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Mapping touchpoint exposure in retailing: Implications for developing an omnichannel customer experience

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**Mapping touchpoint exposure in retailing:
implications for developing an omnichannel customer experience**
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Abstract

Purpose – This paper aims to identify patterns of customer exposure to touchpoints by segmenting consumers based on the frequency of their exposure, and to understand the relationship of patterns of exposure with customer loyalty intentions (relationship commitment, self-disclosure and positive word-of-mouth) and demographic characteristics.

Methodology – An online survey of almost 4,000 customers was employed in a supermarket retail setting. Customers were segmented based on their frequency of recalled exposure to multiple touchpoints, by means of a Latent Class Cluster Analysis, while considering the role of demographic characteristics. Afterwards, loyalty intentions variables were regressed on the resulting customer segments.

Findings – Based on touchpoint exposure, six customer segments emerge. The main differences across segments relate to the intensity of frequency of exposure and the types of touchpoints customers have been exposed to. Sex, age, shopping role and geographic area of residence are related to segment membership. The identified patterns of exposure explain relationship commitment, self-disclosure and positive word-of-mouth: clusters displaying higher exposure to touchpoints display higher loyalty intentions than clusters displaying lower exposure.

Practical implications – The study offers actionable implications for brands and retailers on how to manage touchpoints for implementing omnichannel strategies.

Originality/value – As far as the authors know, this study is the first to identify exposure to multiple touchpoints and to understand the role of demographics as far as touchpoint exposure is concerned. It also provides interesting findings on the relationship of different combinations of touchpoints with customer loyalty.

Keywords: Touchpoints, Segmentation, Loyalty, Latent Class Cluster Analysis

Paper type: Research paper

Introduction

The proliferation of channels has led to an explosion in the number of different touchpoints within the customer journey (Hall and Towers, 2017; Pantano and Viassone, 2015; Simon *et al.*, 2016). Touchpoints are the verbal or nonverbal incidents an individual perceives and consciously relates to a given firm or brand (Baxendale *et al.*, 2015; Duncan and Moriarty, 2006). The increased number of channels and touchpoints is putting pressure on retailers to design omnichannel customer experiences (Verhoef *et al.*, 2015). “Customer experience is the evolvment of a person’s sensorial, affective, cognitive, relational, and behavioural responses to a firm or brand by living through a journey of touchpoints along pre-purchase, purchase, and post-purchase situations” (Homburg *et al.*, 2017, p. 8). In fact, a seamless experience across online and offline touchpoints will deliver a stronger overall customer experience (Lemon and Verhoef, 2016).

To develop customer experience, practitioners have started to adopt customer experience management (Homburg *et al.*, 2017). The customer experience management framework is a firm-wide management approach for designing customer experience. The final goal of customer experience management is achieving long-term customer loyalty by designing and continually renewing touchpoint journeys (Homburg *et al.*, 2017). Defining which touchpoint journeys matter and hence deciding where to begin the (re)design of such touchpoints is indeed a challenging task (Rawson *et al.*, 2013). Despite the growing importance of touchpoints, relatively little is known about their nature and scope (Payne *et al.*, 2017). As far as their nature is concerned, traditionally touchpoints were identified with media, but today it seems necessary to consider touchpoints in a broader view. As far as touchpoint scope is concerned, Lemon and Verhoef (2016) argue that the question of whether specific touchpoints can reach specific customer segments is still unanswered. Hence, identifying customer segments based on their exposure to touchpoints and profiling the segments in demographic terms would expand our knowledge about the scope of touchpoints. Previous research has found that the frequency of exposure to touchpoints influences brand consideration (Baxendale *et al.*, 2015). No research, however, has been produced so far on the relationship between touchpoint exposure and customer loyalty, which is the ultimate goal of customer experience management (Homburg *et al.*, 2017; Payne *et al.*, 2017).

To address these research gaps, this paper aims to:

- 1) identify patterns of customer exposure to touchpoints by segmenting consumers based on the frequency of their exposure. The analysis is based on a sample of almost 4,000 customers involved in grocery shopping in a supermarket retail context;

- 2) identify the contribution of demographic attributes in their relationship with customer exposure to touchpoints;
- 3) estimate how patterns of exposure to touchpoints might be related to customer loyalty.

This study makes the following contributions:

- To the authors' knowledge, it is the first study to identify customer segments at touchpoint level by measuring exposure to 23 touchpoints with a substantial sample of consumers;
- It sheds light on how consumer demographic characteristics are related to exposure to touchpoints and how exposure to touchpoints is related to customer loyalty.

The remainder of this paper is structured as follows. First, it reviews previous research on touchpoints, both in the advertising and services literature, and presents the study's conceptual development and research questions. Then, it employs a Latent Class Cluster Analysis (LCCA) to reveal heterogeneous customer segments with reference to their touchpoint exposure. The paper concludes with a discussion of the results, limitations and implications for practice and future research.

Background and conceptual development

The proliferation of channels and touchpoints has made the customer journey more complex and difficult to manage (Hall and Towers, 2017; Simon *et al.*, 2016) in that consumers have an increasing number of opportunities to decide how and when to be in touch with brands and retailers (Wind and Hays, 2016). Creating and managing a consistent experience across all touchpoints is, therefore, a key issue (Homburg *et al.*, 2017). Touchpoints include and go beyond channels and media, as they encompass any encounter in the customer journey that could be related to a firm (Baxendale *et al.*, 2015). In fact, Baxendale *et al.*, (2015, p. 236) define touchpoints as “episodes of direct or indirect contact with the brand”. These can take many forms, such as online platforms, physical environments or personal interactions (Voorhes *et al.*, 2017). A huge number of touchpoints have been identified in the literature, including traditional media, in-store, telephone, salesforce, catalogues, customer service, payments, returns, loyalty programs, digital, e-mail, paid and organic search, display ads, word-of-mouth, and so forth (Baxendale *et al.*, 2015; Li and Kannan, 2014; Peltier *et al.*, 2003; Romaniuk *et al.*, 2013; Wind and Hays, 2016; Zahay *et al.*, 2004). To cope with this variety and to provide a touchpoint organizing framework, multiple ways of classifying touchpoints have been proposed. Lemon and Verhoef (2016) have classified touchpoints based on the subject that manages and controls them: the company itself, a business partner of the company, the customer, or external factors (e.g. a peer, the environment). Other researchers have distinguished between firm-initiated and customer-initiated touchpoints (e.g. Anderl *et al.*, 2016) with a focus on whom is starting the

occurring interaction. Another proposed classification distinguishes between personal versus non-personal touchpoints (Payne *et al.*, 2017), thus highlighting the presence or absence of a human component within the interaction.

