The effect of COVID-19 on the purchase channels and order transaction value for a printing specialized organization

Robin Verweijmeren
University of Twente
P.O. Box 217, 7500AE Enschede
The Netherlands

ABSTRACT
Purpose – The main aim of this research is to find out the effect the coronavirus pandemic has on the purchase channels and order transaction value for an organization specialized in printing services. Next to this, an overview is given to help firms understand omni- and multi-channel management, channel migration and channel profitability and the intercorrelation of these concepts.
Design/Methodology/Approach – This research is based on a systematic literature review as well as quantitative data analysis. Annual order data from the organization is utilized in order to answer the research question central to this report.
Findings – The coronavirus pandemic did not create a significant shift in channel usage by customers, which originally was hypothesized. However, the lockdown did have a negative effect on customer order frequency. Lower order frequency customers in turn are found to have a negative impact on order transaction value.
Practical implications – This research is not focused at the individual product level. Therefore, it is recommended for the organization to conduct extra research to find out if there has been a shift in product focus for the customers. This research did not calculate the customer lifetime value for all customers. It is recommended that the organization calculates this metric so that adequate amounts of service (and therefore costs) can be made relative to the value each customer provides.
Originality/value – The findings in the literature review bring together relevant theories and summarize (almost) everything firms need to know about channel profitability, channel migration and customer multiple channel usage. The findings from the quantitative research indicate the effect of the immensely current and recent coronavirus pandemic on a organization specialized in printing services.

Graduation Committee members:
First supervisor - Dr. A. Leszkiewicz
Second supervisor – Dr. E. Constantinides

Keywords: Coronavirus pandemic, multichannel marketing, omnichannel marketing, channel migration, order transaction value

---

TABLE OF CONTENTS

1. INTRODUCTION

Nowadays, products and services can be purchased through numerous different channels. This is true either in the business-to-business or business-to-consumer setting. However, customers will always have a particular preference regarding this matter. It is therefore important for organizations to understand what opportunities and challenges might occur when managing these different channels. Because of the increase in technology and therefore the consumer's possibility to purchase products through all kinds of different channels, it is important for organizations develop an efficient multi- or omnichannel customer management strategy. The profitability of these individual purchase channels can be assessed to gather valuable information such as what channels are being used by either low, medium or top (customer lifetime value) customers respectively. Organizations can then be sure to provide the adequate amount of service (and therefore costs) in comparison to the value their customers return. Information about channel profitability can also be used as knowledge for activities such as resource allocation or the promoting, opening or closing of a particular purchase channel.

In this research a very current phenomenon; the coronavirus pandemic, will be taken into account. The coronavirus pandemic logically has a large impact on businesses worldwide and therefore the impact of this epidemic should be studied and considered in order to successfully prepare for future challenges. This paper researches the influence of the coronavirus pandemic on the usage of different purchase channels by customers and their channel profitability. This research is aimed at finding out the influence of the pandemic on customer order frequency and particular customer channel usage.

The data used in this research comes from a company specialized in printing solutions and entails all customer orders between 15 March 2019 and 15 March 2021. This two-year timespan has been chosen as the coronavirus lockdown in the Netherlands officially started on 15 March 2020 when the hospitality industry was forced to close. In this way, the year before the coronavirus lockdown started can be compared with the year since the coronavirus lockdown started. Rules and regulations set up by the Dutch government included staying at home as much as possible and keeping 1,5-meter distance to other individuals. The Dutch population was also advised to stay at home as much as possible. Logically, businesses were all affected immensely by the rules and regulations.

At this point, June 2021, the Netherlands is currently recovering from the second major lockdown. The Dutch government has set-up several base rules; washing your hands often, coughing and sneezing in your elbow, keeping 1,5-meter distance from others, avoiding crowded places and when having coronavirus symptoms; staying at home and getting tested for the virus immediately. Because of the fact that more and more of the Dutch population is being vaccinated against the virus and the amount of people being infected weekly is decreasing, the Dutch government decided to start reopening the society. For this, they have created a roadmap. Currently, we are on 'Step 3' of this roadmap. The roadmap can be found in Figure 1.

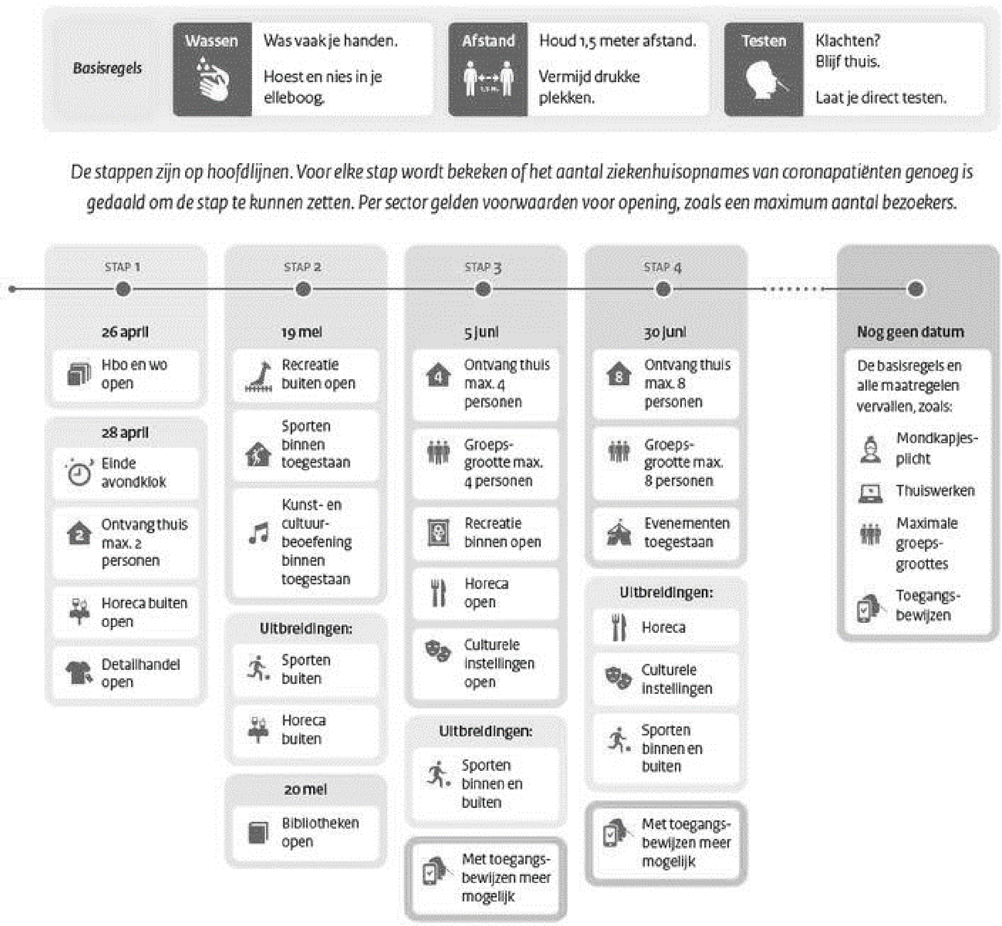


Figure 1 - Coronavirus Dutch government opening plan roadmap

Taking into account the mentioned situation, this research answers the following research question;

What influence does the coronavirus pandemic have on customer channel usage and transaction value?

To help answer this research question, some sub-questions were created. Namely;

What influence does the coronavirus have on customer channel usage?

What influence does particular customer channel usage have an order transaction value?

What influence does the coronavirus have on customer order frequency?

What influence does order frequency have on order transaction value?

These sub-questions will be answered in order to answer the main research question. The thesis is structured as follows. First, a systematic literature review is performed that helps companies with understanding their challenges and opportunities regarding customer channel usage. It explains the phenomena of omni- and multi-channels, customer channel migration and channel profitability. The literature review explains what companies need to keep in mind when managing these concepts. Then, the theoretical framework used in this research will be explained. After this, the research design and sample will be discussed in the methodology section. This section is followed up by the results section, in which the results of the research of this paper will be given. After this chapter, a discussion will be provided in which the most notable findings will be mentioned and discussed. Then, limitations, recommendations and a conclusion will be following. Lastly, acknowledgements will be made.

2. LITERATURE REVIEW

The literature review part of this research is intended to provide a comprehensive, systematic review of 20 research articles regarding multi- and omni-channels, channel migration and channel profitability. This study mainly includes articles dating from the last 17 years, with exception of one older study. The primary goal of this literature review is to provide a clear summary including opportunities and challenges regarding customer use of omni- and multi-channels, customer channel migration and channel profitability. This literature review section helps in gaining and understanding of what firms should take into account when managing their channels, channel migration and channel profitability.

2.1 Methods

Based on the goal of this research, a review protocol was developed in order to direct the literature review. It contained information on what database would be utilized and what search terms and screening criteria were used.

The articles had to meet a set of criteria. First, the article had to be from a business, management and accounting journal. Secondly, the article had to be finalized and published in English. This meant that naturally, other sources such as books and research notes were excluded. The third criteria was that the article should revolve around at least one of the concepts mentioned; multi-channels, omni-channels, channel migration or channel profitability. The last criteria was that the article should be cited at least ten times. This was to ensure that all articles contained at least a certain baseline of credibility.

