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Online channel adoption in supermarket retailing

Marta Frasquet

Faculty of Economics, University of Valencia,

Avda. dels Tarongers s/n, 46022 València (Spain)

email: marta.frasquet@uv.es

Marco Ieva[1]

Department of Economics and Management, University of Parma,

Via Kennedy 6, 43125, Parma (Italy)

email: marco.ieva@unipr.it

Cristina Ziliani

Department of Economics and Management, University of Parma,

Via Kennedy 6, 43125, Parma (Italy)

email: cristina.ziliani@unipr.it

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[1] Corresponding author: marco.ieva@unipr.it. Department of Economics and Management, University of Parma, Via Kennedy 6, 43125, Parma (Italy), +39 0521 902099.

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Abstract

Introducing a new online channel is a crucial decision for brick and mortar retailers that requires insight and forecasts into customers' adoption and subsequent behaviour. The aim of this study is to analyse the dynamics in the behavioural heterogeneity of (new) multichannel supermarket customers when the online channel is introduced. A Latent Class Analysis (LCA) was conducted on 1,151 adopters of the new online channel of a supermarket retailer to segment customers. We employed an extended "Recency, Frequency and Monetary (RFM)" model that includes customers' purchases prior to the introduction of the new channel. Results show that adopters of a new channel are not a homogenous group of customers displaying a similar behaviour: two segments – or 35% of the sample – quit the channel after using it for some time, another segment (5%) left the company altogether, the other four segments remained multichannel to different degrees, with one shifting shopping substantially to online. Based on these results, the paper provides directions to retailers for developing Customer Relationship Management (CRM) strategies to manage the different customer segments and support channel performance evaluation and channel management decisions in a multichannel context.

Keywords: channel adoption; multichannel behaviour segmentation; RFM.

Article classification: Research paper

1. Introduction

Over the last two decades, brick-and-mortar retailers have added online channels and developed multichannel and lately, cross-channel and omnichannel strategies (Alexander and Blazquez Cano, 2020; Verhoef et al., 2015). Adding an online channel is a significant challenge for brick-and-mortar retailers, which have invested a lot in the physical store network and struggle with the risk that online sales would cannibalize store sales (Biyalogorsky and Naik, 2003; Hernant and Rosengren, 2017). The COVID-19 pandemic has spurred retailers to hasten their ecommerce adoption plans, as more and more consumers adopted the online channel or increased their frequency of usage (Jaszczyk, 2020; Liu, 2020). An increasing number of companies are asking themselves questions related to the impact of the new online channel on their bottom line and their customers. Following the introduction of a new channel, in fact, customers develop different adoption behaviours and usage of online and offline channels and multichannel behaviours emerge (Park and Kim, 2018). Companies need to assess how customers continue to use the online channel months into adoption, in order to evaluate and support investment decisions. As more digital channels are involved and the borders between them blur, multichannel retailing morphs into omnichannel (Verhoef et al., 2015). Research in omnichannel retailing is still rather limited and further research is needed to uncover the drivers of the simultaneous customers' choice of channels and how retailers should integrate and synchronise channels (Verhoef et al., 2015).

Two key areas in multichannel consumer research are channel adoption, and customer segmentation and profiling (Dholakia et al., 2010; Verhoef et al., 2015). Channel adoption research is related to the consequences, in terms of customer behaviour, of the introduction of a new channel. Customer segmentation and profiling identifies groups of customers displaying different channel preferences and spending patterns that offer targeting opportunities for the firm. This paper contributes to multichannel research by bridging these two key areas. We aim to uncover the effects of channel adoption on consumer spending and purchase frequency, thus contributing to the current debate on this topic (e.g. Li et al., 2021; Singh & Rosengren, 2020; Beckers, Cárdenas, & Verhetsel, 2018). As far as segmentation and profiling of adopters of the new online channel, we advance research by employing RFM modeling. This is a segmentation approach widely employed in CRM (Kumar and Reinartz, 2018) and in retailing research (e.g. Liu et al., 2017; Shokouhyar et al., 2020) to differentiate customers based on their purchase behaviour, specifically in terms of recency, frequency, and monetary. Despite the popularity of RFM, to our knowledge, few papers have attempted so far to develop the RFM model in a multichannel setting.

The main aim of this study is to analyse the dynamics in the heterogeneity of multichannel customers when the online channel is introduced using a segmentation approach based on purchase behaviour data. In this paper, we extend the RFM model to include the customers' behavioural data prior to the introduction of the online channel. Even though behavioural data-based studies can take into account the dynamics of new channel adoption and cross-channel behaviour, only a few of them have taken this opportunity (Hernant and Rosengren, 2017; Li et al., 2015).

The study seeks to answer the following research questions (RQ):

RQ 1. Which multichannel customer segments emerge following the introduction of the online channel by an offline retailer?