To evaluate the role of touchpoints within the customer journey, scholars and practitioners stress the importance of considering reach and frequency of exposure. Advertising literature has explored reach and frequency of exposure recall with reference to media touchpoints. Reaching consumers belonging to the right segment with the right message is indeed essential for media placement (Romaniuk *et al.*, 2013). Previous research has found differences in terms of recall between brand users and non-users: brand users systematically recall more, having been exposed to brand advertising for longer than non-users (Vaughan *et al.*, 2016). In terms of the intensity of brand usage, social media and word-of-mouth are touchpoints that have been found to reach heavy brand users while television advertising, gift-pack, in-store displays/promotion and outdoor advertisements reach average brand users (Romaniuk *et al.*, 2013). In a nutshell, research on touchpoints in advertising literature does not deal with differences in terms of recalled frequency of exposure to a touchpoint, or combination of touchpoints, nor does it consider non-media touchpoints, such as loyalty programs. Therefore, the following research question was formulated for this study:

Can customer segments be identified based on frequency of exposure to touchpoints? (RQ1)

Exposure to touchpoints has been found to be predicted by consumer attributes. Several studies have showed that males are more oriented towards online media than females (e.g. Ieva and Ziliani, 2017; Van Deursen and Van Dijk, 2014), while Romaniuk *et al.* (2013) did not find any relationship between touchpoint reach and sex. Age has been found to influence the reach of media touchpoints (Romaniuk *et al.*, 2013). Product sampling, social media, websites, public relations, word-of-mouth, events and online advertising tend to reach younger consumers (aged up to 35 years old). Baxendale *et al.* (2015) have found that the frequency of exposure to touchpoints is negatively correlated with age in the cases of word-of-mouth, peer observation and brand advertising. Studies on medium preference for non-promotional communication and loyalty promotions report that younger consumers tend to prefer online over print touchpoints (e.g. Ieva and Ziliani, 2017; Magee, 2013). Lemon and Verhoef (2016) hypothesize that touchpoint preference might differ across generational cohorts, with Millennials more favourable than Baby Boomers and Generation X towards online and non-personal touchpoints. These non-conclusive findings reveal the need for a closer investigation into the relationship between demographic attributes and exposure to touchpoints. Thus, a second research question was formulated:

Are demographic attributes related to consumer exposure to touchpoints? (RQ2)

Frequency of exposure to touchpoints contributes to shaping attitudes and behaviours (e.g. Baxendale *et al.*, 2015). It has been found to influence brand attitudes, such as brand consideration (Campbell and Keller, 2003). Specifically, it is brand advertising, peer observation, in-store communications and retailer advertising that have been found to influence brand consideration (Baxendale *et al.*, 2015). In services literature, studies on customer experience have investigated the relationship between the former and customer loyalty. Klaus and Maklan (2013) have found a positive relationship between customer experience and customer satisfaction, customer loyalty and positive word-of-mouth. Srivastava and Kaul (2016) and Brun *et al.* (2017) have found that customer experience directly impacts attitudinal and behavioural loyalty. However, the mentioned studies did not consider the role of specific touchpoints (nor combinations of them) within the customer experience itself in customer loyalty. Assessing the relationship between exposure to touchpoints and customer loyalty remains an open research area (Lemon and Verhoef, 2016; Payne *et al.*, 2017). Hence, the following final research question was formulated:

How are patterns of exposure to touchpoints related to customer loyalty? (RQ3)

To address the three research questions, this study measures the recalled frequency of exposure to touchpoints, i.e. customers recalled how frequently they encountered a given touchpoint in a specified time period. A list was compiled identifying 23 touchpoints with reference to supermarket shopping by considering and integrating lists of touchpoints employed in previous studies (Baxendale *et al.*, 2015; Li and Kannan, 2014; Peltier *et al.*, 2003; Romaniuk *et al.*, 2013; Wind and Hays, 2016; Zahay *et al.*, 2004). The goal of this selection process was to include all touchpoints that were relevant to the setting of reference. Previous studies did not explicitly provide proper criteria for touchpoint selection or aggregation (e.g. Baxendale *et al.*, 2015) and simply excluded touchpoints that displayed low reach and frequency of exposure (e.g. Romaniuk *et al.*, 2013). As far as demographic attributes related to the frequency of exposure to touchpoints, the following variables are drawn from previous studies (e.g. Konus *et al.*, 2008): sex, age, number of household members, affluency, geographic area of residence, city size and shopping role. Sex and age could be related to the propensity to interact with online versus offline touchpoints. Number of household members, affluency and shopping role could be correlated with price sensitivity, and with the amount of attention devoted to promotional touchpoints. Geographic area of residence and city size are employed as available proxies for lifestyle and education that might differ across geographic regions and city sizes.

As far as customer loyalty is concerned, the study focused on loyalty intentions. Loyalty intentions are defined as the “disposition of customers to either repurchase a product/service from a providing organisation, or go to a competitor” (Jacoby and Chestnut, 1978). Positive word-of-mouth and relationship commitment are constructs of customer loyalty intentions that are widely employed in service research and practice (e.g. Cho, 2006; Klaus and Maklan, 2013; Zeithaml *et al.*, 1996). Specifically, this study investigated the relationship between touchpoint exposure and positive word-of-mouth, relationship commitment and self-disclosure. As touchpoints are also key ways to gather customer information when interaction is taking place (Zahay *et al.*, 2004), it is important to introduce in this context a measure of customer willingness to disclose personal information, such as self-disclosure (Cho, 2006).