A literature search was conducted by making use of a database called Scopus. Secondly, references from articles found in this database were tracked and through the snowball method of backward citation were also added to the research.

The data was gathered from Scopus in April 2021. The search criteria contained ‘purchase channel’ combined with the Boolean Operators ‘AND’ and ‘migration’ OR ‘profitability’ OR ‘omni*’ OR ‘multi*’. The titles, abstracts and keynotes were explored for this information. Furthermore, the results were limited to English-written finished articles in the business, management and accounting journals. The search was conducted by utilizing the following expression:

TITLE-ABS-KEY(("purchase" "channel") AND ("migration" OR "profitability" OR "omni" OR "multi*")) AND (LIMIT-TO(SRCTYPE,"j")) AND (LIMIT-TO (PUBSTAGE,"final")) AND (LIMIT-TO (SUBJAREA,"BUSI")) AND (LIMIT-TO(DOCTYPE,"ar")) AND (LIMIT-TO (LANGUAGE,"English"))*

The first screening was done by the author by inspecting the titles and abstracts for articles that do not fit the scope of the research, although they contained the selected search terms. In this first screening, the author also took into account the amount of times the article was cited; this had to be at least ten times. Then, the full text of the articles was assessed and the remaining articles that did not fit the eligibility criteria and scope of the research were excluded. The PRISMA flow diagram (Page et al., 2021) indicating the different steps of study selection can be found in Figure 2.

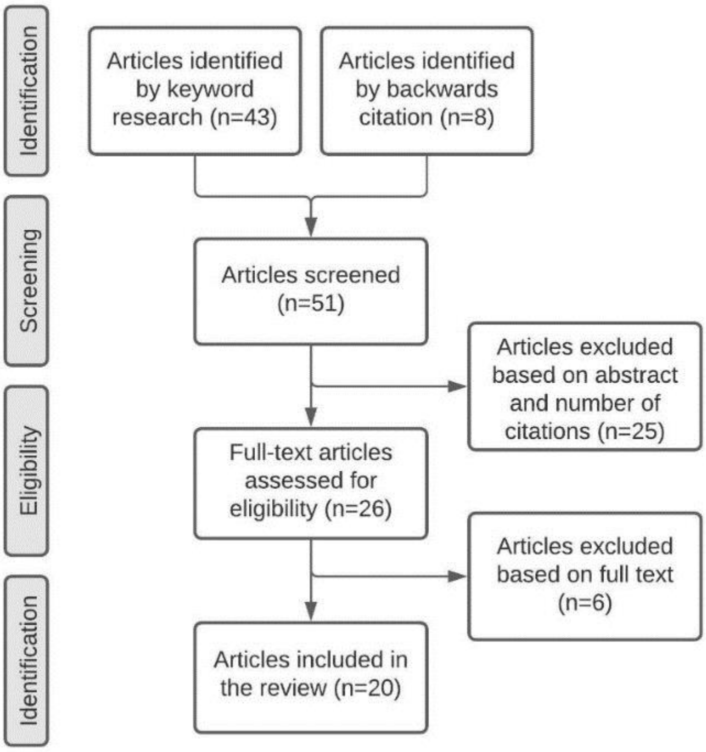


Figure 2 - Flowchart literature review study selection process

2.2 Results

Entering the search string, which is indicated in the methods chapter, resulted in 43 articles. When screening these articles, 22 were immediately excluded as they had been cited less than 10 times. Then, based on titles and abstracts, three remaining articles were excluded as they did not fit the scope of this research although they did contain words mentioned in the search string. The remaining articles were then read by the researcher and another 6 articles were excluded as the papers information was not related to the research. 12 articles remained and through the snowball method of backwards citation another 8 were added to the research as they provide important further information on the concepts. Finally, this resulted in the 20 articles that are analyzed.

In Appendix A, a summary is given of the papers analyzed in this research. The authors and publishing date, key concepts, methods and (if applicable) samples and important findings are all specifically stated in the table.

2.2.1 Omni-channels

A customer channel can be defined as a customer contact point or a medium by which the firm and the customer interact (Neslin et al., 2006). The research of Gao & Su (2017) indicates once more that the customer journey has transitioned towards becoming omnichannel; customers constantly switch between channels to gather product information, compare products and buy products. The researchers stress the importance of retailers becoming aware of the customer preferences and that firms should transition towards an omnichannel strategy. The paper by Bell, Gallino, & Moreno (2014) indicates how retailers should adapt to the 'omnichannel' world. The article provides a framework of how innovations in product fulfillment and information delivery can create a successful omnichannel strategy for firms. This framework is completely focused on the customer perspective, as the researchers indicate that this is the most efficient way of coming up with a successful strategy. The framework can be found in Figure 3. Traditional retailers can be found in quadrant 1, whilst purely online retailers can be found in quadrant 4. To adapt a successful omnichannel strategy, traditional retail firms should pursue strategies found in the other three quarters (2, 3 and 4). To illustrate this, research has found out that traditional retailers can gain larger profitability by implementing so called OOPS (order online, pick-up in store) (Chatterjee, 2010). Inversely, purely online firms, should also focus on strategies found in their respective other three quarters (1, 2 and 3). To implement a successful omnichannel strategy, firms should find the customers' preference regarding the ideal combination of product fulfillment and information delivery. For example, some customers prefer finding information online about the product and then buying the product in-store. Others prefer 'showrooming'; visiting the store to test the product and then buying the product online. These customer preferences are what drives a successful omnichannel strategy. Adding to this, Brynjolfsson, Hu & Rahman (2013) mention another 7 strategies that can be implemented in order to become a successful omnichannel retailer: provide competitive pricing and increase online usability, use data for customer analyses, avoid direct price comparisons, selling niche products, leveraging excellent product knowledge, set costs for customer switching (e.g. firm loyalty) and learning from the competition.

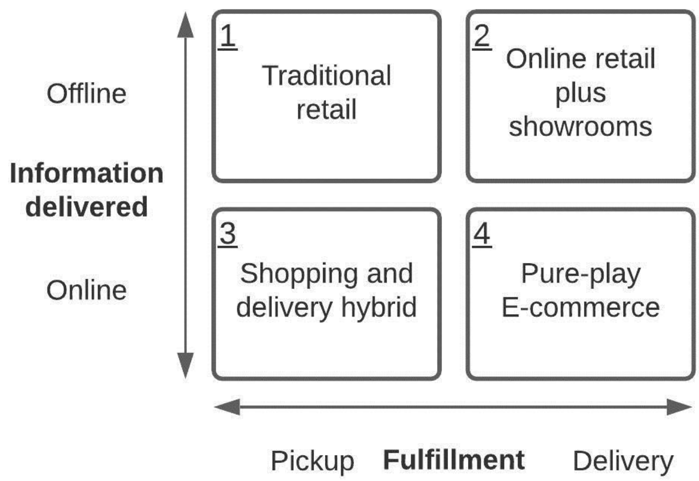


Figure 3 - Information/fulfillment matrix (Bell, Gallino & Moreno, 2014)

2.2.2 Multi-channels

Multichannel customers are customers that use multiple channels to interact with a firm. Because e.g. the increase of technology, customers have become more and more accustomed to making use of multiple channels for information search, product comparisons and purchases. Kumar & Venkatesan (2005) have created a framework that indicates the reasons why customers move towards multichannel shopping. The drivers that affect the multiple channel usage can be found in Figure 4.

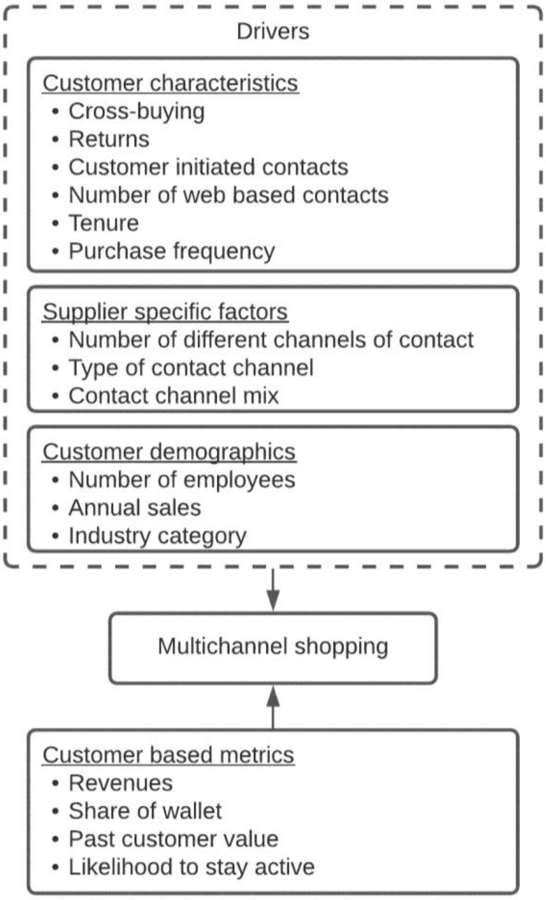


Figure 4 - Multichannel shopping behavior framework (Kumar & Venkatesan, 2005)

Venkatesan, Kumar & Ravishanker (2007) in turn have created a framework that indicates how long it takes for the customer to adopt a specific channel. The factors that influence customer channel adoption are attributes related to the channel, purchasing, frequencies and customer heterogeneity. This framework can be found in Figure 5.