RQ 2. How does customers' previous offline purchase behaviour predict multichannel behavioural heterogeneity?

To this aim, we perform an LCA based on customer level behavioural data spanning 18 months before and 18 months after the introduction of the online channel by a supermarket retailer. The paper contributes to the multichannel literature by uncovering the effects on spending and frequency following the introduction of a new online channel as seven meaningful customer segments are revealed, displaying distinct behaviours as far as the offline and online channels. Three actual multichannel customer segments have adopted the online channel, with some differences in terms of intensity of the online versus offline channel, one segment substantially shifted purchases from offline to online. Two other segments started shopping in the online channel, but after a while stopped using it and the remaining segment stopped buying from the retailer altogether after adopting the online channel.

Regarding RQ2, we contribute to research by showing how behaviour before the introduction of the online channel significantly predicts the behaviour displayed once the online channel is active.

Our research provides retailers with evidence on what they could expect in terms of heterogeneous customer response when introducing a new online channel and points to the need for retailers to develop CRM strategies aimed at different multichannel customer segments. Findings on the relationship between offline purchase behaviour before the channel launch and subsequent purchase behaviour can support retailers in predicting to what extent their customer base might display multichannel behaviour if they introduce the new channel. The choice of an RFM model, that is based on variables commonly available to retail CRM departments adds to the replicability of this study by retailers on their customer bases.

The remainder of this paper is as follows: we provide an overview of relevant studies, before proposing a conceptual framework for our research questions. Next, we describe the methodology, data and retail environment of our study. We then present the results of the empirical analysis, before drawing conclusions on their theoretical significance and implications for management. We end with a brief discussion of the limitations of the study and suggest areas for future research.

2. Literature Review

2.1. Adoption of a new online channel and multichannel behaviour

Since the advent of the Internet, retailers and researchers have shown an interest to explore the impact of the introduction of the online channel. Two related issues were of interest: the changes in purchase patterns and in the value of customers who adopted the new channel.

Regarding purchase patterns across retail channels, researchers have explored sales cannibalization. Some papers found adding an Internet channel cannibalizes offline sales as shoppers adopt the new channel and abandon the old one (Ansari et al., 2008; Hernant and Rosengren, 2017), but others found this effect is nil (Biyalogorsky and Naik, 2003; Pauwels and Neslin, 2015). Other papers found that adding an online channel increases the average transaction amount per customer (Melis et al., 2016), but has negative effect on frequency and regularity of purchases (Gensler et al., 2007). Thus, the net effect is unclear and may be dependent on the product category (Ansari et al., 2008).

If the net effects on sales of adding an online channel are negligible, the interest shifts to explore whether multichannel customers are more valuable than their single-channel counterparts. Multichannel customers show higher spending (Ansari et al., 2008; Breugelmans and Campo, 2016; Kumar et al., 2018; Kushwaha and Shankar, 2013), purchase frequency (Ansari et al., 2008; Kumar et al., 2018) and profitability (Kumar et al., 2018; Montaguti et al., 2016). However, Kushwaha and Shankar (2013), comparing different product categories, obtained that for low-risk product categories, offline customers provided higher monetary value.

A key issue regarding the value of multichannel customers is related to their loyalty. Wallace et al. (2004) found higher behavioural and attitudinal loyalty in multichannel customers. On the contrary, Ansari et al. (2008) found that the adoption of online channels reduces loyalty; however, the authors note that the effects on loyalty may be positive in grocery shopping because of the shopping list feature. In a study on grocery retailing, Melis et al. (2015; 2016), concluded that most customers that adopt the online channel continue shopping with the same retailer and increase the share of wallet with the retailer.

Table 1 shows the aims and research settings of related multichannel retail papers and the intended contribution of the current paper, which investigates channel adoption through an RFM segmentation approach enabled by loyalty data referring to purchase behaviour prior and subsequent to channel adoption in grocery retailing.

[INSERT TABLE 1 ABOUT HERE]

2.2 Segmentation of multichannel customers

Customer segmentation has been established as a crucial marketing strategy since it was defined by Smith (1956) as a way to account for heterogeneity in demand and to adjust marketing strategy accordingly. Retail literature has shown a clear interest in segmentation studies with early papers segmenting offline customers (e.g., Bellenger et al., 1977) and subsequent studies online customers (e.g., Brengman et al., 2005). With the evolution of the retail industry, the interest has shifted to identifying segments of multichannel customers, as we illustrate below.

Multichannel segmentation studies are based either on self-reported (survey) data or behavioural data, with few exceptions integrating both (e.g., Nakano and Kondo, 2018). Table 2 summarizes the characteristics of key multichannel customer segmentation studies that employ a clustering algorithm to detect behavioural heterogeneity.