Relationship commitment can be defined as the enduring desire of the consumer to have a relationship with a company or brand and the intention to try to maintain this relationship (De Wulf *et al.*, 2001; Macintosh and Lockshin, 1997). Relationship commitment has been found to be the key antecedent of relationship maintenance (Aurier and N’Goala, 2010). Advertising literature has shown that ad repetition can lead to a positive attitude towards a given brand or company due to positive habituation (e.g. Campbell and Keller, 2003; Haugtvedt *et al.*, 1994). Hence, consumers displaying higher frequency of exposure to touchpoints might also display higher relationship commitment.

Psychology and consumer marketing literature recognize the role of self-disclosure in individual-to-individual and individual-to-corporate relationship-building (Clore and Schnall, 2005). Self-disclosure, in general, refers to any inside information one provides to another (Collins and Miller, 1994). Hence, in marketing, self-disclosure measures a customer’s intention to provide personal information to a person or organization (Cho, 2006). Previous research has showed that missing personal information in the retailer’s customer database, reflecting customer unwillingness to share it, is a significant predictor of customer defection (Buckinx and Van den Poel, 2005). Higher frequency of exposure to touchpoints might lead consumers to become familiar with encountering them. When consumers feel more comfortable with other consumers or firms, they are more willing to divulge personal information (Cho, 2006; Loiacono, 2015). Hence, habitual exposure to touchpoints might lead to increased consumer propensity to self-disclosure.

Broadly speaking, word-of-mouth includes any information about a target object (e.g. a company or brand) transferred from one individual to another either in person or via some communication medium (Brown *et al.*, 2005; Harrison-Walker, 2001). In the present study, positive word-of-mouth is employed as the intention of customers to provide positive recommendations of a company (Babin *et al.*, 2005). The influence of customer experience on positive word-of-mouth has been reviewed

widely in traditional offline (Babin *et al.*, 2005) and online (e.g. Hennig-Thurau *et al.*, 2002) media. The present study explores the following proposed relationship between touchpoints and positive word-of-mouth: as repeated exposure increases favourable attitudes, one might expect that higher frequency of exposure could lead to higher intention to provide positive recommendations of a given company.

In line with segmentation research (e.g. Konuş *et al.*, 2008; Sands *et al.*, 2016), this study employed a post-hoc segmentation analysis with “a posteriori segments”. Hence, no “a priori hypotheses” will be formulated.

Methodology

Data were collected by means of an online survey conducted in 2016. The survey was run in Italy using the Nielsen online consumer panel. The panel includes 6,212 subjects over 14 years old and it is aimed at being representative of all the age groups that can be considered as shoppers for at least one category of products and services. A total of 4,068 responses was collected from subjects who are in charge or cooperate with the household’s grocery shopping. Respondents were asked to answer the survey with reference to the supermarket retailer which receives the highest share of their wallet for grocery shopping. Respondents were asked to recall the frequency of exposure to each listed touchpoint in the previous three months on a seven-point Likert scale from “never” to “very often”.

Measuring touchpoint exposure by means of recall might be affected by bias. Previous studies have shown that consumers are biased in recalling past purchase behaviour (Wind and Lerner, 1979) and that recall of affective experiences might be inaccurate (Aaker *et al.*, 2008). However, recall is still widely used in advertising research (e.g. Ieva *et al.*, 2017) and it has been specifically employed for studies on touchpoint exposure (Romaniuk *et al.*, 2013) and on channel usage (e.g. Frasquet *et al.*, 2015). To keep potential recall bias to a minimum, recall period was limited to the last three months, which is consistent with previous studies (e.g. Romaniuk *et al.*, 2013).

Respondents had to answer with reference to the following touchpoints: store, store flyers, private label, store associates, loyalty program, coupons, word-of-mouth (in which case respondents were asked if they had received recommendations from others), customer magazine, special promotions, billboards, retailer website, newspaper advertising, e-mailing, customer service, direct mailings, TV and cinema advertising, online advertising, radio advertising, special events, mobile apps, customer satisfaction surveys, social networks and mobile messaging. This list aimed to encapsulate the most relevant encounters between a retailer and a customer within the customer journey. The touchpoint list was randomized for each respondent to avoid order bias. Data was cleaned, and invalid responses

removed. Invalid responses were identified by checking whether a respondent declared the same frequency of exposure for all the considered touchpoints and by evaluating response time. Data cleaning yielded 3,920 responses for analysis. Demographic information was collected directly from Nielsen records. Affluency was measured by means of the Nielsen OECD method that employs a four-level ranking based on revenue per consumption unit. The basis for the calculation is: (i) the household's net income (ii) the number of children in the household, and (iii) the total number of household members. These three components are used to compute the per capita income for each household. City size was also measured in ordinal terms with the following cut-offs: cities up to 20,000 inhabitants; 20,000 to 100,000 inhabitants; 100,000 to 500,000 inhabitants; more than 500,000 inhabitants.

Relationship commitment, self-disclosure and positive word-of-mouth were measured by seven-point Likert scales: the word-of-mouth scale was adapted from Babin *et al.* (2005), measuring agreement with statements concerning intentions to say positive things to others, recommend the retailer to another consumer, and encourage friends and relatives to visit the retailer. The self-disclosure scale was adapted from Cho (2006) and measured the willingness to disclose personal information to the retailer of reference. The relationship commitment scale, adapted from De Wulf *et al.* (2001), measured the desire to continue a relationship and the willingness to make efforts directed at sustaining this relationship with the retailer. These items can be viewed in Appendix A.

The analytic strategy employed LCCA to estimate latent classes or unobserved segments. LCCA differs from traditional cluster analysis (e.g. hierarchical or k-means cluster analysis) as it is a model-based approach providing a probability-based classification through posterior probability of membership (Haughton *et al.*, 2009). LCCA has been widely used in marketing for segmentation purposes (e.g. De Keyser *et al.*, 2015; Madi, 2016). In the LCCA literature, two ways for dealing with covariates have been proposed: a one-step and a three-step approach. The one-step approach involves the simultaneous estimation of the LCCA model of interest with a multinomial regression model in which the latent classes are a function of a set of covariates (Vermunt, 2010). The one-step approach thus considers covariates as predictors of latent segments. The three-step approach entails the following (Vermunt, 2010): after estimating the latent-class model (Step 1), individuals are assigned to latent classes based on the proportional posterior class membership probability (Step 2) and a linear regression analysis is carried out with proportional probability of belonging to the identified segments regressed on covariates or, conversely, outcome variables regressed on the proportional probability of belonging to the identified segments (Step 3). The three-step approach thus could involve variables that have the role of covariates or outcomes. This study employs both one-step and three-step

approaches: the former to estimate latent segments and their relationship with demographic covariates included as predictors, and the latter to estimate the relationship between latent segments and loyalty intentions as outcomes.