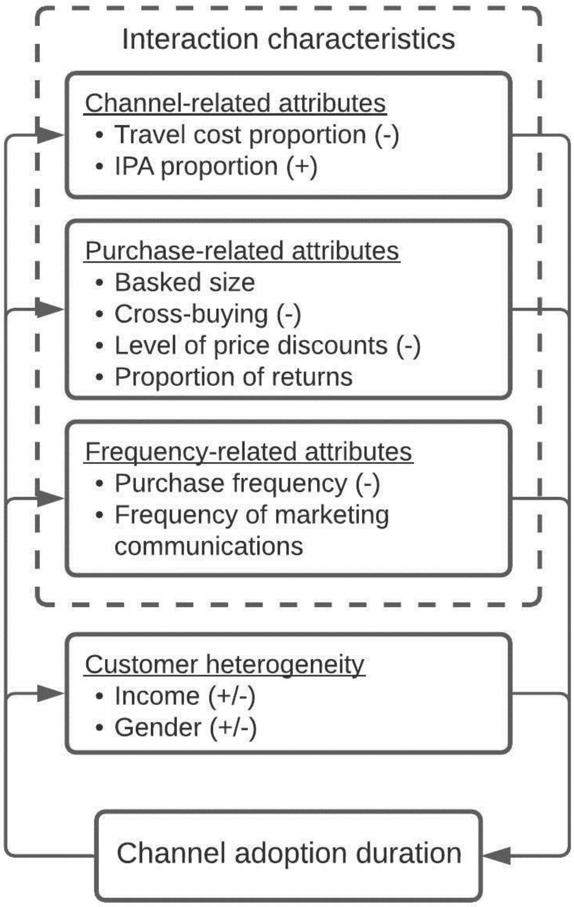


Figure 5 - Drivers of customer channel adoption duration (Venkatesan, Kumar & Ravishanker, 2007)

When multichannel management is done properly, the firm creates superior channel service, strong customer relationships, increases customer retention and decreases customer motivation to move towards competitor offerings (Rangaswamy & Van Bruggen, 2005). Because of this, proper multichannel management strategy is important for firms. Firms need to create a ‘multichannel mindset’ by creating a strategy that leverages their value proposition across multiple channels, designing an organizational structure that facilitates multichannel marketing and by creating metrics to value the performance of their separate channels (Weinberg, Parise, & Guinan, 2007). Next to this, Neslin et al. (2006) have identified 5 challenges that firms face when trying to pursue successful multichannel management. The challenges include data integration, understanding customer behavior, channel evaluation, channel resource allocation and coordinating channel strategies. The framework that they set-up for analyzing channel management can be found in Appendix B.

The framework suggests that customers start with a product need, the problem recognition. Then, they search for information and products, purchase the product and receive after-sales service. The customer then evaluates this whole process, forming perceptions and preferences. The total factors influencing the customer preference regarding channel usage can be found in Figure 6.

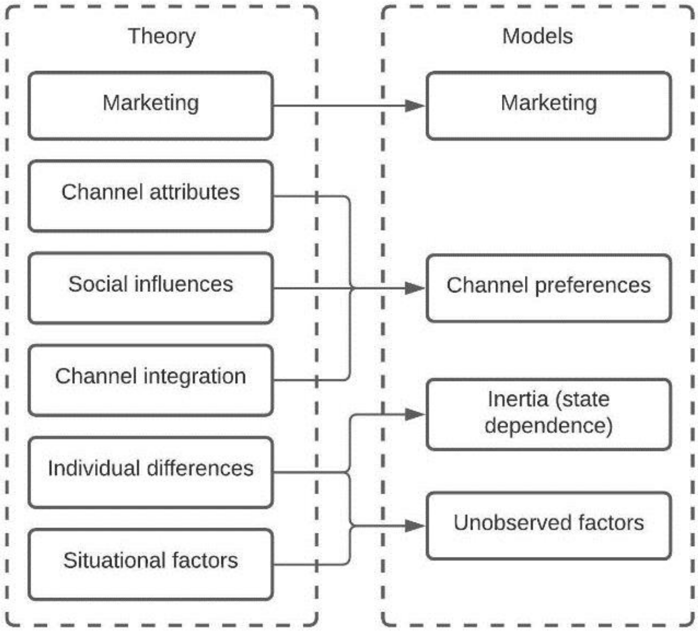


Figure 6 - Factors influencing customer channel usage (Valentini, Montaguti & Neslin, 2011)

This figure depicts the framework set-up by Valentini, Montaguti & Neslin (2011). Interestingly, these researchers have also found that relatively 'new' customers will decide differently on channel choices then 'older' customers. This means that when channel usage is being evaluated, it might also be beneficial for the firm to look at the duration the customer has been at the firm.

This in turn will affect their future behavior. The process also creates data for the firm to analyze so it can evaluate the use of their channels and form channel strategy. This in turn will have an effect on the customer perceptions and preferences and purchasing process. Interestingly in many firms, separate divisions are usually in charge of their respective channel and there is most often no business unit dedicated to creating uniformity between the channels (Rangaswamy & Van Bruggen 2005). Creating a separate business unit dedicated to this could therefore be an important step in implementing successful multichannel management. Research by Chang & Zhang (2016) has found that implementing the combination of online and offline channels increases customer education, revival and retention. Offline channels are best used for customer 'revival'; changing customers from their inactive state back towards an active state, essentially bringing the customers back to life. Online channels are found to be the best at customer retention, keeping the customers in their active state.

One of the major challenges related to multichannel management is cross-channel free riding behavior by customers. Because it is so easy for customers to move between channels, it is also easy for customers to change towards a competitor's channel. Cross-channel freeriding is when a customer looks up information or evaluates a product online, but then switches to a competitor channel to finalize product purchase. For instance, a customer could look up information about a product online, and then go to a competitor's physical store and buy the product there. One way to fight this major challenge in multichannel management is to increase within-firm lock-in (Chiu et al., 2011). Firm lock-in can create obstacles for customers so that switching to a competitors channel is made less attractive, increasing customer retention. Examples of firm lock-in are customized services, loyalty programs or other costs the customer makes when switching to a competitor.

2.2.3 Customer channel migration

Because of the large amount of choices in different channels for customers to utilize, it is made relatively easy for customers to find a different channel that suits their preference. Proper multichannel customer management by a firm is of vital essence as channel migration influences firm profit by affecting the individual channel costs and revenues. Ansari, Mela & Neslin (2008) have structured a framework that illustrates the customer channel migration process. The framework can be found in Figure 7. The model assumes that customer channel behavior consists of channel selection and purchase volumes. These two concepts have individual experience or learning effects that affect the future purchase volume and channel selection. They also have an effect on one another. Finally, marketing communications (catalogs, emails, etc.) have an effect on customer channel behavior.

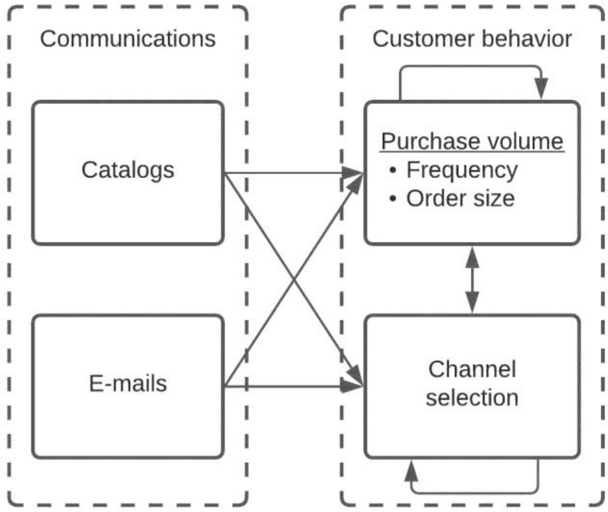


Figure 7 - Customer channel migration framework (Ansari, Mela & Neslin, 2008)

When customer channel migration and customer preferences regarding channels are understood, firms can start to think about possibilities as for example closing or opening new channels. For example, the research by Fornari et al. (2016) analyzed the addition of opening a physical store next to the online website of a web-only retailer. Initially, the opening of a physical store lead to declining sales of the online website as customers saw the physical store as a substitute for the online store. However in the long-term, online sales tended to increase. The research showed that whilst in the initial stage the adding of an extra channel lead to channel migration, it eventually lead to increased synergy between the channels in the long run. In the end, this increase in synergy between the customer channels increased sales and customer satisfaction by making use of a proper omni-channel strategy. Interestingly, when deciding on a proper customer channel management strategy, the channels of competitors should also be taken into account. The research by Li et al (2017) analyzed whether competitor channel offerings had an effect on the adoption of a new online channel introduced by a firm. The results showed that customers who had previously utilized an online channel for a competitor were more likely to adopt the new, later introduced, online channel of the firm.

In conclusion, to conduct a successful customer channel management strategy the firm should take into account multiple factors; customer behavior, marketing communications and competitor’s channel offerings.