[INSERT TABLE 2 ABOUT HERE]

The survey-based studies include a variety of variables such as consumer perceptions, attitudes, and psychographics. Early studies within this research approach profiled customers by focusing on the channel chosen for the purchase phase in the shopping process (e.g. Keen et al., 2004). Building upon the conceptualization of research shopping of Verhoef et al. (2007), Konuş et al. (2008) segmented customers not just on the channel of purchase but also on the information channel, and used as covariates psychographic and demographic data. Subsequent studies followed this research line and extended the consideration of the shopping process to encompass different steps of the shopping journey (Frasquet et al., 2015; 2019; De Keyser et al., 2015; Park & Kim, 2018; Sands et al., 2016). The studies based on declared channel preference may suffer common method bias, a problem that the use of behavioural data could overcome (Wang et al., 2014). This is also a more actionable approach as, for example, RFM variables are readily available in firms' databases (Nakano and Kondo, 2018).

There are fewer papers that have segmented multichannel customers based on behavioural data. Thomas and Sullivan (2005) is an early example of such studies. Their work considered three channels employed by a retailer (catalog, Internet, stores) and used price, product category, distance to store and marketing communication as covariates. The study of Li et al. (2015) is remarkable as it segmented customers based on the speed of adoption of online channels using as covariates purchase amount and channel chosen before and after the online channel introduction. Breugelmans and Campo (2016) segmented customers of a grocery chain to examine the cross-channel effects of price promotions on category purchase decisions. Last but not least, Nakano and Kondo (2018) undertook a segmentation analysis of multichannel customers combining behavioural scan panel data with survey data. This allowed them to consider, in addition to purchase frequency and monetary value, psychographic characteristics (e.g. innovativeness, shopping enjoyment), and information channels. All these studies are multi-category, and not specifically focused on grocery retailing.

2.3 The RFM model

In the domain of CRM, the RFM model is a segmentation approach that was developed by Hughes (1996) to identify key customers in a large customer base with reference to three key variables characterizing customer purchase behaviour: recency, frequency, and monetary. Specifically, recency is defined as the number of days occurring since the last purchase; frequency is described as the number of purchases or visits occurring in a given period; monetary is the amount spent within a given period (Cheng and Chen, 2009). The RFM segmentation is currently a widely employed approach among practitioners, and it has been studied and further developed also in academia (Aghdaie and Tafreshi, 2016; Peker et al., 2017; Tavakoli et al., 2018).

This study focuses on segmenting adopters of a retailer's new online channel based on RFM variables computed separately for their purchase behaviour in the offline and online channels. To our knowledge no studies have adopted an RFM computing and analyzing recency, frequency and monetary per channel rather than overall. Moreover, the present work relates offline purchase behaviour prior to the introduction of the online channel with subsequent multichannel purchase behaviour, thus identifying how past behaviour might change after the adoption of a new online channel. Based on the above, Figure 1 displays our research framework.

[INSERT FIGURE 1 ABOUT HERE]

3. Methodology

The present study employs customer data provided by a supermarket retailer operating in Spain. With more than 700 stores located in different regions of the country and an experience of more than 40 years, the chain has a loyalty program that covers 78.5% of total sales and introduced the online channel at the end of 2016. At the time, this was an early move, as most players (except the multinational hypermarket chains) did not operate an online sales channel. The supermarket serves all online orders through home delivery, i.e., no click-and-collect is offered. The dataset was extracted from the company's loyalty card system and covered a 36-month period: 18 months preceding and 18 months following the launch of the online channel. The sample included customers that comply with the following criteria:

- having completed at least three offline purchases in the period between the launch date of the online channel and the preceding 18 months;
- having completed at least three online purchases and three offline purchases between the launch date of the online channel and the following 18 months.

These requirements allow us to consider only those customers that have adopted the online channel and keep using the offline channel, and they are consistent with criteria employed in previous RFM analyses (e.g., Peker et al., 2017). A series of data pre-processing tasks, such as deleting transactions with missing values, removing duplicate records, and aggregating transaction records at the customer level were also performed to build the final customer table. This includes 1,151 customers, who have completed 225,106 purchase transactions during the 36-month period. For each customer, recency frequency and monetary were computed regarding the online and the offline channel. Specifically, recency is expressed as the number of days elapsing from the last offline (online) purchase, frequency as the number of offline (online) purchases, and monetary as amount spent in euros offline (online).

