reports of 24 companies in 2021. However, we evaluate that this code predominates because it captures the growth of the intention of providing an omnichannel experience to customers. In other words, we noticed that mentioning terms such as "integration of services across channels", "provide omnichannel services" and "offer seamless customer experience" became almost an obligation to companies over the years. Nonetheless, these are very broad terms that do not truthfully reveal the extent of the integrated experience being offered to customers. On the other hand, the next two most mentioned codes in 2021 are much clearer to interpret. "Click and pick up in-store" (usually abbreviated as BOPS) and "Integration of logistics across channels" were both present in the reports of 21 companies in 2021, reinforcing the importance of the integration between online and offline channels in the purchase stage and that, to make BOPS and the other transactional integration features viable, companies need to invest in the optimization of their operational structures and processes.

Another interesting finding from the annual reports is the continuity and even slight growth of actions in the sub-category "Different retail-mix policy" through the years. An illustrative example is the code "Different assortment policies in different channels" that was present for 1 firm in 2012 and grew up to 11 firms in 2021. We interpret this somewhat counter-intuitive move in two directions. The first is that, despite the effort to provide an integrated experience across channels, there are aspects that companies prefer to differentiate, such as prices between online and offline channels (justified by their different value offers), and aspects that are extremely challenging for companies to integrate completely, being assortment one of the main examples of this point. The second direction is that companies are using the differentiation between channels to meet the market demand for personalization. This trend is captured in the firms' annual reports, in which we observe a growing number of mentions of the use of different channels and advanced digital technologies to introduce personalization features, curated offers, and exclusive collections to the customers. For further analyses, the table with the number of companies per cross-channel integration code and year is available in the Appendix.

4.2.2. Insights from the industry sub-segments

In Table 6, we present statistics from our sample data by industry sub-segment (*Firm Segment*), which are helpful to understand the diverse firms' strategies and characteristics in the Fashion and Apparel market. Ordering the segments from highest to lowest average *CCI* level and comparing the four more integrated (left side) versus the four less integrated segments (right side), we can observe some diverging characteristics. In general, the segments on the left side have a lower level of revenue with a slightly higher level of operating margins. Moreover, the segments on the right side appear to be more dependent on the physical structure and more labor intensive, according to their higher numbers of stores and employees, on average. This is reinforced by the lower ratios of sales per store and sales per employee compared to the more integrated companies. Interestingly, these measures are positively correlated with the average percentage of online sales, suggesting that the development of online channels help companies to become more efficient in the use of capital and labor resources. The segments that sell more online also rely more on the use of apps or social media as sales channels, as evidenced by the higher percentages of apps and social media usage among them. On the other hand, there do not seem to be significant differences in the investment in emerging technologies or working capital between more integrated or less integrated segments.

Table 6
Summary of statistics per industry sub-segment (Firm Segment)

	Retail	**Luxury fashion**	**Sports-wear**	**Casual-wear**	**Foot-wear**	**Fast fashion**	**Eyewear**	**Off-price**	**All Segments**
Number of companies	2	11	4	4	2	2	1	1	27
Avg. Revenue (mUSD)	9,920	11,151	7,891	8,487	2,778	24,210	13,135	35,790	11,515

Avg. Operating Margin (t+1) (%)	12	16	15	0.07	8	13	14	10	13
Avg. CCI	3.22	2.74	2.72	2.69	2.62	2.52	2.29	1.37	2.67
Avg. Invest Tech	0.80	2.02	1.13	0.88	0.00	4.60	2.60	0.00	1.62
Sales App.SM (% of firm-years)	85	55	40	90	35	55	0	50	57
Avg. Number Stores	429	1,284	3,472	1,670	686	5,530	10,151	4,006	2,301
Sales/Store (kUSD)	23,118	8,685	2,273	5,082	4,050	4,378	1,294	8,934	5,004
Avg. Number Employees	47,892	26,850	25,918	28,447	4,727	130,045	108,313	255,727	46,006
Sales/Employee (k)	207.13	415.30	304.47	298.35	587.70	186.16	121.26	139.95	250.29
Avg. % Online Sales	53	21	28	30	26	29	7	3	25
Avg. Working Capital (mUSD)	930	3,117	1,778	2,580	841	3,629	1,716	2,766	2,482

As previously stated, the model-free analyses are relevant to gaining depth in our investigation of the impact of cross-channel integration activities on firms' profitability. However, it lacks complexity to consider multiple factors and does not provide statistical validity to generalize any conclusions drawn from data. To address these points, in the next sections we present the results from the short-term and long-term econometric models.

4.3. Short-term models

Table 7 presents the results of three models performed to assess the short-term influence of cross-channel integration maturity on profit margins. Model 1 contains only the control variables, Model 2 adds the main independent variable and moderators, and Model 3 includes the interactions between moderators and cross-channel integration. All models are presented with Beck and Katz's robust errors. To decide about the estimation method, we used the Hausman test, which indicated the fixed effects model as the most suited for our specification (Null hypothesis rejected with p-value < 0.01). The best specification was obtained with time-fixed effects and control for firms' sub-segments as dummies. Because of this configuration, the Covid Time dummy was removed from the models.