2.2.4 *Channel profitability*

In order to assess channel management strategies and to make successful decisions, it is important for firms to understand and calculate the individual channel profitability. It can use this knowledge to for example open a new channel, close a channel or promote the use of a channel. When understanding the individual customer profitability, it will be easy for a firm to allocate resources per customer. To monitor channel profitability, we will use customer lifetime value (CLV). CLV is defined by the sum of cumulated cash flows, discounted by the weighted average cost of capital, of a customer over his lifetime with a firm (Kumar et al., 2004). To understand this concept, we will take a look at the illustrative framework for CLV. This can be found in Figure 8.

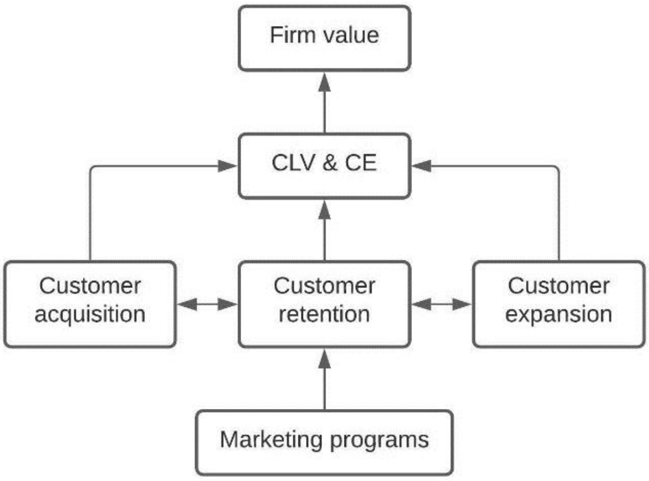


Figure 8 - Customer lifetime value framework (Gupta et al., 2006)

The framework takes into account the firm's marketing programs which affect customer retention. Retention then affects customer acquisition and expansion. The three concepts of retention, acquisition and expansion influence the customer lifetime value or individual customer value to the firm. Following this framework, the total CLV for the firm then concludes an indication of the firm value. CLV can be computed by making use of the following simple formula (Gupta et al., 2006):

$$CLV = \sum_{t=0}^{T} \frac{(p_t - c_t)r_t}{(1+i)^t} - AC$$

Where: pt = customer paid price at time t, ct = direct customer servicing cost at time t, i = firm discount rate, rt = customer probability of repeatedly buying, AC = acquisition cost and T = time horizon for CLV estimation.

The research by Venkatesan & Kumar (2004) also proposes a framework that can aid in measuring and using CLV. This can be found in Appendix C. The framework illustrates that the customer lifetime value can be calculated by discounting the total profit (which is influenced by predicted purchase frequency, marketing costs and contribution margins). This framework illustrates once more that when the customer lifetime value is calculated, it will be made easy for the firm to allocate the appropriate amount of resources per customer. This will in turn again have an effect on the total profit and CLV.

To get the maximum benefits of the CLV approach, the theory by Kumar et al., 2004 suggests that firms should take into account the customer's perspective instead of the product perspective when formulating their firm strategies. There are three main challenges firms also should take into account; proper performance monitoring, progress documentation and application of the time-based probability measure.

Interestingly, the research of Kumar et al. (2006) showed that for a retail firm as much as 30% of their customers showed a negative customer lifetime value. This meant that 30% of their customer base was costing them money instead of making them profit. When there is a wide range of CLV scores for a firm's customer base, it would be wise for the firm to analyze the individual customer insights to increase the CLV scores to the highest point possible for all customers and to eliminate (almost) all negative CLV scoring customers. The same research also showed that multi-channel shoppers scored a higher CLV score in comparison to customers shopping solely from one channel. This suggests once more that firms should develop a multi-channel strategy to increase firm profits.

2.3 Discussion

2.3.1 Evidence summary

The most important finding in this research is that the theories coming from all 20 papers complement each other and are inherently connected. In order for a firm to maximize its channel profitability (and therefore firm profit), it will have to understand concepts such as the customer lifetime value metric. It should also understand the concepts of proper customer omni- and multi-channel management and customer channel migration, as these subsequently have an effect on these firm profits.

2.3.2 Limitations

This study only took into account 20 papers published in journals. Although these articles can be found in top journals, information on the concepts discussed in this research could also be found in other sources such as books or online websites. Moreover, this research only included the articles that were at least cited 10 times. This could mean that there could be relatively new papers, with less citations, that have not been included as they did not meet this criteria. This might mean that new papers with a significant finding could be not included. This study also included only English papers, meaning significant non-English papers might be excluded.

2.4 Conclusion

The literature review section was aimed to provide an understanding of what firms should take into account when managing their channels, channel migration and channel profitability. To come to this, the concepts of omni- and multi-channel retailing was first explained. The articles in this research all stressed the importance of the customer perspective, as this perspective would provide the most valuable insights in creating a successful firm strategy. The papers also stressed the importance of transitioning towards this omni/multichannel strategy, in order for firms to stay competitive. The research suggests that purely online and brick-and-mortar firms should implement strategies found in firms that follow a different strategy, in order to move towards an multi-channel strategy and increase firm profits. The research also shows what drives customers to move towards using multiple channels; customer characteristics, supplier specific factors, customer demographics and customer based metrics. The duration of this customer channel adoption is affected by channel-, purchase- and frequency-related attributes and customer heterogeneity. The factors influencing particular channel usage have also been explained along with a framework to apply proper customer channel management. Then, customer channel migration was explained and how this can affect customer channel management strategies. Lastly, individual channel profitability and customer lifetime value were explained. Throughout this paper, the theories all stressed the importance of moving towards an omni- or multi-channel strategy as moving towards correct use of multiply channels always increased the overall firm profits and customer lifetime value. Concluding, in order for a firm to maximize its firm profit and CLV, it should make use of (and understand) multiple channel management. It should also understand the reasoning behind customer channel selection and when and why customers migrate between channels.

2.4.1 Implications for future research

When analyzing the theory to compute customer lifetime value, it became clear that there are many ways to compute this metric. The customer lifetime value calculation discussed in this research is only the simple version of the metric, but there are several more calculations that can be used in different sectors. It is therefore important for a firm to select a CLV calculation method that suits the firm's operations and environment. It is therefore recommended to research the correct CLV calculation method in an extensive manner.

3. THEORETICAL FRAMEWORK

3.1 Framework

The theoretical framework created and utilized in this research is based on information researched in the literature review section and on the research of Kumar and Petersen (2012) on customer retention. The information gathered has been used to create a custom, research specific framework. The framework consists of two main concepts that influence customer transaction value, namely; *order frequency* and *customer channel selection*. The coronavirus pandemic has been implemented in this framework as an outside concept that influences these two variables that in turn affect the order transaction value. The framework can be found in Figure 9.

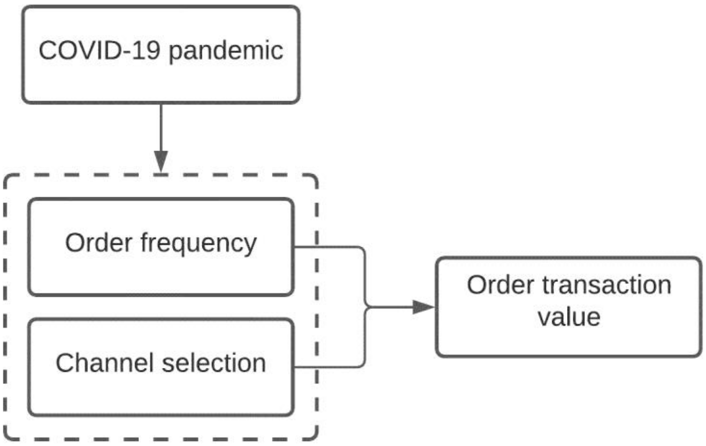


Figure 9 - Theoretical framework

3.2 Hypotheses

One of the main objectives of this research is to find out whether or not the coronavirus pandemic has an effect on the usage of physical channels by customers. The main motivation of this research was the thought that because of the coronavirus, the customer channel usage would shift from physical channels towards online channels. Therefore, the first hypothesis includes:

> H_1: The coronavirus pandemic will cause a shift from usage of physical channels towards online channels

When employees have direct, personal contact with a customer it is believed that this will result in a higher transactional value because of the high amount of service that is provided, in contrast to when a customer has no personal contact. Therefore, channels that provide the customer with this personal contact and service (e-mail/telephone/physical) are believed to provide a higher amount of transactional value. Automated channels (contract/website) logically are Following from this, the second hypothesis includes:

> H_2: Customers ordering through purchase channels that require more personal contact and employee effort will result in orders with higher transactional value than less labor intensive, automated channels

Because of the coronavirus, the customers have less to spend. The customer has to be mindful of every purchase they make. This means, that customers will probably make less orders since the introduction of the coronavirus pandemic then before the coronavirus pandemic. The customer order frequency will then go down. Therefore, the third hypothesis includes:

> H_3: The coronavirus pandemic will have a negative effect on customer order frequency

It is believed that customers that regularly make orders at the company, or partners, will probably place orders that are of higher value than customers that have placed an order sporadically. High frequency customers will therefore place more expensive orders then low frequency customers. The fourth hypothesis includes:

> H_4: Orders made by a high order frequency customer will result in higher transactional value than orders made by a low order frequency customer.