LCA was conducted using Latent Gold 5.1. LCA has been employed in segmentation studies because it allows for identifying the heterogeneity of a population. It is a model-based approach that classifies cases depending on the posterior probability of membership (Haughton et al., 2009). Segments of cases are identified based on internal variables — specifically indicators — that are employed to uncover latent segments within the customer base. The basic latent class cluster model is given by (Haughton et al., 2009):

$$P\ (y_n|\theta) = \sum_1^S \pi_j P_j\big(y_n|\theta_j\big)\ .$$

In the formula y_n is the nth observation of the indicators, S is the number of clusters, and π_j is the prior probability of membership in cluster j. P_j is the cluster-specific probability of y_n given the cluster-specific parameters θ_j (the P_j are probability mass functions if the indicators are discrete and density functions if the indicators are continuous). The LCA employs maximum likelihood estimates to classify cases based on what is referred to as their posterior probability of class membership. Additional independent variables — specifically covariates — can be included in the model to simultaneously influence the estimation of the probability of belonging to a given segment ("one-step approach") or to profile customer segments identified according to indicators ("three-step approach"). In our study the "one-step approach" was employed, which has been used in previous studies on multichannel segmentation (e.g., De Keyser et al., 2015): indicators and covariates simultaneously contribute to identifying subgroups of customers. The “one-step approach” is more straightforward than the “three-step approach” (Vermunt & Magidson, 2016) and it may contribute to reducing the classification error of the model due to the inclusion of covariates within the estimation (Vermunt & Magidson, 2005). Covariates can contribute to improving the prediction of the probability of belonging to a given cluster. Recency, frequency, and monetary computed at the customer level regarding, respectively, online and offline purchases after the introduction of the online channel, were employed as indicators. Recency, frequency, and monetary related to offline purchases before the introduction of the online channel, together with gender and age, were employed as covariates.

LCA considers a range of solutions with a varying number of segments and offers statistical indexes to select the most appropriate number of segments. In this respect, the Bayesian Information Criterion (BIC) has been reported and chosen as one of the best information criteria for selecting the number of clusters (Haughton et al., 2009; Nylund et al., 2007). We used BIC to compare model fit among the obtained models and to choose the best solution as the one with the minimum BIC value. Interpretability of the identified segments and related cluster size were evaluated together with the BIC index to assess the choice of the best model (Collins and Lanza, 2009).

4. Results

4.1. Descriptive statistics

For the sake of clarity, in the following descriptions we will refer to period 1 as the period before the introduction of the online channel and to period 2 as the period after the introduction of the online channel. Table 3 displays descriptive statistics as far as recency, frequency, and monetary related to offline and online purchases in period 2.

[INSERT TABLE 3 ABOUT HERE]

Table 4 displays descriptive statistics related to age, gender, as well as recency, frequency, and monetary related to offline purchases for those customers under analysis in period 1. Table 4 also shows that the considered customer base includes active customers, mainly females, with an average age of 44 years old.

[INSERT TABLE 4 ABOUT HERE]

4.2.Model selection and *results*

LCA was performed considering solutions with a number of clusters varying from one to ten and employing the Classification Expectation-Maximization algorithm, which maximizes the classification log-likelihood and leads to convergence in a finite number of iterations (Hennig et al., 2015). This procedure increases the default values - as suggested by Vermunt and Magidson (2005) - from 16 to 100 random sets and from 50 to 500 iterations for each number of clusters. This was done to avoid local minima: several iterations are required to counter the risk of identifying a local minimum instead of the global minimum of the BIC for each cluster solution (Haughton et al., 2009). Generally, the selected solution is the one with the lowest BIC value (Collins and Lanza, 2009). However, there might be cases where the BIC value might decrease steadily across the solutions due to the high number of variables. In this situation, the elbow rule is employed to identify the point at which adding another segment does not offer a relevant gain in terms of model fit (Todd, 2013). Table 5 displays BIC values and number of parameters estimated per each clustering solution. After an evaluation of Table 5 and Figure 2 (see Appendix A), the seven-cluster solution seemed to be the preferred solution based on the elbow rule.

This choice was further confirmed by evaluating the interpretability and size of the selected clusters: each cluster included an acceptable number of subjects - at least five percent of the total number of individuals as suggested by previous studies (Nasserinejad et al., 2017; Nylund et al., 2007), and the profiles stemming from the clusters were meaningful and different. Hence, the seven-cluster option was chosen as the best solution.

[INSERT TABLE 5 ABOUT HERE]

After selecting the seven-cluster solution, the significance of each model indicator was assessed through the Wald test. Table 6 reports indicator parameters (betas) and covariate parameters (gammas). A positive sign displays a positive relationship while a negative sign points to a negative relationship. Betas indicate the strength of the effects of the clusters on the indicators. The associated p-values were lower than 0.05, thus showing that the employed indicators could be considered as discriminating among the identified segments (Vermunt and Magidson, 2016). Gammas are the parameters of the multinomial logit model used to predict the clusters as a function of the covariates. All the covariates, except gender, significantly influence the probability of belonging to the latent segments. Therefore, latent class segmentation revealed the presence of a relationship between the customers' purchase behaviour after the introduction of the online channel and their previous purchase behaviour.

[INSERT TABLE 6 ABOUT HERE]

4.3.Profile of the clusters

Each segment was profiled by looking at both indicators and covariates (Table 6) and at descriptive statistics (Table 7). Table 7 shows the mean values of each indicator and covariate per cluster, thus displaying an average profile of each cluster.