By analyzing Model 1, we observe that most of the control variables have a statistically significant influence on the $Operating\ Margin$. The $adjusted\ R^2$ indicates that 39,64% of the variance of the dependent variable is explained by this model. Model 2 has a very similar explanation power, with an $adjusted\ R^2$ of 39,77%. Based on the results shown in Table 7, cross-channel integration has a slightly negative and non-significant coefficient ($\beta = -0.004, p = 0.76$). The moderators are also not significant. In turn, Model 3 presents 42.33% of explanation capacity, and statistically significant results for *CCI* and the interaction *CCI x Number Stores*. Thus, the cross-channel integration has a positive effect on operating profit margin ($\beta = 0.148, p < 0.05$) that is negatively moderated by the number of proprietary physical stores ($\beta = -0.02, p < 0.05$). Interestingly, the individual coefficient of *Number Stores* is positive and statistically significant ($\beta = 0.04, p < 0.05$). Combined, the interpretation of these results is that the effect of cross-channel integration is positive when companies have low levels of physical presence, however, as the number owned physical stores increase, moving towards a higher level of cross-channel integration is less rewarding in terms of operating margin gains. According to this analysis, Hypothesis 1 is rejected, and Hypothesis 3 is supported.

Proceeding with the interpretation of Model 3 results, the coefficients of the other two moderators (*Invest Tech* and *Sales App.SM*) are positive and non-significant, while their interaction terms with *CCI* have negative and also non-significant coefficients. These results lead us to reject Hypothesis 5 and support Hypothesis 7. Lastly, regarding the control variables, *Working Capital* ($\beta = 0.01, p < 0.01$), *Rel. Adv. Integration* ($\beta = 0.01, p < 0.1$), *Rel. Sales Growth* ($\beta = 0.132, p < 0.01$), and *Imp. Online Sales* ($High: \beta = -0.111, p < 0.01, Medium: \beta = -0.149, p < 0.01$ versus the reference category "low") are statistically significant, whereas *Sales Store* and *Number Employees* are not significant.

Table 7
Regression results for short-term (dependent variable: Operating Margin (t+1))

Variable		**Model 1**			**Model 2**			**Model 3**		
		Coef.		**S.E.**	**Coef.**		**S.E.**	**Coef.**		**S.E.**
Main effects										
CCI	H1 (-)				-0.004		0.014	0.148	**	0.060
Moderating effects										
Number Stores					-0.002		0.015	0.048	**	0.024
CCI x Number Stores	H3 (-)							-0.021	**	0.008
Sales App.SM=1					-0.025		0.017	0.003		0.050
CCI x Sales App.SM	H5 (+)							-0.010		0.018
Invest Tech					0.001		0.004	0.024		0.037
CCI x Invest Tech	H7 (0)							-0.007		0.012
Control Variables										
Rel. Sales Growth		0.112	***	0.042	0.105	**	0.042	0.133	***	0.042

Rel. Adv. Integration	0.019	***	0.007	0.014	*	0.008	0.015	*	0.008
Sales Store	-0.001		0.001	-0.001		0.002	-0.002		0.002
Working Capital	0.012	***	0.004	0.012	***	0.004	0.011	***	0.004
Number Employees	0.011		0.011	0.016		0.016	0.017		0.015
Imp. Online Sales=High	-0.099	***	0.032	-0.102	***	0.033	-0.111	***	0.031
Imp. Online Sales=Medium	-0.133	***	0.029	-0.135	***	0.029	-0.149	***	0.028
Time effects	Yes			Yes			Yes		
Firm Segment effect	Yes			Yes			Yes		
Observations	270			270			270		
Number of firms	27			27			27		
Adjusted R^2	0.3964			0.3977			0.4233		

Notes: *** p < .01, ** p < .05, * p < .1; Coefficients are presented with Beck and Katz robust standard errors; Coefficient values are rounded to three decimal places.

4.4. Long-term models

Following the same guidelines, Table 8 shows the results of the three long-term models performed to assess the effects of cross-channel integration on operating profits after three years. Once more, the Hausman test indicated the fixed effects as the most appropriate model specification (Null hypothesis rejected with p-value < 0.01). Therefore, all three long-term models contain time-fixed effects and dummies to control for firms' sub-segment. Also, the coefficients' significance is evaluated with Beck and Katz's robust errors.

Table 8 shows similar results for the long-term models in comparison to the short-term estimates. Model 4 explains 38.15% of the long-term *Operating Margin*, based on the $adjusted\ R^2$. These numbers vary marginally in Model 5 and Model 6 to 38.65% and 40.29%, respectively. Additionally, in Model 4, the *Rel. Sales Growth* is not significant to explain the long-term effects as it was to explain short-term effects in Model 1. In Model 5, the level of cross-channel integration remains non-significant, although it inverted the sign compared to Model 2 and now presents a slightly positive coefficient ($\beta = 0.007, p = 0.62$). As both coefficients are not significant, this change is not relevant to the interpretation of results. Still in Model 5, the moderators *Invest Tech* and *Number Stores* have non-significant estimates, while *Sales App.SM* has a negative and marginally significant coefficient ($\beta = -0.02, p < 0.1$).

The main conclusions obtained from Model 3 are valid to interpret the results of the complete long-term model. Thus, in Model 6, cross-channel integration has a positive effect on operating profit margins in the long-term ($\beta = 0.12, p < 0.1$), and this effect is negatively moderated by the number of proprietary physical stores ($\beta = -0.01, p < 0.1$). This interpretation supports Hypothesis 2 and Hypothesis 4. In contrast, the individual estimate of *Number Stores* is not significant in Model 6, and the significance and coefficients of *CCI* and *CCI x Number Stores* are smaller than in Model 3. Considering coefficients and standard error values from both models, we can interpret the estimated effects as statistically identical in the short- and long-terms. However, the reduced significance may indicate that the cross-channel integration level is not as relevant to explaining the profit margins in Model 6 as it is in Model 3.

Regarding the other moderators in Model 6, *Sales App.SM* and *Invest Tech* are not significant individually or when interacting with the *CCI*. Thus, we reject Hypothesis 6 and Hypothesis 8. Among the control variables, *Rel. Adv. Integration* ($\beta = 0.02, p < 0.01$), *Sales Store* ($\beta = -0.002, p < 0.1$), *Working Capital* ($\beta = 0.009, p < 0.05$), and *Imp. Online Sales* ($High$: $\beta = -0.138, p < 0.01, Medium$: $\beta = -0.168, p < 0.01$ versus the reference category "low") are statistically significant, while *Number Employees* is not significant.