The LCCA was used to segment respondents based on their exposure to 23 different touchpoints while considering the impact of demographic variables on segment membership. One could argue that with such a high number of touchpoints, data reduction techniques might be necessary. However, as far as LCCA is concerned, Wurpts and Geiser (2014) point out that adding more indicators is beneficial because it decreases the occurrence of solutions with low accuracy in terms of class assignment. The LCCA was run on a number of clusters varying from two to eight. The procedure runs the algorithm with 100 random sets and 200 iterations for each number of clusters (this to avoid local minima), and retains the model yielding the minimal value of the BIC. BIC is regarded as the best among all the information criteria to select the number of clusters for the LCCA (Haughton *et al.*, 2009; Nylund *et al.*, 2007). Once the best model for each number of clusters is retained, BIC is used to compare model fit and to choose the best solution as the one with the minimum BIC value.

Moreover, as the study aimed to investigate the relationship between segment membership and loyalty intentions as outcomes (relationship commitment, self-disclosure and positive word-of-mouth), the three-step approach was performed with bias adjustment (Bakk *et al.*, 2013) that corrects classification error. In Step 3, the Bolck-Croon-Hagenaars (BCH) correction method is employed, which is less sensitive to violations of distributional assumptions (Bakk *et al.*, 2013). Finally, paired comparisons across clusters have been performed to identify significant differences in terms of relationship commitment, self-disclosure and positive word-of-mouth. The performed paired comparisons are based on Chi-squared Wald tests comparing parameters across each pair of latent classes (Vermunt and Magidson, 2016). The analyses were conducted using R statistical software and LatentGold statistical software 5.1.

Results

Sample description

Table I displays the demographics of the sample. Respondents are mainly female (58%) with an average age of 52 years old. Respondents belong to families with an average of three members and tend to live in smaller cities. In addition, 52% of respondents state that they are in charge of their household grocery shopping, and the remaining 48% state that they cooperate with other family members for shopping.

[INSERT TABLE I HERE]

Touchpoint exposure

Table II displays descriptive statistics of recalled reach and frequency of exposure to the touchpoints considered. Descriptive statistics provide a first overview of which touchpoints are encountered by consumers. “Traditional” retail touchpoints, such as store, store flyers, private label, store associates, and loyalty program reach a higher percentage of customers. Mobile and social media touchpoints display the lowest frequency of exposure.

[INSERT TABLE II HERE]

To better assess the validity and reliability of the scales, a Confirmatory Factor Analysis was conducted using R statistical software. To avoid redundancy one item was dropped from the positive word-of-mouth scale, which improved reliability measures (Cronbach’s α ; AVE and Composite Reliability). To increase validity one item was dropped from the self-disclosure scale as its

standardized loading was below .60 (Appendix A). Results of the definitive measurement model are displayed in Table III. Fit indexes displayed an acceptable fit, CFI=0.99, TLI=0.98, RMSEA=0.08 (0.07–0.08), Chi Square (11) = 262.293, $p < 0.001$. Table III below also shows adequate values regarding indicators of convergent validity (factorial loads > 0.6 and significant) and reliability (Cronbach's $\alpha > 0.7$; AVE > 0.5 , Composite Reliability > 0.7) for all the considered measures.

[INSERT TABLE III HERE]

The LCCA was run on the variables showing frequency of exposure to 23 touchpoints. Where models include a high number of variables, as in this case, it can be difficult to identify the best solution because BIC tends to decrease when solutions with a high number of clusters are considered (Masyn, 2013). The usual solution to this is to identify an elbow in the BIC curve across the considered cluster solutions (e.g. Petras and Masyn, 2010; Sands *et al.*, 2016). BIC values were therefore here examined to identify an elbow point across the possible solutions, and a six-cluster LCCA solution with a BIC value of 153, 277 was selected. Table IV and Figure 1 show the different BIC values per each number of groups. All the employed indicators—i.e. all the considered touchpoints—within the model have been found to be significant. In other words, all the indicators can be considered as discriminating between the groups in a significant manner (Vermunt and Magidson, 2005). Segments are labelled and described as follows below. Table V shows how segments differ in terms of their exposure to touchpoints.

[INSERT TABLE IV HERE]

[INSERT FIGURE 1 HERE]

[INSERT TABLE V HERE]

Cluster 1 (“Unexposed”) represents 36% of the total sample. “Unexposed” customers display the lowest frequency of exposure to almost all touchpoints. Moreover, they are exposed to the smallest number of touchpoints, 14 out of 23. Within this segment, two “traditional” retail touchpoints attain the highest scores: the store and the store flyer. Cluster 2 (“Low exposed”) represents 22% of the sample. “Low exposed” display levels of exposure that are slightly lower than the average across all the considered touchpoints. Cluster 3 (“Average exposed”) represents 16% of the sample and displays average levels of exposure across most considered touchpoints. Cluster 4 (“Omni-exposed”) represents 12% of the sample and displays consistently higher than average levels of exposure to all 23 touchpoints. Cluster 5 (“Promotion exposed – Ad unexposed”) represents 7% of the total sample. They display higher levels of exposure than the sample average to promotional touchpoints such as coupons, loyalty programs and special promotions. At the same time, they show lower than average levels of exposure to advertising touchpoints such as TV and cinema advertising, radio advertising, and newspaper advertising. Cluster 6 (“Overexposed”) represents 7% of the total sample. They show the highest exposure levels across all touchpoints.