[INSERT TABLE 7 ABOUT HERE]

Group 1 is the cluster with the highest number of customers (24%) and includes customers that purchase both online and offline. These customers adopted the new online channel and displayed a multichannel purchase behaviour. They represent the “average customer” as their monetary, frequency, and recency levels are quite close to the sample average. Overall, their monetary increased in period 2, while frequency and recency were quite similar between period 1 and period 2.

Cluster 2 includes 19% of customers. These customers started to use the online channel but discontinued its usage, as the high value of online recency in comparison to the low value of offline recency shows. Before online channel adoption, they were high-spending customers, and seemed to maintain this behaviour as their monetary and frequency did not change across the two periods. It could be hypothesized that some dissatisfaction with the online channel might have led them to stop using the new channel.

Cluster 3 includes 16% of customers that display the lowest monetary levels both before and after the adoption of the online channel. The high value of online recency shows that these customers abandoned the online channel just like Cluster 2. Their offline frequency increased substantially after the launch of the online channel: however, their amount spent did not augment from period 1 to period 2. These customers are mainly offline low-value customers for the retailer.

Cluster 4 represents 13% of the customer base. These customers substantially shifted their purchases from offline to online from period 1 to period 2: their online monetary and frequency are higher than the offline ones. The high offline recency leads us to conclude that they almost stopped going to the store. However, their online recency is high as well - equal to 62 days - a potential signal that they have churned.

Customers in Cluster 5 were the top-spending customers before the launch of the online channel. Afterwards, they increased their overall spending and frequency, maintaining a preference for the offline channel. However, they purchased online almost once per month, spending substantial amounts through the new channel. The online recency value of nearly 50 days could also reveal that they might be likely to abandon the online channel or to increase the inter-purchase time in the online channel.

Cluster 6 includes 11% of customers. These customers were the second top-spending customer segment in period 1. After the launch of the online channel, they shifted the majority of their spending to the online channel: they show the highest online frequency and monetary and the lowest online recency within the customer base. Therefore, it can be concluded that these customers are the most valuable and persuaded adopters of the new channel. The low value of online recency and the high value of online frequency might signal a steady future for their use of the online channel.

Finally, Cluster 7 displayed average values of monetary, frequency, and recency in period 1, but high values of both online and offline recency in period 2. It can be concluded that these customers started to display multichannel behaviour after the launch of the online channel. However, after a while, they stopped shopping with the retailer both offline and online. This cluster represents 5% of the customer base and displays the lowest age.

Concerning RQ1 asking which segments emerge when a retailer introduces an online channel, the LCA has revealed meaningful customer segments displaying distinct behaviours as far as the offline and online channels:

- Three actual multichannel customer segments (clusters 1, 5, and 6 that equal to 47% of adopters) that have adopted the online channel, with some differences in terms of intensity of the online versus offline channel.
- Two customer segments (cluster 2 and cluster 3, that equal to 35% of the adopters) that tried the online channel but, after a while, they stopped using it.
- One customer segment (cluster 4, 13% of the adopters) that substantially shifted purchases from offline to online (cluster 4).
- One customer segment (cluster 7, 5% of the adopters) that adopted the online channel, and subsequently stopped buying from the retailer altogether.

Regarding RQ2, which investigated whether behaviour before the introduction of the online channel explains the behaviour displayed once the online channel is active, our findings reveal that past offline purchase behaviour significantly predicts the probability of belonging to a given cluster. With reference to cluster profiles, it emerges that:

- High spending occurring in period 1 is related to actual multichannel behaviour in period 2.
- The top three spending customer segments in period 1 tend to increase their monetary in period 2.
- High frequency and low recency in period 1 are related to a preference towards the offline channel when the online channel is adopted.

5. Discussion and conclusions

This study has investigated the dynamics of consumer purchase behaviour related to the introduction of a new online channel by a supermarket retailer. We discuss the theoretical and practical contributions of our findings below.

5.1. Theoretical contributions

Our paper differs from previous segmentation studies based on behavioural data in that we identify RFM-based segments considering the influence of purchase behaviour prior to the adoption of the new online channel. In this way, we bridge two key areas of research in multichannel consumer research, as suggested by Dholakia et al. (2010): new channel adoption and multichannel segmentation. The present study contributes to research by shedding light on the heterogeneity of multichannel purchase behaviour as far as the dynamics of channel adoption are concerned. Specifically, our results provide the following contributions. First, we add to the multichannel literature by uncovering the effects on spending, frequency, and the potential cannibalization following the introduction of a new online channel by a supermarket retailer. Most of the previous findings in this line are related to non-grocery product categories. Furthermore, we add to this line of research by predicting multichannel purchase patterns from offline patterns before the online channel introduction. Second, we contribute to the CRM literature by implementing the RFM approach in a multichannel setting, showing that monetary, frequency, and recency might significantly differ between channels within each customer segment and among different segments.