Table 8
Regression results for long-term (dependent variable: Operating Profit (t+3))

Variable		Model 4			Model 5			Model 6		
		Coef.		S.E.	Coef.		S.E.	Coef.		S.E.
Main effects										
CCI	H2 (+)				0.007		0.014	0.126	*	0.067
Moderating effects										
Number Stores					-0.001		0.016	0.036		0.025
CCI x Number Stores	H4 (-)							-0.017	*	0.009
Sales App.SM=1					-0.028	*	0.017	-0.066		0.052
CCI x Sales App.SM	H6 (+)							0.014		0.019
Invest Tech					0.003		0.005	0.039		0.045
CCI x Invest Tech	H8 (+)							-0.011		0.014
Control Variables										
Rel. Sales Growth		0.015		0.043	0.010		0.043	0.029		0.044
Rel. Adv. Integration		0.022	***	0.007	0.021	**	0.009	0.023	***	0.009
Sales Store		-0.002		0.001	-0.002		0.002	-0.003	*	0.002
Working Capital		0.010	**	0.005	0.010	**	0.005	0.010	**	0.005
Number Employees		0.015		0.012	0.018		0.017	0.023		0.017
Imp. Online Sales=High		-0.126	***	0.035	-0.130	***	0.034	-0.139	***	0.033
Imp. Online Sales=Medium		-0.155	***	0.031	-0.159	***	0.031	-0.169	***	0.030

Time effects	Yes	Yes	Yes
Firm Segment effect	Yes	Yes	Yes
Observations	216	216	216
Number of firms	27	27	27
Adjusted R^2	0.3815	0.3865	0.4029

Notes: *** p < .01, ** p < .05, * p < .1; Coefficients are presented with Beck and Katz robust standard errors; Coefficient values are rounded to three decimal places.

4.5. Robustness tests and results summary

The first measure to confirm the robustness of our results was performing diagnostic tests with the models and their residuals. Before running the models, we executed the Dickey-Fuller unit root test, with which we attested that the dependent variable (*Operating Margin*) does not have unit root. Then, after running the models, we tested for multicollinearity with the VIF calculation (using a pooled version of our models, because the VIF cannot be calculated in models without intercept), cross-sectional dependence using the Pesaran's test, normality of the residuals with the Shapiro-Wilk's test, residuals' heteroscedasticity with the Breusch-Pagan's test and serial correlation using the Wooldridge's test.

In summary, all models presented serial correlation and residuals that are not normally distributed. Moreover, the short-term models presented heteroscedastic residuals, whereas the long-term models presented homoscedastic errors. To address these issues, we used Beck and Katz's robust errors to interpret the results of the models, as mentioned in sections 4.3 and 4.4 (Croissant & Millo, 2019). Regarding the VIF measures, we only identified high correlation among the *Firm Segment* dummies and in the variables with interaction terms (in Models 3 and 6), which is expected and not considered harmful (Allison, 2012). And, finally, the tests did not identify cross-sectional dependence in the models. Thus, we conclude that our estimates are statistically robust.

An additional concern beyond the statistical validity of our models was the influence of the COVID-19 period on the results. We know that the pandemic caused a great disruption in companies' operations and financial outcomes, as well as in the speed of firms' digital transformation and migration to online channels. All these consequences are directly related to the phenomenon under investigation in this paper. Hence, we performed new versions of the complete short-term and long-term models (Models 3 and 6) considering only the period before the first COVID-19 outbreak in 2020, which means, for the short-term, years 2012 to 2018, and for the long-term, years 2012 to 2016. The results of these models confirmed the conclusions presented in the previous sections. For both the short- and long-term, the level of cross-channel integration had a positive impact on operating profits, negatively moderated by the intensity of the firm's physical presence. The smaller significance and β coefficients for these variables in the long-term model also remained true. The $adjusted\ R^2$ increased considerably in the two models (to 55% and 56%, respectively), possibly because of the reduction of variability in the data. Curiously, the only relevant difference found in both models was that *Invest Tech*'s coefficients became significant with a positive sign individually and a negative sign in the interaction with *CCI*. This could be an indicative that the combined investment in cross-channel integration activities and emerging technologies generates more costs than sales growth or operational efficiency for companies, causing a reduction in the operating margin. However, based solely on our data and models, we cannot confirm if the divergence between full period and pre-covid estimates is related to real changes that reduced the importance of the *Invest Tech* variable or if the full-period model was just not able to capture *Invest Tech*'s significant effect amidst the COVID-19 volatility. Therefore, we will refer to these differences in the limitations and we conclude that our findings are consistent and statistically valid according to the robustness tests performed. For further analysis, the complete results of the pre-covid models are reported in the Appendix.

We close this chapter by presenting a summary of the implication of our analyses to the research hypotheses. As shown in Table 9, of the eight hypotheses proposed, four were rejected and four were supported.