4. METHODOLOGY

To answer the research question, sub-questions and to test the hypotheses made in the previous chapter, quantitative order data was collected from the company. Annual order data was chosen as data source as this is the most logical, reliable source of information to answer the research question. The data consisted of all orders from one year prior to 15 March 2020 to one year after this date. This meant that all order data was collected from 15 March 2019 to 15 March 2021. 15 March 2020 was selected as the 'turning point', as this was the data the original lockdown started in the Netherlands. In this case, the year before the lockdown and the year since the lockdown could be compared. The dataset was then completely anonymized in order to protect key company and client information. The dataset was implemented into SPSS and included information such as customer ID's, order numbers, order prices, order dates and which channels had been used by customers when placing an order. The customer order frequency for the whole period, the year before the lockdown and the year since the lockdown was calculated from this data. Dummy variables were created for the order frequency; low frequency customers with 1-20 orders placed, medium frequency customers with 21-140 orders placed and high frequency customers with more than 140 orders placed. Dummy variables were also created for the channels used by the customers; the contract channel, e-mail channel, physical channel, telephone channel and website channel. These dummy variables were created to enable the regression analysis that was performed. Lastly, a dichotomous variable was created that indicated whether the orders were placed before the lockdown or since the lockdown. This dichotomous variable was used to split the statistics in two sections; 'before lockdown' and 'since lockdown'.

5. RESULTS

The dataset used in this research consists of 10233 separate orders made by customers of the company. It consists of information such as customer ID's, order numbers, order prices, order dates and what channel has been used by the customer. The dataset includes a timespan of two years, between 15 March 2019 and 15 March 2021. The 10233 total orders were placed in this timespan. The minimum price for an order was €0.00, whilst the maximum price for an order was €157,300.00. The mean average price of an order was €1,082.30, with a standard deviation of €4,740.68. The descriptive statistics for the order frequency of the whole, two year period can be found in Table 1.

In order to assess the influence of the coronavirus and the lockdown, the dataset was split in half; before the lockdown and since the lockdown. In the year before the lockdown, 5253 orders were placed. These orders also had a minimum price of €0.00 and a maximum price of €157,300.00. The mean average price of an order was €1,079.8095 with a standard deviation of €4,866.33201. In the year since the lockdown, 4980 orders were placed. The minimum order price was €0.00 and the maximum price was €148,222.58. The mean average price of an order was €1,084.9342 with a standard deviation of €4,604.91438. The descriptive statistics for the order price per period (before and since the lockdown) can also be found in Table 1.

Table 1 - Descriptive statistics order price

	Whole period		***Before lockdown***		***Since lockdown***	
	Order price	***Valid N***	***Order price***	***Valid N***	***Order price***	***Valid N***
N	10233	10233	5253	5253	4980	4980
Min.	.00		.00		.00	
Max.	157,300.00		157,300.00		148,222.58	
Mean	1,082.3035		1,079.8095		1,084.9342	
Std. dev.	4,740.68090		4,866.33201		4,604.91438	

These descriptive statistics show that in the year before the lockdown more orders were placed then since the lockdown (5253 vs. 4980). The maximum order price has also decreased by €9077.42. The mean has stayed roughly the same, whilst the standard deviation has also decreased slightly.

Over the complete two year timespan, a total of 906 unique customers placed an order at the company. The minimum amount of orders placed by a customer was 1, whilst the maximum amount of orders placed by a single customer was 556. The mean average of orders placed by a single customer was 10,98, with a standard deviation of 38,663. The descriptive statistics of the order frequency over the whole, two year timespan can be found in Table 2.

Table 2 - Descriptive statistics order frequency

	Whole period		***Before lockdown***		***Since lockdown***	
	Order freq.	***Valid N***	***Order freq.***	***Valid N***	***Order freq.***	***Valid N***
N	906	906	616	616	667	667
Min.	1		1		1	
Max.	556		330		452	
Mean	10,98		8,53		7,47	
Std. dev.	38,663		23,794		24,347	

In the year before the lockdown, a total of 616 unique customers placed an order at the company. The minimum amount of orders placed by a single customer was still 1, whilst the maximum amount of orders was 330. The mean average of orders placed by a single customer was 8,53, with a standard deviation of 23,794. In the year since the lockdown, a total of 667 unique customers have placed an order. The minimum amount of orders placed since the lockdown was still 1, with a maximum amount of 452. The mean average of orders placed by a single customer was 7,47, with a standard deviation of 24,347. The descriptive statistics for the order frequency per period (before and since the lockdown) can also be found in Table 2.

These descriptive statistics show some interesting facts. The amount of unique customers increased from 616 in the year before the lockdown to 667 customers since the lockdown. The maximum amount of orders placed by a customer also increased to 452 since the lockdown from 330 before the lockdown. However, the mean average of orders placed decreased to 7,47 from 8,53. The standard deviation increased slightly.

To answer H_1, frequency analysis was conducted. As stated previously, over the two year timespan 10233 orders were placed by customers. The orders were categorized by the channel they were acquired with respectively. There are five different channels included; contract, e-mail, physical, telephone and website. In the complete two year timespan 4,1% of the orders were automatically placed through running contracts, 42% of orders were placed through e-mail, 9,4% of orders were placed in a physical environment, 37,4% of orders were placed through the telephone and 7,1% of orders were placed through the company website. The frequencies for the channel usages over the whole, two year timespan can be found in Table 3.

Table 3 - Frequency table customer channel usage

	Whole period			***Before lockdown***			***Since lockdown***		
	Freq.	***Percent***	***Cum. Percent***	***Freq.***	***Percent***	***Cum. Percent***	***Freq.***	***Percent***	***Cum. Percent***
Contract	423	4,1	4,1	202	3,8	3,8	221	4,4	4,4
E-mail	4296	42,0	46,1	2342	44,6	48,4	1954	39,2	43,7
Physical	958	9,4	55,5	485	9,2	57,7	473	9,5	53,2
Telephone	3832	37,4	92,9	1969	37,5	95,1	1863	37,4	90,6
Website	724	7,1	100,0	255	4,9	100,0	469	9,4	100,0
Total	10233	100,0		5253	100,0		4980	100,0	

In the year before the lockdown, 3,8% of the orders were placed through automatic contracts, 44,6% were placed through e-mail, 9,2% were placed in a physical environment, 37,5% were placed through the telephone and 4,9% was placed through the company website. In the year since the lockdown, 4,4% of the orders were automatically placed through a contract, 39,2% were placed through e-mail, 9,5% was placed through a physical environment, 37,4% were placed through the telephone and 9,4% of orders were placed on the company website. The frequencies per period (before and since lockdown) for the channel usages of customers can be found in Table 3.

The frequency tables show once more some interesting facts. The most noteworthy channel changes include e-mail channel usage declining by 5,4%, from 44,6% before the lockdown to 39,2% since the lockdown. Interestingly, the amount of orders placed through a physical environment did not decline.

The physical channel even increased from 9,2% before the lockdown to 9,5% since the lockdown. The amount of orders placed through the company website however increased from 4,9% before the lockdown to 9,4% since the lockdown.

The statistics do not show a shift from the physical channel towards the online channels; they mainly show a shift from e-mail towards website. <u>This means that H_1 is rejected.</u>

To answer H_2, linear regression was conducted. This analysis was made to see if usage of a particular purchase channel by customers resulted in a higher transactional order value. First, linear regression was conducted for the whole, 2-year period. Then, linear regression was conducted for the period before the lockdown and the period since the lockdown. The model summary for these three tests can be found in Table 4.

Table 4 - Model summary purchase channels with order price

Period	*R*	*R Square*	*Adjusted R Square*	*Std. Error of the Estimate*
Whole period	,039[a]	,002	,001	4,738.02779
Before lockdown	,042[a]	,002	,001	4,863.85941
Since lockdown	,045[a]	,002	,001	4,602.04930

a. Predictors: (Constant), channel_website, channel_physical, channel_telephone, channel_email

The multiple correlation coefficients (R), coming forth from the analyses show low values; 0,039 for the whole period, 0,042 before the lockdown and 0,045 since the lockdown. These values correspond to very weak values. This means that there is no indication for a linear relationship between the variables. The adjusted R-square (R^2) values are all 0,001, which means that in all models the independent variables (the purchase channels) only explain 0,1% of the dependent variable (the order price).

Considering the ANOVA table in Appendix D, the regression is mostly a good fit for the data. Only the before lockdown period is barely not significant. The ANOVA outcomes are $F(4,10228) = 3,866$, $p < 0,004$, $F(4,5248) = 2,335$, $p < 0,053$ and $F(4,4975) = 2,550$, $p < 0,037$.

Although there now is already an indication that the usage of a particular purchase channel will not affect the order price, the coefficients table will still be considered. These statistics can be found in Table 5. Because dummy variables were created, 'Channel_contract' was left out of the statistic to serve as a comparison. The other dummy variables, 'Channel_email', 'Channel_physical', 'Channel_telephone' and 'Channel_website' will be compared to the dummy variable that was left out. This table shows that in all three models (whole period, before lockdown, after lockdown) there is only one statistically significant difference. Only when the whole period is considered, the e-mail channel has a significant effect (where $p < 0{,}05$) on order price in comparison to the contract channel (the dummy variable left out). This means that only when the whole 2-year period is considered, e-mail channel users tend to make orders with a higher order price (620,475). However, the table shows no significant effects for all channels when either before or since the lockdown is considered. This means that before the lockdown, particular channel usage had no effect on order price and since the lockdown, this has not changed. Altogether, this means that H_2 is rejected.