5.1.1. Multichannel customers segments arising from online channel introduction

As far as the first research question, our findings show a meaningful heterogeneity in the purchase behaviour of online channel adopters. We have identified three customer segments, namely clusters 1, 5 and 6, that after adopting the online channel show a joint use of offline and online, also displaying an increase in the overall spending. The finding of these clusters of multichannel customers is common to other segmentation studies, such as in the case of “multichannel enthusiasts” found by Konuş et al. (2008), or Nakano and Kondo (2018) who also identified seven segments, being two of them in the category of multichannel enthusiasts. Therefore, the introduction of the online channel by a supermarket retailer might lead to a substantial shift from offline to online in some customer groups. In fact, we found a segment (cluster 4) that displays online spending that reaches up to five times the amount spent offline. Sands et al. (2016) and Nakano and Kondo (2018) also encountered this type of segment. It is worth noting that two segments out of seven (clusters 2 and 3) tried the online channel but discontinued its use, while sticking with the offline channel. This finding is in accordance with the findings of Konuş et al. (2008), who labeled this group as store-focused customers. Lastly, one customer segment (cluster 7) displays churning behaviour, thus raising concerns as far as the quality of the experience with the new channel. A similar segment of uninvolved customers is usually found in segmentation studies (Konuş et al., 2008; Nakano and Kondo, 2018). It could be of interest to analyze if dissatisfaction with the new channel might have negatively affected the relationship between the customer and the retailer.

5.1.2. Predicting multichannel shopping patterns from behaviour prior to online channel introduction

As far as the second research question, our findings show that past purchase behaviour can explain different degrees of adoption of the new online channel. Specifically, those segments displaying higher frequency prior to the online channel introduction adopt the new channel but spend more and purchase more often offline than online. This appears to add to the findings from Hernant and Rosengren (2017), who found that online adopters decreased overall purchase frequency. In our study, purchase frequency is inversely associated with the extent of online channel adoption: customers who displayed a lower purchase frequency before online adoption tend to spend more online.

A second finding emerges from the comparison of the period before and after the introduction of the online channel. In general, adopters have increased overall spending. Four segments increase spending both offline and online after the launch of the online channel. However, three segments display an overall decrease as the increase in one channel does not compensate for the reduction in the other. Such heterogeneity might explain the conflicting results emerging from previous studies as far as the cannibalization effect of the online channel adoption (e.g., Ackermann & von Wangenheim, 2014; Ansari et al., 2008; Biyalogorsky & Naik, 2003). There might be alternative or additional explanations for the decrease in overall spending, such as poor service or a disappointing experience occurring in the online channel.

5.2. Managerial implications

Retailers could benefit from the results of the present study to support the evaluation of: i) channel performance, ii) appropriate CRM strategies, and iii) adequate planning and investment for multi- and omnichannel strategies.

i) Results as far as RQ1 provide evidence on what retailers could expect in terms of heterogeneous customer response when introducing the online channel. Resorting to the mere measurement of orders and sales per channel, and/or their growth rate, especially in the short term, appears therefore misleading; in fact, under the surface of overall increased spending, some customers' monetary declines, while other customers churn. We suggest the analysis of each channel's performance be conducted alongside a "multichannel customer performance analysis", including metrics such as number of multichannel customers continuing to spend in both channels; number of multichannel customers whose total spending across channels is maintained/decreases/increases. As retail strategies evolve towards multi- and omnichannel, sales and margin goals would be better set in terms of multi/omnichannel customer behaviour gains, rather than at individual channel level, as is traditionally done in retailing.

ii) Our study points to the need for retailers to develop CRM strategies aimed at different multichannel customer segments. First and foremost, to retain top spenders who use both channels. They can provide incentives, such as free delivery or discounts to increase the amount spent online and to reduce the likelihood of adopters discontinuing their use of the online channel. Non-monetary incentives such as "status" recognition of these top spenders by means of exclusive services or by telling their stories on the retailer's media outlets may also be employed, which could also attract other customers to try the new channel. Secondly, retailers are urged to carefully monitor those adopters that start to display high recency across both online and offline channels, as this is a hint of likely churn. Retention strategies targeted at specific customer groups could be particularly effective through online channels: timely, personalized actions could be triggered.