Table 9
Summary of hypotheses evaluation

	Hypothesis	**Result**
H1	Cross-channel integration has a negative effect on operating profit margin in the short term.	Rejected
H2	Cross-channel integration has a positive effect on operating profit margin in the long term.	Supported
H3	Proprietary physical stores negatively moderate the effect of cross-channel integration on operating profit margin in the short term.	Supported
H4	Proprietary physical stores negatively moderate the effect of cross-channel integration on operating profit margin in the long term.	Supported
H5	Sales through proprietary apps or social media positively moderate the effect of cross-channel integration on operating profit margin in the short term.	Rejected
H6	Sales through proprietary apps or social media positively moderate the effect of cross-channel integration on operating profit margin in the long term.	Rejected
H7	The investment in emerging technologies has a neutral influence on the effect of cross-channel integration on operating profit margin in the short term.	Supported
H8	The investment in emerging technologies positively moderates the effect of cross-channel integration on operating profit margin in the long term.	Rejected

5. Discussion and conclusions

The main objective of this thesis was to investigate the impact of cross-channel integration on retailers' financial performance in the short and long run. Moreover, we aimed to identify firm-level factors that moderate this relationship. Based on our research results, we can now reflect on answers to these questions.

First, we found that a higher level of cross-channel integration is positively associated with higher profit margins in the short and long term. These results are partially unexpected. According to our conceptual framework, we anticipated negative effects in the short term and positive effects in the long term. However, it seems that companies have been able to manage the costs from their cross-channel integration measures and achieve immediate positive outcomes from their efforts. One caveat in this interpretation is that, despite being statistically identical in intensity to the short-term results, the long-term coefficients are only marginally significant. This may indicate that the effects of cross-channel actions are less relevant to explain profit margin variations in the long term.

Moreover, model-free analyses showed two distinct phases of cross-channel development among the companies in our sample. From 2012 to 2015, there was a strong growth in the penetration of cross-channel integration activities across companies, based on investments in more basic integration measures (from levels 2 and 3 in the framework). This phase coincides with the rise of the buzz around omnichannel marketing, which most probably compelled retailers to push ahead at least the minimum integration features demanded from market players. After the initial boost, the progress of laggard companies was slower and the most advanced ones started to invest in more challenging integration actions, such as organizational transformation and centralization of back-end systems. These nuances across companies and periods can also help to explain the differences in importance of cross-channel integration in the short- and long-term results.

Second, we attested that the number of physical stores owned by the retailer negatively moderates the impact of cross-channel integration on profit margin in the short and long run. In this case, the results were aligned with our conceptual rationale and hypotheses. As expected, companies with an extensive physical presence obtain fewer benefits from channel integration measures, which can be explained for a general loss of differentiation from traditional physical stores (Kumar et al., 2017) followed by an evolution in their roles as part of the transition to the omnichannel customer experience. In other words, in the omnichannel context, the quality of the physical presence is more important than the quantity, therefore, as companies develop their cross-channel capabilities, they rely less on the physical presence to obtain competitive advantage.

Finally, we did not find statistical evidence that using apps or social media as sales channels influences the cross-channel integration impacts on profits. Likewise, we also did not find statistical significance for the moderating effect of emerging technologies. Although contrary to our hypothesis, these results are not unexpected, considering that selling through social media and emerging technologies are not widely disseminated in the market, and even for the most innovative companies, the usage of these features may still be incipient. As a result, it may be too early to capture the effects of these variables on the financial outcomes of retail companies.

5.1. Implications for theory

In this paper, we proposed to use a previously developed framework (Cao & Li, 2015) to uncover the effects of cross-channel integration measures on firms' profit in the short- and long-term. By doing so, we expanded on the limited empirical evidence available in this research stream. Cao & Li (2015) found that cross-channel integration positively affects sales growth, Tagashira & Minami (2019) identified that cross-channel integration increases cost efficiency, and Oh et al. (2012) concluded that channel integration enhances firms' competences and general performance. We complement these findings by showing that higher levels of cross-channel integration are related to higher operating profit margins in the short and long run.

In particular, by focusing on profits and modeling not only short- but also long-term effects, we addressed three important gaps in the literature. First, we extend the findings from previous studies that considered sales, returns or cost efficiency as outcome variables (Cao & Li, 2015, Tagashira & Minami, 2019, Akturk et al., 2018) by using an important financial measure that covered sales and costs at the same time. Secondly, we performed our analyses using a ten-years longitudinal data set, which allowed us to obtain robust results in the short-term model and also capture long term effects. By doing so, we answered the call to examine long-term consequences of channel integration using longer timeframes of analysis (Cao & Li, 2015, Liu et al., 2018). Thirdly, previous studies on cross-channel integration outcomes used data from one country and, sometimes, one company (e.g. Cao & Li, 2015, Tagashira & Minami, 2019, Gallino & Moreno, 2014, Oh et al., 2012). In our research, we expanded the scope of analyses by studying leading companies from different countries with global operations. Although focusing on one retail industry, our sample also included players with diverse characteristics and strategic focuses that, together with the multinational profile, augmented the robustness and generalization of our findings.

Another relevant contribution of our research was proposing a new calculation for the consolidation of the actions captured using the cross-channel integration framework from Cao & Li (2015). We believe that the codes in the framework are still relevant to assess firms' development towards an omnichannel management, however, assuming the highest-level activity as the final score of the year is not anymore. In a context where most companies are taking actions from all levels with diverse approaches, the weighted average measure helps to evaluate firms more holistically and gives higher emphasis to their evolutionary process.

With the addition of firm-level moderators in our research, we took an RBV approach to investigate the influence of internal factors on the association between cross-channel integration and profit margin. Our findings extend the previous evidence that firms' physical presence negatively moderates the effect of cross-channel integration on sales (Cao & Li, 2015). Moreover, despite the noted importance of mobile apps to multichannel retailing (e.g. Narang & Shankar, 2019, Van Heerde et al., 2019), we did not find evidence that selling through apps affects the impact of channel integration measures on profits, possibly indicating that this channel is not a source of differentiation or acquisition of profitable customers for companies. Lastly, we also could not attest to a moderating effect of the investment in emerging technologies. Aligned with the literature (Verhoef et al., 2021), the annual reports show an intense movement from traditional companies towards incorporating new technologies, however, it seems that these investments are still not reflecting in productivity gains on channel integration efforts.