Table 5 - Regression coefficients purchase channels with order price

Coefficients[a]				
		Unstandardized coefficients		
Period		***B***	***Std. Error***	***Sig.***
Whole period	***(constant)***	651,850	230,371	,005
	Channel_email	620,475	241,446	,010
	Channel_physical	155,526	276,593	,574
	Channel_telephone	370,419	242,753	,127
	Channel_website	235,952	289,961	,416
Before lockdown	***(constant)***	646,012	342,220	,059
	Channel_email	651,438	356,673	,068
	Channel_physical	362,418	407,299	,374
	Channel_telephone	270,535	359,346	,452
	Channel_website	174,954	458,135	,703
Since lockdown	***(constant)***	657,186	309,567	,034
	Channel_email	585,026	326,605	,073
	Channel_physical	-55,965	374,977	,881
	Channel_telephone	476,820	327,414	,145
	Channel_website	266,955	375,486	,477

a. Dependent variable: order price

To answer H_3, the descriptive statistics from Table 2 will be considered. In order to create these statistics, separate datasets were created. One dataset containing the orders made before the lockdown and one dataset containing the orders made since the lockdown. As stated previously, in the year before the lockdown, 616 unique customers placed an order. Before the lockdown the average amount of orders placed by a single customer was 8,53. Since the lockdown, the average amount of orders placed by a single customer was 7,47.

The unique customers during are also divided further into three segments; low frequency (1-20 orders made) customers, medium frequency (21-140 orders made) customers and high frequency (141+ orders made) customers. A frequency table was created for these customer segments, which can be found in Table 6. This table shows an increase in low frequency customers from before the lockdown to since the lockdown. It also shows a decrease of medium frequency customers from before the lockdown to since the lockdown. This also fuels the assumption that since the coronavirus lockdown, the amount of orders per customer has reduced. Therefore, H_3 is accepted.

Table 6 – Frequencies customer order segments

Before or since lockdown	*Customer order frequency segment*	*Frequency*	*Percentage*	*Cumulative percentage*	*Unique customers*
Whole period	***Frequency_low***	819	90,4	90,4	906
	Frequency_medium	74	8,2	98,6	
	Frequency_high	13	1,4	100	
Before lockdown	***Frequency_low***	565	91,7	91,7	616
	Frequency_medium	48	7,8	99,5	
	Frequency_high	3	0,5	100	
Since lockdown	***Frequency_low***	623	93,4	93,4	667
	Frequency_medium	41	6,1	99,5	
	Frequency_high	3	0,5	100	

In order to answer H_4, another regression analysis was conducted. This analysis was made in order to see if a customer belonging to a certain order frequency segment would result in a higher transactional order value. First, linear regression analysis was conducted for the whole, 2-year period. Then, linear regression was conducted for the period before and since the lockdown. The model summary of these tests can be found in Table 7.

Table 7 - Model summary order frequency segments with order price

Period	*R*	*R Square*	*Adjusted R Square*	*Std. Error of the Estimate*
Whole period	,052[a]	,003	,003	4,734.73176
Before lockdown	,040[a]	,002	,001	4,863.28023
Since lockdown	,069[a]	,005	,004	4,594.75983

a. Predictors: (Constant), frequency_high, frequency_medium

The multiple correlation coefficients (R), coming forth from the analyses show low values; 0,052 for the whole period, 0,040 before the lockdown and 0,069 since the lockdown. These values correspond to very weak values. This means that there is no indication for a linear relationship between the variables. The adjusted R-square (R^2) values are 0,003, 0,001 and 0,004 respectively, which means that in the models the independent variables (customer order segments) only explain 0,3%, 0,1% and 0,4% of the dependent variable (the order price). Considering the ANOVA table in Appendix E, the regression is a good fit for the data in all models with $F(2,10230) = 13{,}864$, $p < 0{,}001$, $F(2,5250) = 4{,}297$, $p < 0{,}014$ and $F(2,4977) = 12{,}016$, $p < 0{,}001$.

The regression statistics can be found in Table 8. The dummy variable ‘Frequency_low’ was left out. The other dummy variables, ‘Frequency_medium’ and ‘Frequency_high’, will therefore be compared to the dummy variable that was left out. This table shows that in the whole period, medium frequency customers and high frequency customers both have a significant effect on the order price (as $p < 0.05$). For customers with a medium order frequency, orders increase by 509,756. For customers with a high order frequency, orders increase by 544,126.

Before the lockdown, only customers with a high order frequency had a significant effect on the order price (as $p < 0.05$). Order price respectively increased with 487,536 comparing to low frequency customers.

Since the lockdown, both medium order frequency customers and high frequency customers had a significant effect on the order price (as for both $p < 0.05$). Interestingly, medium order frequency customers increased the order price by a larger amount (738,247) than high order frequency customers (597,651).

This means that, considering the statistics, customers with a higher order frequency indeed result in higher order prices. The only exception is that since the coronavirus, medium order frequency customers result in higher order price than high order frequency customers. However, it is true that when compared to low order frequency customers, higher order frequency customers result in higher order price. Therefore, H_4 can be accepted.

Table 8 - Regression coefficients order frequency segments with order price

Coefficients[a]				
		Unstandardized coefficients		
Period		***B***	***Std. Error***	***Sig.***
Whole period	***(constant)***	724,611	82,584	,000
	Frequency_medium	509,756	115,249	,000
	Frequency_high	544,126	115,185	,000
Before lockdown	***(constant)***	809,436	120,792	,000
	Frequency_medium	300,126	165,041	,069
	Frequency_high	487,536	167,373	,004
Since lockdown	***(constant)***	642,077	112,571	,000
	Frequency_medium	738,247	160,858	,000
	Frequency_high	597,651	158,058	,000

a. Dependent variable: order price

6. DISCUSSION

In this section the results from the previous chapter will be discussed and notable findings will be mentioned. For reference, an overview of the hypotheses that were accepted and rejected is given in Table 9.

Table 9 - Hypothesis acceptance/rejection

Hypothesis	Accepted / rejected
1	Rejected
2	Rejected
3	Accepted
4	Accepted

Table 2 in the results chapters shows that in the year before the lockdown less unique customer ID's were used to place an order than in the year since the lockdown. This means that since the lockdown, more unique customers placed an order camping to before the lockdown. Interestingly, the total amount of orders (which can be found in Table 1) decreased since the lockdown. The average price of an order stayed roughly the same, whilst the average amount of orders placed by a single customer decreased by 1 order. Another notable change is that since the lockdown, the maximum amount of orders placed by a single customer increased with 120 orders from 330 to 452.

A possible explanation of these changes could be a shift in customer product focus. This research however does not take into account the specific products that are bought per order. The company is specialized in printing solutions and an example could be that since the lockdown, customers could be ordering a larger amount of stickers than they did before the lockdown. Stickers are used on a large scale since the introduction of the coronavirus, in order to e.g. indicate the public to keep 1,5-meter distance or visualize waiting lines.

One of the main research goals of this paper was to find out if the introduction of the coronavirus pandemic resulted in a shift of customers using the physical channel to place an order to more online channels. However, the frequencies in Table 3 indicate almost no change in usage of the physical channel since the lockdown.

A possible explanation of this could be the fact that this company already has a very small amount of orders being placed by the physical channel and that these orders can only be placed physically. For instance, these orders are most likely either maintenance, installations or interventions. These orders can only be done in a physical matter and therefore the usage of the physical channel is absolutely necessary. This means that since the introduction of the lockdown, the usage of the physical channel simply cannot go much lower. Lockdown or not, these orders are necessary either way.

A change in customer channel usage that however was noticeable was the decrease in e-mail channel usage and the almost doubling usage of the website channel.

A possible explanation of this was presented by one of the company representatives. The executive indicated that the website and webshop were developed and finetuned further in 2019. These developments alone could be the reason why the website channel usage increased by this amount in 2020. The better functioning website and webshop and the fact that customers could be more aware of this channel could be the reason of the shift from the e-mail to the website channel, as opposed to the corona lockdown.

The regression statistics in Table 5 indicate that there is no clear connection between the usage of a particular order channel by the customer and order price. This means that the usage of a specific channel does not necessarily lead to either higher or lower order prices. Channel selection has no influence on order price, either before or since the lockdown.

The regression statistics in Table 8 show that when a customer has a higher order frequency, the average order price also tends to be higher. Interestingly, since the coronavirus, medium order frequency customers increase the order price by a larger amount than high order frequency customers. A possible explanation could be that since the lockdown, some customers place less orders with a higher order price.

7. LIMITATIONS & RECOMMENDATIONS

As stated in the previous chapter, this research only focuses on the usage of different purchase channels and order prices. This research does not look at the orders in such detail that the specific products bought in each order are considered. Therefore, a shift in product focus from the customers could be one of the reasons why since the lockdown, the profitability has stayed roughly the same for the company. It is therefore recommended that the company does research at the individual product level, to see if there has been a shift in product focus. This could lead to interesting insights and information that can be used to prepare for the future.

This research eventually did not calculate and consider the customer lifetime value associated with each customer. It is therefore recommended to the company to try and calculate this metric for each of their customers so that adequate amounts of service (and therefore costs) can be made relative to the value that each customer brings the company.