Results for RQ1: Consumers can be classified into six segments as far as their frequency of exposure to touchpoints is concerned. All segments are of a relevant size and display differences in terms of exposure intensity and types of touchpoints they are exposed to.

Demographics and segment membership

By employing the one-step approach, the relationship between demographic variables and segment membership is considered in the estimation stage. “Unexposed” was chosen as the reference group for the multinomial logistic regression because these consumers display the lowest levels of frequency of exposure to all touchpoints considered. Descriptive and inferential statistics are shown in Table VI.

[INSERT TABLE VI HERE]

Results show that cluster membership is significantly related to sex ($p < .01$), age ($p < .001$), shopping role ($p < .001$) and geographic area of residence ($p < .001$). Number of household members, affluency and city size have been found not to be significant.

Descriptive statistics reveal that “Unexposed” includes the highest percentage of females (59.8%), while “Overexposed” include the highest percentage of males across the clusters (45.7%). The “Average exposed” cluster displays the highest average age (55.7 years old) and “Overexposed” the lowest (46.7 years old) across clusters. Customers in charge of the grocery shopping are less present in the “Unexposed” cluster (47.9%), while their presence is the highest in the “Promotion exposed – Ad unexposed” cluster (62.1%).

Table VII below displays odds ratios of significant demographic variables. Odds ratios show that the role of demographic variables is not only significant but also relevant as far as their correlation with segment membership is concerned. For instance, the relative probability of belonging to “Overexposed” rather than “Unexposed” is 49% higher for males than for females with the same other demographic characteristics. The relative probability of belonging to “Overexposed” or to “Average exposed” rather than “Unexposed” is respectively 3% higher and 1% lower for any one-year increase as far as age is concerned—holding constant the same other demographic characteristics. Interestingly, the relative probability of belonging to “Promotion exposed – Ad unexposed” rather than “Unexposed” is 48% higher for subjects in charge of shopping than for subjects cooperating with others for grocery shopping with the same other demographic characteristics.

[INSERT TABLE VII HERE]

Results for RQ2: several demographic variables are significantly related to touchpoint exposure, specifically: sex, age, shopping role and geographic area of residence.

Segment membership and loyalty intentions

Loyalty intentions have been found to be significantly related to segment membership. The “Unexposed” cluster was chosen as the reference group. Overall, cluster membership is significantly related to relationship commitment, self-disclosure and positive word-of-mouth. Table VIII below shows descriptive statistics and overall significance of cluster membership. Table IX displays results from pairwise comparisons across clusters.

[INSERT TABLE VIII HERE]

[INSERT TABLE IX HERE]

Comparisons show that, at the segment level:

- “Unexposed” display significantly lower self-disclosure and relationship commitment than all the other clusters and significantly lower positive word-of-mouth than all the other clusters apart from “Omni-exposed”.
- “Overexposed” display significantly higher relationship commitment than all the other clusters and significantly higher self-disclosure than all the other clusters apart from “Promotion exposed – Ad unexposed”.

- “Promotion exposed – Ad unexposed” display significantly higher self-disclosure than all the other clusters apart from “Overexposed”.

Results for RQ3: Segment membership is found to be significantly related to relationship commitment, self-disclosure and positive word-of-mouth. Specifically, “Unexposed” customers display the lowest scores in terms of loyalty intentions, and “Overexposed” the highest.

Discussion and conclusion

Discussion

This study identifies customer segments based on exposure to touchpoints by means of an analysis on almost 4,000 consumers in a supermarket retail setting. It sheds lights on how demographic attributes are related to the frequency of exposure to touchpoints. Moreover, the study estimates how different patterns of exposure to touchpoints are correlated to loyalty intentions such as relationship commitment, self-disclosure and positive word-of-mouth.

Findings show that consumer differences in terms of frequency of exposure to touchpoints are consistent across all touchpoints as far as five clusters are concerned: “Unexposed”, “Low exposed”, “Average exposed”, “Omni-exposed” and “Overexposed” could be ranked in increasing order of frequency of exposure to the majority of the considered touchpoints. This leads to the conclusion that 93% of consumers can be segmented based only on how frequently they encounter a comprehensive set of touchpoints. One cluster, instead, displays frequency differences in terms of types of touchpoints it is exposed to. “Promotion exposed – Ad unexposed” display high exposure to promotional touchpoints but low or no exposure to traditional advertising touchpoints.

The comparison of the theoretical frameworks for classifying touchpoints (personal versus non-personal; customer-initiated versus firm-initiated; brand-owned versus partner-owned, customer-owned and social/external) with the study’s empirically-based patterns reveals interesting conclusions. Consumer exposure emerged as not skewed towards a specific category of touchpoints identified in these classifications: for instance, no cluster displayed high exposure to personal touchpoints and low exposure to non-personal touchpoints, or vice versa. Rather, consumers are exposed, at different intensity levels, to combinations of touchpoints that belong to multiple theoretical categories. Hence, these results highlight the complexity for customer experience management in managing touchpoints consistently and allocating investment across them.

In terms of mere absolute frequency of exposure, the touchpoints that attain highest exposure among all customers, regardless of the cluster they belong to, are store, store flyers, store associates and private label. These share the common characteristic of being brand-owned touchpoints.

As far as covariates are concerned, this study finds that demographics are significantly related to frequency of exposure to touchpoints. Key findings are as follows:

- Males are more likely than females to belong to segments displaying higher levels of exposure to touchpoints rather than to the “Unexposed”. The literature had found that males tend to prefer online media more than females (e.g. Ieva and Ziliani, 2017). The present study extends previous findings by demonstrating that men are more likely to encounter a higher number of touchpoints with higher frequency, in general, than women.
- Age positively influences the likelihood of belonging to the “Unexposed” than to all the other clusters. Thus, older consumers are less likely to be exposed to touchpoints, both in terms of number of touchpoints and frequency of exposure. While previous studies have found that younger consumers are more exposed to online touchpoints (e.g. Romaniuk *et al.*, 2013), this study has found that younger consumers tend to be more exposed to any touchpoint.
- Customers in charge of grocery shopping are less likely to be “Unexposed” than to belong to any other cluster. As subjects in charge of the grocery shopping are more involved in purchase decisions, they might pay more attention to retail touchpoints.
- Geographic area of residence also plays a role in influencing the likelihood of exposure to touchpoints. This reveals the importance of the context of reference in driving touchpoint exposure.