5.2. Implications for practice

As intended, our findings can provide valuable insights for retailers striving to succeed in the competitive omnichannel landscape. To begin with, the model results indicate that higher levels of cross-channel integration are related to better profit margins in the short and long terms. Thus, companies should continue investing in channel integration measures. Based on our research setting, we are unable to distinguish whether more integration leads to exceptional sales growth or cost reduction or both. Nevertheless, in the model-free analyses, we observed that the sub-segments with less integration are more capital- and labor-intensive, which suggests a less efficient use of the company's resources. Also, previous studies showed that customers respond to channel integration signs with increased purchases, willingness to pay and loyalty (Gallino & Moreno, 2014, Herhausen et al., 2015, Bendoly et al., 2005). Hence, it is not unreasonable to infer that advancing to higher levels of channel integration can contribute positively to both revenue and cost aspects.

Importantly, our results point out that the positive impact of cross-channel integration on profits is contingent on the number of physical stores owned by the firm. This does not imply that physical stores are not relevant to retail businesses, but that retailers should reassess their physical store network to optimize its role inside their omnichannel strategies. In practice, this may involve renovating, opening, and closing stores to increase profitability and synergy among channels. Moreover, in prioritizing efforts, the non-significance of the usage of mobile apps or social media as sales channels may indicate that launching or maintaining a mobile app is not a game-changer strategy for retailers. In analyzing the annual reports, we noted that some companies preferred to invest in responsive websites instead of separate apps, while other firms discontinued their proprietary apps, retaining only the website and social media pages as online channels. Therefore, considering the growing number of options to reach customers, companies must evaluate which channel composition is more suitable for them, taking into account their market positioning and target audiences.

5.3. Limitations and suggestions for future research

We conclude by presenting some limitations of this paper that can be converted into avenues for future research. First, our main independent variable, the measure of cross-channel integration, was derived through qualitative coding of companies' annual reports. Thus, as much as we sought to follow standard procedures throughout the data collection, the subjectivity in the processing of the text into codes was inevitable. Moreover, the qualitative analysis of annual reports is a complex and time-intensive activity, directly impacting on the capacity to scale the process and obtain larger data sets. To address both issues, future studies applying the framework should invest in automatizing the analysis of the reports, possibly using text analytics or artificial intelligence techniques.

In addition, researchers should consider different methods to consolidate the cross-channel activities executed each year. We proposed the weighted average to update the "maximum" approach from Cao & Li (2015), but researchers could propose more sophisticated approaches to capture the nuances in companies' omnichannel maturity. Also, as the extent of implementation of each cross-channel action varies considerably (especially for large-scale companies), it would be worthwhile to evaluate companies' activities with a continuous measure, rather than using 1 or 0, as has been done so far.

Secondly, we selected the operating profit margin as a suitable measure of a firm's performance because of its proximity to operating outcomes compared to other profit measures. However, other studies used measures such as the ROA (return on assets) or the net income to assess the effects in profit. Thus, we suggest that future studies test different performance indicators to expand on our findings.

Thirdly, we used the same explanatory variables to model short- and long-term effects, and we found weaker significance in the long-term. This imposes a limitation on the interpretation of our results. It raises the question of whether using a set of variables specifically chosen to measure long-term effects would have led to different findings, which could be further explored in future research.

Finally, we obtained our results from a relatively small sample from the fashion and apparel industry. Also, the COVID-19 pandemic occurred during our period of analysis, causing great disruption in the market conditions, and consequently, volatility in the data. Due to these factors, our results should be generalized with caution. Despite the COVID-19 influence, and based on the robustness tests, we believe that our results hold for companies focused on non-digital product segments, operating in markets with high levels of competition and dynamism. Future studies could replicate this research for companies and markets with different characteristics.

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Appendix

Table 10. Moderators coding - Keywords and example excerpts

Moderator	Keywords	Sample excerpts
n. of proprietary physical stores	retail stores, boutiques, directly operated	"*At the end of Fiscal 2018, the Company operated 861 stores.*" **(Abercrombie & Fitch. annual report 2018)**
sales in prop. Apps and/or SM	app or mobile, social media, live sales, live stream*, social commerce, live commerce, livestream	"*CDC's launch of a mobile shopping app for Europe in spring 2014 captured customer attention, as did the oneclick payment feature and 48-hour delivery service offered as part of its Fast Shopping campaign.*" **(Uniqlo. annual report 2014)**
investment in emerging techs*	advanced analytics, AI, artificial intelligence, VR, virtual reality, AR, augmented reality, robotics, web3, metaverse, NFT, Iot, internet of things, machine learning, analytics, big data	"*At the beginning of 2020, we launched an AR shopping tool through Google Search technology, which allows consumers to experience Burberry products embedded in the environment around them.*" **(Burberry. annual report 2020)**

*Included emerging techs after coding process: 3D, advanced analytics, AI, AR, digital showroom, innovative fitting rooms, interactive screens, IoT, magic mirror, manufacturing automation, metaverse, mobile POS, RFID, smart cart, voice app, VR, NFT

Table 11. Results of the "investment in emerging technologies" measurement for Inditex, 2012-2021

	2012	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**
advanced analytics								1	1	1
AI								1	1	1
AR							1	1	1	1
innovative fitting rooms				1	1	1	1	1	1	1
interactive screens							1	1	1	1
IoT								1	1	1
logistics automation						1	1	1	1	1
magic mirror						1	1	1	1	1
metaverse										1
mobile POS						1	1	1	1	1
RFID			1	1	1	1	1	1	1	1
VR							1	1	1	1
Total number of activities	**0**	**0**	**1**	**2**	**2**	**5**	**8**	**11**	**11**	**12**