The research has shown that a large proportion of orders is being made through either the telephone or e-mail channels. These channels are some of the most labor intensive channels and therefore require a lot of work and service provided by employees. A recommendation for the company is to try and shift lower value customers from these channels to less labor intensive, automated channels such as the website. This results in employees having more time to provide high value customers with better service, which in turn will lead to more profits.

This research only considers the usage of particular channels by customers, but does not actually consider the actual customer preference regarding channel usages. The bare fact that they use a particular channel does not mean that they prefer the usage of this channel above the usage of other channels. It might therefore be useful to conduct additional qualitative research about the company customers and about their channel preferences. This can then be used to tailor the customer experience in a better manner, which eventually will result in higher profits. This information can also be used to make decisions about company strategies, e.g. meeting the preference of high value customers above the preference of low value customers.

8. CONCLUSION

The aim of this research paper was to find out whether or not the coronavirus pandemic has an effect on the customer channel usage and channel profitability. The main research question is answered by setting up multiple sub-questions, followed up by several hypotheses. These hypotheses are mentioned in the theoretical framework chapter and are all answered in the results chapter. These hypotheses are made up after extensive review of previous literature. This research did not find any evidence that the coronavirus pandemic had any significant effect on particular customer channel usage or channel profitability for this company. There is also no evidence that the usage of a particular customer channel has any influence on the order price. This research however did find that the coronavirus pandemic and lockdown had a negative effect on order frequency per customer. It has also shown that orders placed by low frequency customers are generally of lower order price then orders placed by higher frequency customers.

This research concludes that the coronavirus pandemic and lockdown had a negative effect on order frequency per customer for this company. The lockdown did not lead to a shift from physical channels to online channels, which at first was expected. Even if the lockdown would have caused a large shift in channel selection by customers, the research found that usage of a particular channel by a customer would have no effect on the order price either way.

9. ACKNOWLEDGEMENT

I would like to thank my first supervisor, dr. A. Leszkiewicz, for her guidance and feedback during the creation of this research. I would also like to thank my second supervisor, E. Constantinides, for reviewing the final research paper.

Finally, I would like to thank my family and friends for their support and motivation during the completion of my bachelor and master's degree.

10. REFERENCES

Ansari, A., Mela, C. F., & Neslin, S. A. (2008). Customer channel migration. Journal of Marketing Research, 45(1), 60–75.

Bell, D. R., Gallino, S., & Moreno, A. (2014). How to win in an omnichannel world. MIT Sloan Management Review, 56(1), 45–53.

Brynjolfsson, E., Hu, Y. J., & Rahman, M. S. (2013). Competing in the Age of Omnichannel Retailing Brought to you by. International Journal of Electronic Commerce, 18(4), 5–16.

Chang, C. W., & Zhang, J. Z. (2016). The Effects of Channel Experiences and Direct Marketing on Customer Retention in Multichannel Settings. Journal of Interactive Marketing, 36, 77–90.

Chatterjee, P. (2010). Multiple-channel and cross-channel shopping behavior: role of consumer shopping orientations. Marketing Intelligence & Planning, 28(1), 9–24.

Chiu, H. C., Hsieh, Y. C., Roan, J., Tseng, K. J., & Hsieh, J. K. (2011). The challenge for multichannel services: Cross-channel free-riding behavior. Electronic Commerce Research and Applications, 10(2), 268–277.

Chu, W., & Messinger, P. R. (1997). Information and channel profits. Journal of Retailing, 73(4), 487–499.

Fornari, E., Fornari, D., Grandi, S., Menegatti, M., & Hofacker, C. F. (2016). Adding store to web: migration and synergy effects in multi-channel retailing. International Journal of Retail and Distribution Management, 44(6), 658–674.

Gao, F., & Su, X. (2017). Online and offline information for omnichannel retailing. Manufacturing and Service Operations Management, 19(1), 84–98.

Gupta, S., Hanssens, D., Hardie, B., Kahn, W., Kumar, V., Lin, N., Ravishanker, N., & Sriram, S. (2006). Modeling customer lifetime value. Journal of Service Research, 9(2), 139–155.

Kumar, V., & Petersen, J. A. (2012). Statistical Methods in Customer Relationship Management. In *Statistical Methods in Customer Relationship Management.*

Kumar, V., Ramani, G., & Bohling, T. (2004). Customer lifetime value approaches and best practice applications. Journal of Interactive Marketing, 18(3), 60–72.

Kumar, V., Shah, D., & Venkatesan, R. (2006). Managing retailer profitability-one customer at a time! Journal of Retailing, 82(4), 277–294.

Kumar, V., & Venkatesan, R. (2005). Who are the multichannel shoppers and how do they perform?: Correlates of multichannel shopping behavior. Journal of Interactive Marketing, 19(2), 44–62.

Li, J., Konuş, U., Langerak, F., & Weggeman, M. C. D. P. (2017). Customer Channel Migration and Firm Choice: The Effects of Cross-Channel Competition. International Journal of Electronic Commerce, 21(1), 8–42.

Neslin, S. A., Grewal, D., Leghorn, R., Shankar, V., Teerling, M. L., Thomas, J. S., & Verhoef, P. C. (2006). Challenges and opportunities in multichannel customer management. Journal of Service Research, 9(2), 95–112.

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. PLoS Medicine, 18(3), 1–11.

Rangaswamy, A., & Van Bruggen, G. H. (2005). Opportunities and challenges in multichannel marketing: An introduction to the special issue. Journal of Interactive Marketing, 19(2), 5–11.

Valentini, S., Montaguti, E., & Neslin, S. A. (2011). Decision process evolution in customer channel choice. Journal of Marketing, 75(6), 72–86.

Venkatesan, R., & Kumar, V. (2004). A Customer Lifetime Value Framework for Customer Selection and Resource Allocation Strategy. Journal of Marketing, 68(October), 106–125.

Venkatesan, R., Kumar, V., & Ravishanker, N. (2007). Multichannel shopping: Causes and consequences. Journal of Marketing, 71(2), 114–132.

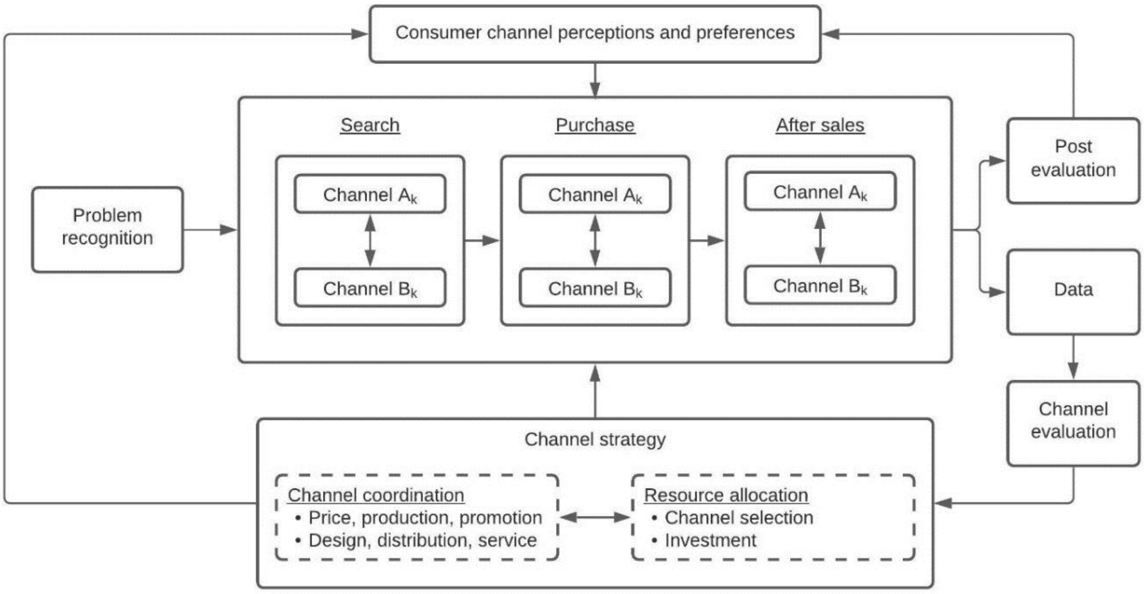
Weinberg, B. D., Parise, S., & Guinan, P. J. (2007). Multichannel marketing: Mindset and program development. Business Horizons, 50(5), 385–394.