The study provides evidence for the correlation between touchpoint exposure and loyalty intentions, specifically, relationship commitment, self-disclosure and positive word-of-mouth:

- It revealed a general positive relationship between high touchpoint exposure (versus average exposure, low exposure or un-exposure) and the intention to commit to a long-term relationship: “Unexposed” display lower relationship commitment than all other segments, and “Overexposed” a higher one. This result evokes what is known in advertising as the usage effect, where intensity of use is related to positive consumer response (Romaniuk *et al.*, 2012; Vaughan *et al.*, 2016).
- As far as self-disclosure is concerned, segments displaying lower levels of exposure display lower levels of self-disclosure, and vice versa. Being familiar with the retailer touchpoints seems to be positively related with the likelihood of revealing personal information to that

retailer. Moreover, as no difference emerges in terms of self-disclosure between “Overexposed” and “Promotion exposed – Ad unexposed”, the conclusion can be made that exposure to promotional touchpoints is similar to over-exposure in its relationship with self-disclosure.

- As far as positive word-of-mouth is concerned, differences across clusters emerge with a less conclusive pattern. Over-exposure to all touchpoints, or exposure to promotion, is only related to higher positive word-of-mouth when compared to un-exposure or low levels of exposure.

From a managerial perspective, this study has implications for retailers and brands. First, the findings show that consumers are exposed to a relevant number of touchpoints and what differs in exposure is primarily the frequency and, secondarily, the type of touchpoint. For this reason, retailers are advised to pursue omnichannel strategies to ensure that all touchpoints are consistent, thematically coherent and connected to offer a seamless and unique customer experience, since this is what the majority of customers will experience. Second, results show that efforts in increasing consumer exposure to touchpoints are worthwhile because high levels of touchpoint exposure are related to higher relationship commitment with the retailer, higher willingness to share personal information and higher positive word-of-mouth. This makes the argument for retailers to make their presence more conspicuous in the everyday life of customers. To identify customers less exposed to touchpoints, marketers should target females and older consumers. Moreover, as males and younger consumers are more likely to be exposed more frequently to a higher number of touchpoints, companies should ensure that customers with these characteristics are reached with consistent messages across all touchpoints.

Finally, given that consumers more exposed to promotional touchpoints and less exposed to advertising touchpoints display higher loyalty intentions than the other four clusters, retailers are advised to enhance the reach of touchpoints related to loyalty program and price promotions, in order to leverage consumers’ loyalty intentions.

Limitations and further research directions

This study has several limitations. First, given the cross-sectional research design employed, this study provides correlational—not causal—evidence to establish conclusions between exposure of touchpoints and loyalty intentions. Second, even though surveys are widely used for academic and practitioner studies on touchpoint exposure (e.g. Romaniuk *et al.*, 2013), respondents might find it hard to recall the experience with touchpoints they had some time ago (Wind and Lerner, 1979). Third, touchpoint exposure is affected by the retailer’s targeting strategies and by the availability of touchpoints offered by each retailer in the context of the study, although the self-selection that occurs

as far as consumer exposure to touchpoints is concerned might reduce this (e.g. Ieva *et al.*, 2017; Lemon and Verhoef, 2016). Moreover, respondents were asked to answer questions with reference to the retailer that takes the highest share of their wallet, so the results are not representative of any retailer's entire customer base. Finally, the external validity of the study might be increased by extending the study to different industries, different time periods and to retailers with a relatively low share of customers' wallets. Further studies are called for to provide theoretical and methodological contributions to the identification and classification of customer experience touchpoints within the customer journey across different settings. It would also be of key relevance to identify causal inference relationships between touchpoint exposure, customer experience, and attitudinal and behavioural customer outcomes. Recent studies have already made preliminary contributions (e.g. Anderl *et al.*, 2016; Baxendale *et al.*, 2015) but more insight is needed in this area.

Appendix A

Items of relational intention constructs

Relationship Commitment – adapted from De Wulf *et al.* (2001)

RC_1 – I am willing ‘to go the extra mile’ to remain a customer of this retailer.

RC_2 – I feel loyal towards this retailer.

RC_3 – Even if this retailer would be more difficult to reach, I would still keep buying in its stores.

Self-disclosure – adapted from Cho (2006)

SD_1 – I am willing to provide my personal information when asked by this retailer.

~~SD_2 – I am willing to disclose even sensitive personal information to this retailer~~ (*dropped to increase validity*).

SD_3 – I am willing to be truthful in revealing my personal information to this retailer.

Positive word-of-mouth – adapted from Babin *et al.* (2005)

WOM_1 – I will say positive things about this retailer to other people.

~~WOM_2 – I will recommend it to someone who seeks my advice~~ (*dropped to avoid redundancy*).

WOM_3 – I will encourage friends and relatives to visit the retailer.