Table 12. Measurement tool for cross-channel integration variables

General category (cross-channel integration level)	Distinguishing subcategory	Empirical codes	Keywords	Sample excerpts
Multichannel – silo mode (level 1)	Presence in different channels	Presence in different channels (website, catalog, kiosks, mobile, social media, call center)	distribution channel*, *channel*	"*We have three primary sales channels: wholesale, retail and internet.*" **(Crocs. annual report 2012)**
Facet of control - Retailers sell goods or services through more than one channel but independently operate these channels	Different retail-mix policy	Different price policies in different channels	pric*, and *channel*	"*Our e-commerce businesses operate at lower profit margins and at STP, we incurred additional costs as we work to transition this business to be less promotional to align more closely with our off-price model and to adjust its merchandise mix.*" **(TJX Companies. annual report 2015)**
		Different brands in different channels	brand*, and *channel*	"*In a nod to its Paris address, Le Bon Marché launched its "24 Sèvres" digital platform in June 2017.*" **(LVMH. annual report 2017)**
		Different assortment policies in different channels	product*/merchandis*/collection, and *channel*/online	"*UNIQLO offers a full range of exclusive online sizes and products to meet diverse customer needs.*" **(Uniqlo. annual report 2020)**
		Different service in different channels	service*, and *channel*	"*All of the brands provide services segmented by countries and sales channels (bricks-andmortar stores and electronic trade).*" **(Inditex. annual report 2013)**
Multichannel – minimal integration (level 2)	Integrated marketing communication	Consistent use of the same brand in all channels	same/identical/similar/ equivalent/consistent, brand*, *channel*	"*We invested a portion of these improved gross margins in additional demand creation activities in order to bring each brand's story to life online, in-store and in print.*" **(Columbia. annual report 2014)**
Facet of control - Retailers optimize established channels, collaboratively focusing on activities linked to mkt communication with consumers		Consistency of marketing message across channels	align*, and communication*/stor*/brand*	"*…delivering a focused message and a clear brand point of view across all marketing channels and ensuring consistency of our product messaging through global marketing campaigns.*" **(Capri Holdings. annual report 2016)**
Multichannel – moderate integration (level 3)	Integration of consumer order fulfillment	Click and pick up in-store	click-and*, click and*, pick up, pickup, collect	"*Omni-Channel Light features (e.g. buy online, pickup in-store) have been implemented across 24 brands, connecting 1,400 boutiques to enhance the service experience.*" (**Compagnie Financière Richemont. annual report 2018**)

Facet of control - Retailers optimize established channels collaboratively, focusing on activities linked to the transaction with consumers		Click-to-call	click-to-call, click to call, click-to-chat, click-to*, contact center, real time or real-time	"*The Center provides a contact for customers and consumers in both the pre-sale phase (dealing with requests for information on specific eyewear styles, for example) and the after-sales phase, forwarding requests to the after Sales team if necessary.*" **(Essilor Luxottica. annual report 2018)**
		Buy online and return in-store	return*, and *store*	"T*oday, we offer more immediate engagement in our social media channels and in-store returns for e-commerce orders.*" **(Skechers. annual report 2013)**
	Integration of consumer information access	Access to online inventory and online orders fulfilled by staff in-store	store-to-door, in-store, and inventory/deliver*	"*Burberry equipped all sales associates with access to iPads in store. These can be used to access burberry.com, allowing customers in physical stores to explore the full Burberry offering.*" **(Burberry. annual report 2013)**
		Allowing online consumers to browse the inventory in-store	inventory/in-store, and online	"T*hese include allowing customers to check in-store availability online, make online purchases, collect online product purchases in stores, and reserve goods online, etc.*" **(Kering. annual report 2016)**
		Linkage between store and mobile app (WiFi in-store, locating store by mobile app)	store*, and mobile/app/cellphone, wifi, wi-fi, wi fi	"*This involves country and region-specific websites, social media, product notification emails, mobile apps, including mobile apps on in-store devices that allow demand to be fulfilled via our distribution centers, and online order fulfillment through stores.*" **(Lululemon Athletica. annual report 2019)**
Multichannel – full integration (level 4)	Alignment of fundamentals	Aligned services across channels	align, and service*/and experience, same/identical/similar/ equivalent/consistent, and experience, and *channel*	"*Greater attention will also be paid to integrating online activities with bricks and mortar retail to offer consumers a seamless and convenient shopping experience.*" **(Hugo Boss. annual report 2012)**
Facet of control - Retailers optimize established channels collaboratively, focusing on activities linked to consumers' seamless shopping experience		Aligned promotion across channels	align, and promotion/online, same/identical/similar/equivalent/ consistent, and promotion	"*We have standardized all of our online product launch schedules, query priorities and styles, which has created synergy to prevent competition among online and offline retailers*." **(Anta. annual report 2016)**
		Aligned price across channels	same/identical/similar/equivalent/consistent, and pric*, or/and *channel*	"*Thanks to our omni-channel approach, we will integrate all sales channels and marketing activation activities, utilise cross-selling opportunities and align pricing across all channels.*" **(Adidas. annual report 2014)**
		Aligned loyalty program across channels	loyalty, loyalty program, reward* program, member* and customer*,	"*H&M Club is accessed via mobile, and customers collect points on everything they buy.*" **(H&M. annual report 2017)**
		Aligned assortment across channels	same/identical/similar/equivalent/consistent, and *channel*, and "product", align*, and *channel*, assortment	"*We provide customers with the same quality merchandise available at N ordstrom full-line stores and online.*" **(Nordstrom. annual report 2018)**