11. APPENDIX A: LITERATURE REVIEW - PAPER CONCEPTS, METHODS AND FINDINGS

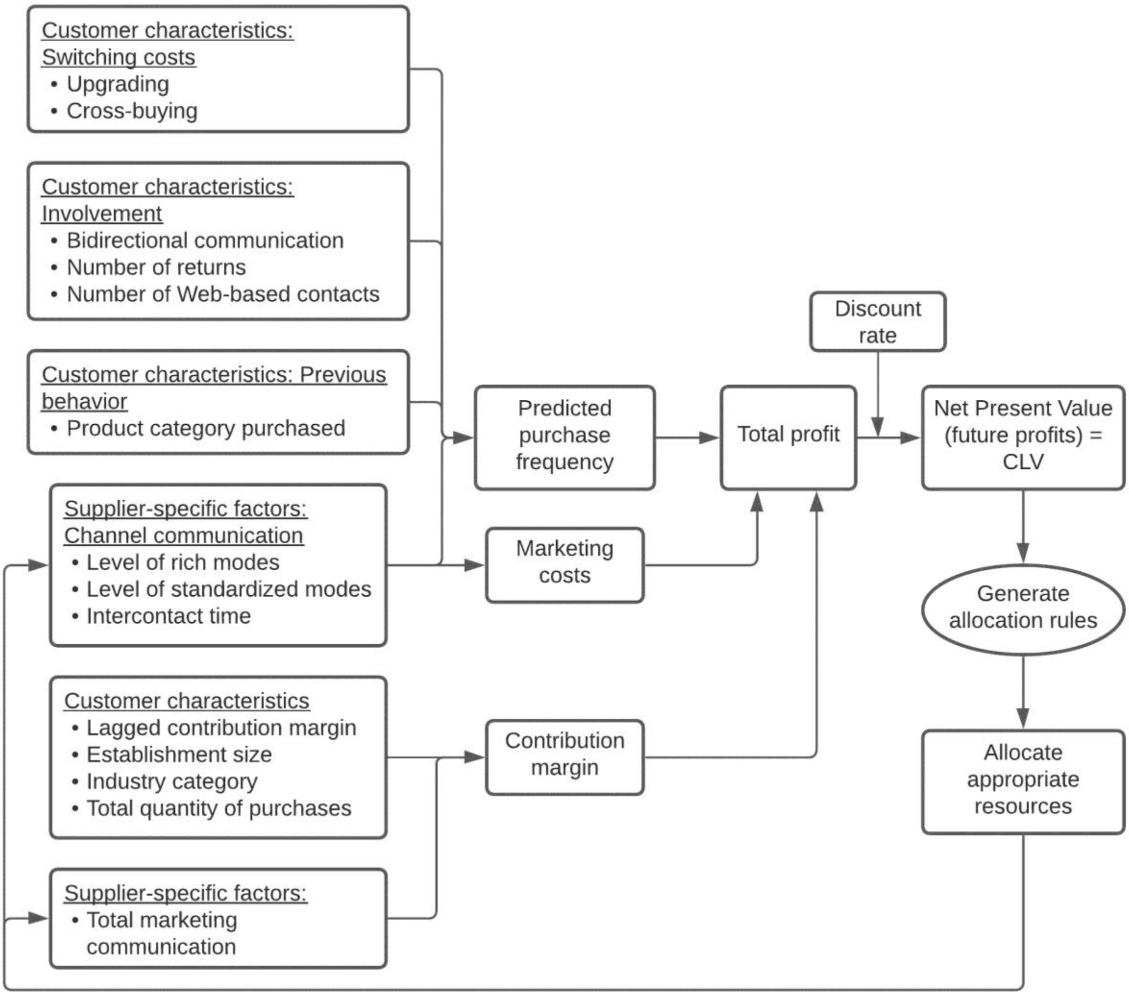
Authors	***Key concept***	***Method***	***Sample***	***Important findings***
Ansari, A., Mela, C. F., & Neslin, S. A. (2008)	Customer channel migration	Data analysis	500 randomly selected customers	The development of a customer channel migration model
Fornari, E., Fornari, D., Grandi, S., Menegatti, M., & Hofacker, C. F. (2016)	Customer channel migration and multichannel retailing	Data analysis	151700 customers of 3 stores	Opening of stores lead to short-term migration from online to offline, but tends to move back in long-term
Li, J., Konuş, U., Langerak, F., & Weggeman, M. C. D. P. (2017)	Customer channel migration and multichannel shopping	Data analysis	20570 randomly selected customers	Previous online purchases from competitors increases chance of online channel adoption by customer
Bell, D. R., Gallino, S., & Moreno, A. (2014)	Omnichannels	Customer behavior data analysis		Traditional and online retailers should consider hybrid online-offline approaches
Brynjolfsson, E., Hu, Y. J., & Rahman, M. S. (2013)	Omnichannels	Sales data analysis	Customers medium-sized retail company	New strategies to compete in an omnichannel environment
Gao, F., & Su, X. (2017)	Omnichannels, online and offline	Creation of models		Online showrooms might hurt profits due to excessive channel migration to online
Chang, C. W., & Zhang, J. Z. (2016)	Multichannels	Data analysis	Customer data multichannel retailer	Offline channels best at customer education or revival, online best at retention
Chatterjee, P. (2010)	Multichannels and cross-channel shopping	Analyzing multiple data sources	Surveys, transaction data	Cross channel customers are less likely to search for competitor offerings than multiple channel customers
Chiu, H. C., Hsieh, Y. C., Roan, J., Tseng, K. J., & Hsieh, J. K. (2011)	Multichannels and cross-channel free-riding	Questionnaire analysis	322 useful respondents	More self-efficacy leads to more-cross channel free-riding behavior, competitor offline store service and risk level also increase cross-channel free-riding
Kumar, V., & Venkatesan, R. (2005)	Multichannel shopping behavior	Analysis customer database	Two samples of 3578 and 3721 customers	Conceptual framework identifying customer characteristics and supplier factors associated with purchasing across multiple channels
Neslin, S. A., Grewal, D., Leghorn, R., Shankar, V., Teerling, M. L., Thomas, J. S., & Verhoef, P. C. (2006)	Multichannel customer management	Data analysis	Data from referenced articles	Framework of 5 challenges and how to adopt in multichannel customer management

Rangaswamy, A., & Van Bruggen, G. H. (2005)	Multichannel marketing opportunities and challenges	Literature analysis		Overview of multichannel marketing and several challenges and opportunities for multichannel marketing
Valentini, S., Montaguti, E., & Neslin, S. A. (2011)	Multichannel customer choice	Data analysis	1018 active customer households	Customers decision processes evolve, sizeable segment changes decision process
Venkatesan, R., Kumar, V., & Ravishanker, N. (2007)	Multichannel shopping causes and consequences	Customer database analysis	1165 customers	Identified characteristics influencing 2nd and 3rd channel adoption and adoption time. Framework created for forward looking allocation of multichannel marketing resources
Weinberg, B. D., Parise, S., & Guinan, P. J. (2007)	Multichannel marketing mindset and program development	Interviews	30 senior executives and managers from major multichannel firms	Several recommendations given to adopt a multichannel mindset and to design a multichannel marketing program
Chu, W., & Messinger, P. R. (1997)	Channel profitability	Case analysis	Three different case analyses	Improved demand information always improves absolute profit. Informed channel members gather greater profitability as they can finetune prices to changes in demand. Price finetuning results in smoothing sales
Gupta, S., Hanssens, D., Hardie, B., Kahn, W., Kumar, V., Lin, N., Ravishanker, N., & Sriram, S. (2006)	Customer lifetime value	Literature analysis		CLV basics are given, several CLV models are reviewed and insights are given for further research
Kumar, V., Ramani, G., & Bohling, T. (2004)	Customer lifetime value approaches and applications	Observations of cross section firms and literature analysis		Two approaches to compute CLV are given next to challenges when implement CLV approaches
Kumar, V., Shah, D., & Venkatesan, R. (2006)	Customer lifetime value	Data analysis	303431 customers divided into two cohorts	How CLV can be computed for individual customers to maximize profitability in retail. Multichannel customers have higher CLV. Relative large proportion of customers found with negative CLV.
Venkatesan, R., & Kumar, V. (2004)	Customer lifetime value framework	Data analysis	Two cohorts of 1316 and 873 customers from large multinational hard- and software manufacturer	Framework that improves customer relationships and maximizes CLV. Customers selected on CLV have higher future profitability then when selected on other metrics

APPENDIX B: FRAMEWORK MULTICHANNEL MANAGEMENT



APPENDIX C: FRAMEWORK FOR MEASURING AND USING CLV



APPENDIX D: ANOVA TABLE CUSTOMER CHANNELS WITH ORDER PRICE

ANOVA[a]

Period		*Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*
Whole period	***Regression***	347110500,938	4	86777625,235	3,866	,004[b]
	Residual	229607423934,220	10228	22448907,307		
	Total	229954534435,158	10232			
Before lockdown	***Regression***	220985307,688	4	55246326,922	2,335	,053[b]
	Residual	124152609838,674	5248	23657128,399		
	Total	124373595146,363	5252			
Since lockdown	***Regression***	216054913,078	4	54013728,270	2,550	,037[b]
	Residual	105364817235,821	4975	21178857,736		
	Total	105580872148,899	4979			

a. Dependent Variable: Order price

b. Predictors: (Constant), channel_website, channel_physical, channel_telephone, channel_email

APPENDIX E: ANOVA TABLE FREQUENCY SEGMENTS WITH ORDER PRICE

ANOVA[a]

Period		*Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*
Whole period	***Regression***	621618138,476	2	310809069,238	13,864	,000[b]
	Residual	229332916296,682	10230	22417684,877		
	Total	229954534435,158	10232			
Before lockdown	***Regression***	203248569,800	2	101624284,900	4,297	,014[b]
	Residual	124170346576,562	5250	23651494,586		
	Total	124373595146,363	5252			
Since lockdown	***Regression***	507354398,272	2	253677199,136	12,016	,000[b]
	Residual	105073517750,627	4977	21111817,913		
	Total	105580872148,899	4979			

a. Dependent Variable: Order price

b. Predictors: (Constant), frequency_high, frequency_medium