References

- Aaker, J., Drolet, A. and Griffin, D. (2008), "Recalling mixed emotions", *Journal of Consumer Research*, Vol. 35 No. 2, pp. 268-278.
- Anderl, E., Becker, I., von Wangenheim, F. and Schumann, J.H. (2016), "Mapping the customer journey: Lessons learned from graph-based online attribution modelling", *International Journal of Research in Marketing*, Vol. 33 No. 3, pp. 457-474.
- Aurier, P. and N'Goala, G. (2010), "The differing and mediating roles of trust and relationship commitment in service relationship maintenance and development", *Journal of the Academy of Marketing Science*, Vol. 38 No. 3, pp. 303-325.
- Babin, B.J., Lee, Y.K., Kim, E.J. and Griffin, M. (2005), "Modeling consumer satisfaction and word-of-mouth: restaurant patronage in Korea", *Journal of Services Marketing*, Vol. 19 No. 3, pp. 133-139.
- Bakk, Z., Tekle, F.B. and Vermunt, J.K. (2013), "Estimating the association between latent class membership and external variables using bias-adjusted three-step approaches", *Sociological Methodology*, Vol. 43 No. 1, pp. 272-311.
- Baxendale, S., Macdonald, E.K. and Wilson, H.N. (2015), "The impact of different touchpoints on brand consideration", *Journal of Retailing*, Vol. 91 No. 2, pp. 235-253.
- Bolck, A., Croon, M. and Hagenaars, J. (2004), "Estimating latent structure models with categorical variables: One-step versus three-step estimators", *Political Analysis*, Vol. 12 No. 1, pp. 3-27.
- Brown, T.J., Barry, T.E., Dacin, P.A. and Gunst, R.F. (2005), "Spreading the word: Investigating antecedents of consumers' positive word-of-mouth intentions and behaviors in a retailing context", *Journal of the Academy of Marketing Science*, Vol. 33 No. 2, pp. 123-138.
- Brun, I., Rajaobelina, L., Ricard, L. and Berthiaume, B. (2017), "Impact of customer experience on loyalty: a multichannel examination", *The Service Industries Journal*, pp. 1-24.
- Buckinx, W. and Van den Poel, D. (2005), "Customer base analysis: partial defection of behaviourally loyal clients in a non-contractual FMCG retail setting", *European Journal of Operational Research*, Vol. 164 No. 1, pp. 252-268.
- Campbell, M.C. and Keller, K.L. (2003), "Brand familiarity and advertising repetition effects", *Journal of Consumer Research*, Vol. 30 No. 2, pp. 292-304.
- Cho, J. (2006), "The mechanism of trust and distrust formation and their relational outcomes", *Journal of Retailing*, Vol. 82 No. 1, pp. 25-35.
- Clore, G.L. and Schnall, S. (2005), "The influence of affect on attitude", in Albarracín, D., Johnson, B.T. and Zanna, M.P. (Ed.), *The Handbook of Attitudes*, Lawrence Erlbaum, Mahwah, NJ, pp. 437-489.
- Collins, N.L. and Miller, L.C. (1994), "Self-disclosure and liking: a meta-analytic review", *Psychological bulletin*, Vol. 116 No. 3, pp. 457-475.
- De Keyser, A., Schepers, J. and Konuş, U. (2015), "Multichannel customer segmentation: Does the after-sales channel matter? A replication and extension", *International Journal of Research in Marketing*, Vol. 32 No. 4, pp. 453-456.
- De Wulf, K., Odekerken-Schröder, G. and Iacobucci, D. (2001), "Investments in consumer relationships: A cross-country and cross-industry exploration", *Journal of Marketing*, Vol. 65 No. 4, pp. 33-50.

- Duncan, T. and Moriarty, S. (2006), "How integrated marketing communication's 'touchpoints' can operationalize the service-dominant logic", in Lusch, R.F. and Vargo, S.L. (Ed.), *The service-dominant logic of marketing: dialog, debate, and directions*, Routledge, New York, NY, pp. 236-249.
- Hall, A. and Towers, N. (2017), "Understanding how millennial shoppers decide what to buy: digitally connected unseen journeys", *International Journal of Retail & Distribution Management*, Vol. 45 No. 5, pp. 498-517.
- Harrison-Walker, L.J. (2001), "The measurement of word-of-mouth communication and an investigation of service quality and customer commitment as potential antecedents", *Journal of Service Research*, Vol. 4 No. 1, pp. 60-75.
- Houghton, D., Legrand, P. and Woolford, S. (2009), "Review of three Latent Class Cluster Analysis packages: Latent Gold, poLCA, and MCLUST", *The American Statistician*, Vol. 63 No. 2, pp. 81-91.
- Haugtvedt, C.P. and Wegener, D.T. (1994), "Message order effects in persuasion: An attitude strength perspective", *Journal of Consumer Research*, Vol. 21 No. 1, pp. 205-218.
- Hennig-Thurau, T., Gwinner, K.P. and Gremler, D.D. (2002), "Understanding relationship marketing outcomes: an integration of relational benefits and relationship quality", *Journal of Service Research*, Vol. 4 No. 3, pp. 230-247.
- Homburg, C., Jozić, D. and Kuehnl, C. (2017), "Customer experience management: toward implementing an evolving marketing concept", *Journal of the Academy of Marketing Science*, Vol. 45 No. 3, pp. 377-401.
- Ieva, M. and Ziliani, C. (2017), "Towards digital loyalty programs: insights from customer medium preference segmentation", *International Journal of Retail & Distribution Management*, Vol. 45 No. 2, pp. 195-210.
- Ieva, M., Ziliani, C., Gàzquez-Abad, J.C. and D'Attoma, I. (2017), "Online versus offline promotional communication: Evaluating the effect of medium on customer response", *Journal of Advertising Research*.
- Jacoby, J. and Chestnut, R. (1978), *Brand Loyalty Measurement and Management*, Wiley, New York, NY.
- Klaus, P. and Maklan, S. (2013), "Towards a better measure of customer experience", *International Journal of Market Research*, Vol. 55 No. 2, pp. 227-246.
- Konus, U., Verhoef, P.C. and Neslin, S.A. (2008), "Multichannel shopper segments and their covariates", *Journal of Retailing*, Vol. 84 No. 4, pp. 398-413.
- Leeflang, P.S., Verhoef, P.C., Dahlström, P. and Freundt, T. (2014), "Challenges and solutions for marketing in a digital era", *European Management Journal*, Vol. 32 No. 1, pp. 1-12.
- Lemon, K.N. and Verhoef, P.C. (2016), "Understanding customer experience throughout the customer journey", *Journal of Marketing*, Vol. 80 No. 6, pp. 69-96.
- Li, H. and Kannan, P.K. (2014), "Attributing conversions in a multichannel online marketing environment: an empirical model and a field experiment", *Journal of Marketing Research*, Vol. 51 No. 1, pp. 40-56.
- Loiacono, E.T. (2015), "Self-disclosure behavior on social networking web sites", *International Journal of Electronic Commerce*, Vol. 19 No. 2, pp. 66-94.
- Macintosh, G. and Lockshin, L.S. (1997), "Retail relationships and store loyalty: a multi-level perspective", *International Journal of Research in Marketing*, Vol. 14 No. 5, pp. 487-497.