Recalling results from RQ2, findings on the relationship between offline purchase behaviour before the launch of the online channel and subsequent purchase behaviour can support retailers in predicting to what extent their customer base – down to the individual customer's probability score - might display multichannel behaviour if they introduce the online channel. These estimates will prove valuable for channel decision-making and CRM activities aimed at stimulating channel adoption by targeting the customers who are predicted to have a high propensity to adopt.

iii) As far as supporting channel decision making, our findings can support management in planning scalable capacity for the new channel, and allocation of investment over time. The current and projected future size of the segments could be used as benchmark to evaluate the potential of each store's customer base to cover the costs of offering home delivery from such a store. In fact, retailers tend to launch a new channel using their best stores as support hubs, and are then left with the crucial question of what other stores to extend the service to, and when to stop as smaller, less profitable customer bases in marginal stores may not provide an adequate return on the investment. Typically, overall store sales and margins are used to choose the stores that will offer the new service: armed with results from segmentations such as the one we provide in this work, retailers might identify the stores where the size of segments prone to maintain a multichannel behaviour over time is the highest, regardless of the overall store results.

A final remark is in order: retailers have employed loyalty data and RFM models for a long time, but typically in single-channel situations (stores). Our work shows how valuable data sources and models that are widely available and understood can prove in multichannel retailing. This might provide a stimulus for retailers tackling the decision to move towards omnichannel. In fact, by striving to track their individual customers' behaviour in each of the new channels made available (as in our case, in the new online channel) via ID's or other identifiers, retailers set the foundation to offer customers seamless omnichannel shopping experiences.

5.3.Limitations and future research opportunities

The present paper involves several limitations. In order to focus on multichannel purchasing behaviour, our study selected only adopters of the new online channel. Further research could examine how adopters and non-adopters differ in their purchase behaviour before and after the launch of the new online channel. Second, in this study we take into account the recency of the last online and offline purchases, but we did not consider the different timing of online adoption, i.e., how early each customer was in taking up the new channel. Third, no psychographic variables, such as customer loyalty, shopping enjoyment, or convenience seeking, were measured in the present study. The contributions of our study could be extended by further research examining whether the identified patterns might change depending on the share of wallet of customers, on the type of grocery store and the type of industry. Finally, it would be interesting to study whether customers displaying low purchase frequency with a brick and mortar retailer might be more likely to adopt the online channel and to purchase more online than offline.

Appendix A

[INSERT FIGURE 2 ABOUT HERE]

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Tables

Table 1. Contribution of current study to relevant research

Authors (Year)	Channel(s)	Product category (ies)	Aim of study	Data prior to online channel introduction	RFM segmenta-tion
Biyalogorsky & Naik (2003)	Online channel added to store channel	Music	Assess the sales effect of adding an online channel	√	No
Gensler et al. (2007)	Call center and online channel	(Semi) durables: housewares, cosmetics, jewellery	Evaluate channel performance over time	No	No
Ansari et al. (2008)	Catalog and online channel	Durables and apparel	Investigate channel migration and channel loyalty	No	√
Kushwaha & Shankar (2013)	Catalog and online channel	22 non-grocery categories	Compare the monetary value of single- and multichannel customers	No	No
Hernant & Rosengren (2017)	Online channel added to store channel	Non-grocery utilitarian products	Assess the sales effect of adding an online channel	√	No
Pauwels & Neslin (2015)	Store channel added to catalog and online channel	Durables and apparel	Assess the sales effect of adding an offline channel	√	No
Melis et al. (2016)	Online channel added to store channel	Groceries	Investigate whether online channel adoption increases share of wallet	No	No
Montaguti et al. (2016)	Stores, mail-order, phone and online channel	Books	Investigate if a marketing campaign increases multichannel shopping and profitability	No	No
Kumar et al. (2018)	Stores and online	Alcoholic beverages	Analyse effects of multichannel shopping on spending, frequency and profitability	No	No
Our paper	Online channel added to store channel	Groceries	Identify customer segments considering the dynamics of channel adoption	√	√

Table 2. Review of relevant algorithm-based segmentation studies on multichannel customer behaviour

Authors (Year)	Type of data	Channel adoption	Methodology	Product categories	Segmentation variables
Thomas & Sullivan (2005)	Behavioural	No	Logit model and LCA	Eleven (unidentified) product categories	Price, product category, distance to store, marketing communications
Konus et al. (2008)	Self-reported	No	LCA	Mortgage, health insurance, holidays, books, computers, electronics, and clothing	Psychographics (price consciousness, loyalty, enjoyment, time pressure, motivation to conform, innovativeness), and demographics
Li et al. (2015)	Behavioural	Yes	Type II Tobit model and LCA	Health and natural products	Monetary, channel chosen before and after online channel introduction
Frasquet et al. (2015)	Self-reported	No	Linear regression and k-means clustering	Clothing and consumer electronics	Usefulness, ease of use, security, time pressure, enjoyment, hedonic orientation, involvement, and demographics
Breugelmans & Campo (2016)	Behavioural	No	Hurdle model and LCA	Groceries	Purchase frequency, purchase incidence, purchase quantity, loyalty, promotions
Sands et al. (2016)	Self-reported	No	LCA	Clothing, consumer electronics, and holiday travel	Enjoyment, innovativeness, loyalty, prices consciousness, time pressure
Nakano & Kondo (2018)	Behavioural & self-reported	No	Multinomial logit model and LCA	Groceries, beverages, sundries, cosmetics, and drugs.	Purchase frequency, monetary, information channel, psychographics
Park & Kim (2018)	Self-reported	No	K-means clustering and Association rules mining	Unidentified	Most important factors for shopping (e.g.information, delivery), information channel, payment method, delivery method, purchase channel