Centralization of back-end system	Integration of merchandize planning systems across channels	merchandis*, and *channel*	"*Our designers are also supported by a strong merchandising team that analyzes sales, market trends and consumer preferences to identify market opportunities that help guide each season's design process and create a globally relevant product assortment. Merchandisers also manage the product life cycle to maximize sales and profitability across all channels.*" **(Tapestry. annual report 2016)**
	Integration of logistics across channels	logistic*, fulfil*, and *channel*, ship from store	"*Our two distribution centers are fully omni-channel and service both stores and digital businesses.*" **(American Eagle Outfitters. annual report 2016)**
	Integration of information systems across channels	system, and channel, integration	"*The aim is to bring the technology infrastructure and systems in line with the increasing needs of users and the group's métiers, to guarantee good operational performance, to keep IT-related risks under control and to prepare systems for the future, especially for new digital services.*" **(Hermès. annual report 2014)**
	Centralized call center service across channels	call center, callcenter, customer service*, contact center	"*Inditex brands have more than 40 call centres located on all continents, capable of attending to the over 20 million queries that our customers made through the various channels in 2017.*" **(Inditex. annual report 2017)**
	Integration of database of clients across channels	customer data*, customer relationship, database, CRM	"*Deliver more personalised experiences that adapt to the consumer's preferences by leveraging the full potential of our CRM solutions.*" **(Adidas. annual report 2012)**
Organization transformation	Sharing knowledge across channels	shared, and *channel*	"*NEXT Customer Services interacts with Retail and Directory customers to resolve enquiries and issues. Findings are recorded and the information is used by other areas of the business to review how a product or service can be improved.*" **(Next PLC. annual report 2013)**
	Recruiting talents with double competences in retail and digital commerce	team/people/squad, and digital, and competence/skill/ability/capability	"*Tommy Hilfiger employs advertising, marketing and communications staff, including an in-house creative team, as well as outside agencies, to implement its global marketing and communications strategy across all channels of distribution.*" **(PVH Corp. annual report 2015)**
	Changing organizational structure to adapt to the integration of different channels	*channel*, and people/organization/team, transformation, and business/digital	"*At the beginning of the fourth quarter of Fiscal 2015, the Company restructured its international operations to support its omnichannel initiatives.*" **(Abercrombie & Fitch. annual report 2015)**
	Incentive system linked to both online and offline sales	incentive*, incentive* system*, reward* program*, incentive* program*, SIP, sales incentive*	No quotations

Table 13. Weighted average cross-channel integration calculation for Ralph Lauren, 2012-2021

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
1 - SILO MODE: 1:Presence in different channels (website, catalog, kiosks, mobile, social media, call center)	1	1	1	1	1	1	1	1	1	1
2 - MINIMAL INTEGRATION: 2:Consistency of marketing message across channels	1	1	1	1	1	1	1	1	1	1
3 - MODERATE INTEGRATION: 3:Access to online inventory and online orders fulfilled by staff in-store						1	1	1	1	1
3 - MODERATE INTEGRATION: 3:Buy online and return in-store										1
3 - MODERATE INTEGRATION: 3:Click and pick up in-store							1	1	1	1
3 - MODERATE INTEGRATION: 3:Click-to-call							1	1	1	1
4 - FULL INTEGRATION: 4:Aligned services across channels						1	1	1	1	1
4 - FULL INTEGRATION: 4:Centralized call center service across channels							1	1	1	1
4 - FULL INTEGRATION: 4:Integration of database of clients across channels							1	1	1	1
4 - FULL INTEGRATION: 4:Integration of information systems across channels						1	1	1	1	1
4 - FULL INTEGRATION: 4:Integration of logistics across channels										1
4 - FULL INTEGRATION: 4:Integration of merchandize planning systems across channels										1
Total number of activities	2	2	2	2	2	5	9	9	9	12
Weighted sum	3	3	3	3	3	14	28	28	28	39
final CCI score	**1.500**	**1.500**	**1.500**	**1.500**	**1.500**	**2.800**	**3.111**	**3.111**	**3.111**	**3.250**

Table 14. Number of companies per cross-channel integration code and year (source: annual reports)

		2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
1 - SILO MODE: 1:Different assortment policies in different channels	Different retail-mix policy	1	3	3	7	7	9	9	11	11	11
1 - SILO MODE: 1:Different brands in different channels	Different retail-mix policy	0	0	0	0	0	2	2	2	2	2
1 - SILO MODE: 1:Different price policies in different channels	Different retail-mix policy	0	0	0	1	1	1	1	1	1	1
1 - SILO MODE: 1:Different service in different channels	Different retail-mix policy	0	1	1	1	1	1	2	2	3	3
1 - SILO MODE: 1:Presence in different channels (website, catalog, kiosks, mobile, social media, call center)	Presence in different channels	21	24	26	27	27	27	27	27	27	27
2 - MINIMAL INTEGRATION: 2:Consistency of marketing message across channels	Integrated marketing communication	10	13	13	14	14	15	15	16	16	16
2 - MINIMAL INTEGRATION: 2:Consistent use of the same brand in all channels	Integrated marketing communication	3	7	10	12	12	13	13	13	13	13
3 - MODERATE INTEGRATION: 3:Access to online inventory and online orders fulfilled by staff in-store	Integration of consumer information access	2	3	4	9	10	15	18	18	19	19
3 - MODERATE INTEGRATION: 3:Allowing online consumers to browse the inventory in-store	Integration of consumer information access	0	0	3	6	7	9	10	12	12	13
3 - MODERATE INTEGRATION: 3:Buy online and return in-store	Integration of consumer order fulfillment	1	3	4	4	8	11	12	12	12	13
3 - MODERATE INTEGRATION: 3:Click and pick up in-store	Integration of consumer order fulfillment	2	3	6	9	14	16	19	19	20	21
3 - MODERATE INTEGRATION: 3:Click-to-call	Integration of consumer order fulfillment	1	2	2	3	4	4	8	9	10	10
3 - MODERATE INTEGRATION: 3:Linkage between store and mobile app (WiFi in-store, locating store by app)	Integration of consumer information access	2	3	3	4	8	8	12	12	13	13