- Madi, A. (2016), "Using values to segment virtual consumers on social networking sites", *Marketing Intelligence & Planning*, Vol. 34 No. 5, pp. 623-645.
- Magee, R.G. (2013), "Can a print publication be equally effective online? Testing the effect of medium type on marketing communications", *Marketing Letters*, Vol. 24 No. 1, pp. 85-95.
- Masyn, K.E. (2013) "Latent class analysis and finite mixture modelling", in Little, T.D. (Ed.), *The Oxford Handbook of Quantitative Methods in Psychology: Vol. 2: Statistical Analysis*, Oxford University Press, New York, NY.
- Nylund, K.L., Asparouhov, T. and Muthén, B.O. (2007), "Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study", *Structural Equation Modeling*, Vol. 14 No. 4, pp. 535-569.
- Pantano, E. and Viassone, M. (2015), "Engaging consumers on new integrated multichannel retail settings: Challenges for retailers", *Journal of Retailing and Consumer Services*, Vol. 25, pp. 106-114.
- Payne, M.E., Peltier, J. and Barger, V.A. (2017), "Omni-channel marketing, integrated marketing communications, and consumer engagement: a research agenda", *Journal of Research in Interactive Marketing*, Vol. 11 No. 2, pp. 185-198.
- Peltier, J.W., Schibrowsky, J.A. and Schultz, D.E. (2003), "Interactive integrated marketing communication: combining the power of IMC, the new media and database marketing", *International Journal of Advertising: The Review of Marketing Communications*, Vol. 22 No. 1, pp. 93-115.
- Petras, H. and Masyn, K. (2010), "General growth mixture analysis with antecedents and consequences of change", in Piquero, A.R. and Weisburd, D. (Ed.), *Handbook of quantitative criminology*, Springer, New York, NY, pp. 69-100.
- Rawson, A., Duncan, E. and Jones, C. (2013), "The truth about customer experience", *Harvard Business Review*, Vol. 91 No. 9, pp. 90-98.
- Romaniuk, J., Beal, V. and Uncles, M. (2013), "Achieving reach in a multi-media environment", *Journal of Advertising Research*, Vol. 53 No. 2, pp. 221-230.
- Romaniuk, J., Bogomolova, S. and Dall'olmo Riley, F. (2012), "Brand image and brand usage", *Journal of Advertising Research*, Vol. 52 No. 2, pp. 243-251.
- Sands, S., Ferraro, C., Campbell, C. and Pallant, J. (2016), "Segmenting multichannel consumers across search, purchase and after-sales", *Journal of Retailing and Consumer Services*, Vol. 33, pp. 62-71.
- Simon, M., Van Den Dries, F. and Wilms, T. (2016), "Driving customer-centric growth: A practical roadmap", *Journal of Advertising Research*, Vol. 56 No. 2, pp. 159-168.
- Srivastava, M. and Kaul, D. (2016), "Exploring the link between customer experience–loyalty–consumer spend", *Journal of Retailing and Consumer Services*, Vol. 31, pp. 277-286.
- Van Deursen, A.J. and Van Dijk, J.A. (2014), "The digital divide shifts to differences in usage", *New media & society*, Vol. 16 No. 3, pp. 507-526.
- Vaughan, K., Beal, V. and Romaniuk, J. (2016), "Can brand users really remember advertising more than nonusers?", *Journal of Advertising Research*, Vol. 56 No. 3, pp. 311-320.
- Vermunt, J. and Magidson, J. (2005), "Factor analysis with categorical indicators: A comparison between traditional and latent class approaches", in Van der Ark, A., Croon, M. and Sijtsma, K. (Ed.), *New developments in categorical data analysis for the social and behavioral sciences*, Lawrence Erlbaum Associates, Mahwah, NJ, pp. 41-62.

- Vermunt, J.K. and Magidson, J. (2016), "Technical guide for Latent GOLD 5.1: basic, advanced, and syntax", Statistical Innovations Inc., Belmont, MA.
- Voorhees, C.M., Fombelle, P.W., Gregoire, Y., Bone, S., Gustafsson, A., Sousa, R. and Walkowiak, T. (2017), "Service encounters, experiences and the customer journey: Defining the field and a call to expand our lens", *Journal of Business Research*, Vol. 79, pp. 269-280.
- Verhoef, P.C., Lemon, K.N., Parasuraman, A., Roggeveen, A., Tsiros, M. and Schlesinger, L.A. (2009), "Customer experience creation: Determinants, dynamics and management strategies", *Journal of Retailing*, Vol. 85 No. 1, pp. 31-41.
- Verhoef, P.C., Kannan, P.K. and Inman, J.J. (2015), "From multi-channel retailing to omni-channel retailing: introduction to the special issue on multi-channel retailing", *Journal of Retailing*, Vol. 91 No. 2, pp. 174-181.
- Vermunt, J.K. (2010), "Latent class modeling with covariates: Two improved three-step approaches", *Political analysis*, Vol. 18 No. 4, pp. 450-469.
- Wind, Y.J. and Hays, C.F. (2016), "Research implications of the 'beyond advertising' paradigm", *Journal of Advertising Research*, Vol. 56 No. 2, pp. 142-158.
- Wind, Y. and Lerner, D. (1979), "On the measurement of purchase data: surveys versus purchase diaries", *Journal of Marketing Research*, Vol. 16 No. 1, pp. 39-47.
- Wurpts, I. C. and Geiser, C. (2014), "Is adding more indicators to a latent class analysis beneficial or detrimental? Results of a Monte-Carlo study", *Frontiers in psychology*, Vol. 5 No. 920, pp. 1-15.
- Zahay, D., Peltier, J., Schultz, D.E. and Griffin, A. (2004), "The role of transactional versus relational data in IMC programs: Bringing customer data together", *Journal of Advertising Research*, Vol. 44 No. 1, pp. 3-18.
- Zeithaml, V.A., Berry, L.L. and Parasuraman, A. (1996), "The behavioral consequences of service quality", *Journal of Marketing*, Vol. 60 No. 2, pp. 31-46.