Table 3. Descriptive statistics on indicators in period 2

Variable	Minimum	Maximum	Average	Standard deviation
Offline monetary	10.53	14952.91	2005.44	1874.21
Offline frequency	3.00	636.00	80.75	80.62
Offline recency	1.00	518.00	32.54	64.46
Online monetary	45.51	11750.78	1139.01	1201.84
Online frequency	3.00	77.00	12.42	11.50
Online recency	1.00	526.00	88.71	125.95

Table 4. Descriptive statistics on covariates: RFM variables in period 1 and demographic characteristics of the sample

Variable	Minimum	Maximum	Average	Standard deviation
Monetary	13.24	14265.29	2809.90	2271.21
Frequency	3.00	611.00	102.41	89.24
Recency	0.00	298.00	13.72	25.14
Age	20.00	103.00*	43.99	10.64
Sex (females)			76%	

**This maximum age value has been carefully checked with the company and is related to a real customer who is the eldest of the customer base.*

Table 5. BIC values for model selection

Cluster solutions	**BIC(LL)**	**Number of parameters**
1-Cluster	89774.1009	14
2-Cluster	85486.5232	32
3-Cluster	83073.2149	50
4-Cluster	81948.4666	68
5-Cluster	81175.1117	86
6-Cluster	80580.6945	104
7-Cluster	**80048.3683**	**122**
8-Cluster	79786.6357	140
9-Cluster	79661.3066	158
10-Cluster	79394.0754	176

Table 6. Parameters of the model

Variable	**Cluster 1**	**Cluster 2**	**Cluster 3**	**Cluster 4**	**Cluster 5**	**Cluster 6**	**Cluster 7**
Indicator parameters (Period 2)							
Offline monetary* **	-359.97	1343.91	-1196.18	-1771.99	2738.13	-362.94	-390.95
Offline frequency* **	-16.6263	61.6998	-50.9212	-70.5209	119.71	-30.77	-12.57
Offline recency* **	-39.26	-44.30	-19.28	71.98	-44.18	-20.55	95.59
Online monetary* **	-243.99	-782.66	-887.94	-138.55	319.88	2227.00	-494.75
Online frequency* **	-2.08	-7.78	-8.85	-1.28	3.29	21.22	-4.51
Online recency* **	-73.82	60.10	92.39	-41.36	-52.43	-87.31	102.43
Covariates parameters (Period 1)							
Monetary* **	-0.0003	0	-0.0002	-0.0001	0.0003	0.0004	-0.0001
Frequency* **	-0.0007	0.0071	-0.0066	-0.0021	0.0101	-0.0126	0.0049
Recency* **	-0.0014	-0.0825	0.0666	0.0763	-0.1029	0.0229	0.021
Sex (female)	0.0785	0.0231	0.0448	0.1564	-0.1533	0.1707	-0.3202
Age* **	0.0154	0.0042	0.0144	0.0286	0.0088	-0.0037	-0.0677

*Parameters are expressed in effect coding. Variables in bold are significant at the 0.05 level by means of overall Wald testing. Significance is expressed as follows: *p<.05, **p<.01, ***p<.001.*

Table 7. Profile of the different clusters

Variable (*)	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7
Means of indicators related to the period following the launch of home delivery							
Offline Monetary	1637.3	3346.5	820.9	236.8	4765.1	1689.6	1632.7
Offline Frequency	63.8	142.3	29.8	10.0	201.8	50.6	70.2
Offline Recency	8.6	3.3	30.5	124.1	3.6	30.3	152.1
Online Monetary	1004.0	461.1	355.1	1127.1	1567.1	3489.4	758.0
Online Frequency	11.4	5.6	4.6	12.4	16.8	34.7	9.0
Online Recency	23.9	168.8	197.3	61.9	48.4	9.8	206.4
Means of covariates related to the period preceding the launch of home delivery							
Monetary	2002.3	3400.5	1622.2	1963.3	5299.6	3738.7	2488.2
Frequency	76.9	142.7	54.4	65.4	209.0	85.3	110.9
Recency	8.2	3.7	27.1	36.3	3.0	10.3	10.2
Sex (%females)	78%	78%	75%	80%	73%	80%	60%
Age	43.4	44.2	42.9	45.0	46.9	45.0	37.9
% of customers	**24%**	**19%**	**16%**	**13%**	**12%**	**11%**	**5%**

(*) Monetary is expressed in euros, frequency in number of purchases and recency in number of days since the last purchase