4 - FULL INTEGRATION: 4:Aligned assortment across channels	Alignment of fundamentals	1	5	5	5	6	6	6	7	7	7
4 - FULL INTEGRATION: 4:Aligned loyalty program across channels	Alignment of fundamentals	0	1	1	1	5	6	7	7	7	7
4 - FULL INTEGRATION: 4:Aligned price across channels	Alignment of fundamentals	0	1	1	1	2	3	3	3	3	3
4 - FULL INTEGRATION: 4:Aligned promotion across channels	Alignment of fundamentals	0	0	1	1	1	1	1	1	1	1
4 - FULL INTEGRATION: 4:Aligned services across channels	Alignment of fundamentals	5	8	8	8	15	20	22	22	23	24
4 - FULL INTEGRATION: 4:Centralized call center service across channels	Centralization of back-end system	2	2	2	3	4	4	6	8	8	8
4 - FULL INTEGRATION: 4:Changing organizational structure to adapt to the integration of different channels	Organization transformation	0	2	4	7	8	8	10	13	13	14
4 - FULL INTEGRATION: 4:Integration of database of clients across channels	Centralization of back-end system	7	8	10	11	12	14	16	17	19	20
4 - FULL INTEGRATION: 4:Integration of information systems across channels	Centralization of back-end system	1	2	3	6	8	10	12	13	14	15
4 - FULL INTEGRATION: 4:Integration of logistics across channels	Centralization of back-end system	1	2	7	9	13	16	17	17	18	21
4 - FULL INTEGRATION: 4:Integration of merchandize planning systems across channels	Organization transformation	2	4	6	7	8	9	10	11	12	13
4 - FULL INTEGRATION: 4:Recruiting talents with double competences in retail and digital commerce	Organization transformation	4	6	7	9	10	10	11	13	14	15
4 - FULL INTEGRATION: 4:Sharing knowledge across channels	Organization transformation	1	1	1	3	3	3	3	4	4	5
4 - FULL INTEGRATION: 4:Incentive system linked to both online and offline sales	Organization transformation	0	0	0	0	0	0	0	0	0	0
	Average number of companies per year	2.48	3.85	4.85	6.22	7.70	8.93	10.07	10.74	11.19	11.67

Table 15
Descriptive statistics for quantitative variables in the long-term models

	Mean	Median	Sd	Min	Max
CCI	2.60	2.80	0.74	0.00	3.50
Operating Margin (t+3)	0.13	0.11	0.09	-0.15	0.40
Invest Tech	1.20	0.00	1.90	0.00	11.00
Rel. Sales Growth	0.07	0.05	0.13	-0.32	0.96
Rel. Adv. Integration	0.00	0.00	0.91	-1.00	1.00
Sales Store	8.50	6.10	8.60	0.13	50.00
Number Stores	2,173	1,114	2,595	63	12,943
Working Capital	2,205	1,291	2,673	-681	16,349
Number Employees	43,131	17,900	54,162	2,468	286,000

Notes: Sample size = 216. Original values are used when calculating summary statistics.

Table 16
Descriptive statistics for categorical variables in the long-term models

Variable	Obs.	%
Firm Segment	216	
Off-price	8	4%
Casualwear	32	15%
Eyewear	8	4%
Fast fashion	16	7%
Footwear	16	7%
Luxury fashion	88	41%
Retail	16	7%
Sportswear	32	15%

Variable	Obs.	%
Sales App.SM	216	
0	105	49%
1	111	51%

Variable	Obs.	%
Imp. Online Sales	216	
low	40	19%
medium	64	30%
high	112	52%

Variable	Obs.	%
Covid Time	216	
0	189	88%
1	27	12%

Table 17. Regression results for short- and long-term with pre-covid data

Variable		Operating Profit (t+1)			Operating Profit (t+3)		
		Coef.		S.E.	Coef.		S.E.
Main effects							
CCI	H1 (-); H2 (+)	0.156	***	0.057	0.122	*	0.062
Moderating effects							
Number Stores		0.045	**	0.022	0.032		0.023
CCI x Number Stores	H3 (-); H4 (-)	-0.021	***	0.008	-0.016	*	0.008
Sales App.SM=1		0.038		0.043	-0.053		0.047
CCI x Sales App.SM	H5 (+); H6 (+)	-0.021		0.015	0.014		0.017
Invest Tech		0.062	*	0.034	0.093	**	0.047
CCI x Invest Tech	H7 (0); H8 (+)	-0.019	*	0.011	-0.027	*	0.015
Control Variables							
Rel. Sales Growth		0.139	***	0.043	0.123	**	0.059
Rel. Adv. Integration		0.016	**	0.007	0.020	**	0.008

Sales Store	-0.003	*	0.001	-0.004	**	0.001
Working Capital	0.013	***	0.004	0.010	**	0.005
Number Employees	0.012		0.012	0.021		0.015
Imp. Online Sales=High	-0.115	***	0.025	-0.152	***	0.027
Imp. Online Sales=Medium	-0.153	***	0.022	-0.177	***	0.025
Time effects	Yes			Yes		
Firm Segment effect	Yes			Yes		
Observations	189			135		
Number of firms	27			27		
Adjusted R^2	0.5685			0.5533		

Notes: *** $p < .01$, ** $p < .05$, * $p < .1$; Coefficients are presented with Beck and Katz robust standard errors; Coefficient values are rounded to three decimal places.