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Customer segmentation with purchase channels and media touchpoints using single source panel data

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ABSTRACT

This study examines how customers use multiple channels and media in modern retail environments. It segments customers by using Latent-Class Cluster Analysis, which focuses on the purchase channels of bricks-and-mortar and online stores, media touchpoints of PC, mobile, and social media, and psychographic and demographic characteristics. It extends the framework of prior research by analyzing 2595 Japanese single source panelists' data in which purchase scan panel data on low-involvement, more frequently purchased categories, media contact log data, and survey data are tied to the same ID. The analyses reveal seven segments including the properties of research shoppers and multichannel enthusiasts.

1. Introduction

The multichannel retail environment has developed over the past decade. As the number of firms selling their products both online and offline has increased, achieving synergy by integrating sales and communication channels has assumed greater importance (Zhang et al., 2010). The development of communication channels based on multimedia such as mobile devices and social media has enabled the firm to build a direct relationship with the customer (Ganesan et al., 2009; Van Bruggen et al., 2010). The firm can now build an interactive relationship by providing product information through its own website or through social media platforms, such as Facebook and Twitter, in addition to traditional communication channels. Conversely, from the point of view of customers, opportunities for customers to select information are increasing. They can now obtain the information they need whenever and wherever they want without visiting bricks-and-mortar stores, since they can purchase anything online. Subsequently, it has become more important for firms to understand how customers utilize multiple channels and media and how to integrate them seamlessly (Dholakia et al., 2010; Verhoef et al., 2015).

One effective way is to design channel strategies based on customer segmentation (Neslin et al., 2006). A number of studies have examined the characteristics of multichannel customers (e.g., Kushwaha and Shankar, 2013; Chintagunta et al., 2012; Gensler et al., 2012; Valentini et al., 2011; Ansari et al., 2008; Thomas and Sullivan, 2005). In addition to this background, studies have begun to emerge that do not simply focus on customers' purchase channels, but instead reference their purchase stages including information search stage and purchase stage. (Konus et al.,2008) proposed a Latent-Class Cluster Analysis scheme based on customers' channel use that considers the information search and purchase stages as well as the individual differences in their psychographic and demographic covariates. This scheme has become a universal scheme adopted in several studies (Wang et al., 2014; Keyser et al., 2015; Sands et al., 2016). Sands et al. (2016) extended the scheme to evaluate communication channels more precisely by taking into account the influence of mobile devices and social media.

However, there are certain limitations in these studies because the results are based on self-reported surveys. Among past studies of multichannel customer segmentation, the problem of common method bias pertaining to survey data has been pointed out. Additional validation based on actual behavioral data has been recommended as a future study issue (Konus et al., 2008; Wang et al., 2014). Validating the scheme by using actual behavioral data is also important for making use of the abundant digital marketing data now available. Indeed, firms' customer databases offer various behavioral log data, including both online and offline behavior. Hence, there are increasing opportunities to create synergies among sales and communication channels by promoting marketing automation (Jarvinen and Taiminen, 2016).

This study posits that one way of developing multichannel customer segmentation research is (a) segmenting customers based on actual behavioral data, which means creating actionable segments for a firm's promotional activities, and (b) understanding customer characteristics in the segment by combining survey data, rather than just grasping actual behavior. In particular, when using only actual behavioral data, it is difficult to understand the psychological characteristics behind customer behavior. Conventionally, researchers have used survey data

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Table 1
Types of customer segmentation.

	Multichannel setting	Purchase stages	Multi device/media	Individual differences		Data type
				Psychographic	Demographic	
Gupta and Chintagunta (1994)	Offline channel	–	–	–	✓	Actual data (pruchase scan panel)
Bhatnagar and Ghose (2004)	e-shoppers	–	–	✓	–	Survey
Thomas and Sullivan (2005)	Multichannel	–	–	–	–	Actual data (retailer database)
Konus et al. (2008)	Multichannel	Search & purchase	–	✓	✓	Survey
Wang et al. (2014)	Multichannel	Search & purchase	–	✓	✓	Survey
Keyser et al. (2015)	Multichannel	Search, purchase & after-sales	–	✓	✓	Survey
Sands et al. (2016)	Multichannel	Search, purchase & after-sales	Internet, Mobile, Social media	✓	✓	Survey
This study	Multichannel	Search & purchase	PC, Mobile, Social media	✓	✓	Actual data (pruchase scan panel, media panel) & survey

to capture individual differences in the customer's perception of channels, while purchase history data such as consumer panel data have been adopted to capture actual behavior. In other words, different types of data have been studied separately. By contrast, we aim to achieve an integrated interpretation of actual behavioral patterns and the perception behind such behavior.

We aim to achieve this goal by using a new kind of data source: single source panel data in the Japanese market in which purchase scan panel data, media contact log data, and survey data are tied to the same ID. The processes of collecting data, including behavior logs and surveys, and turning these data into single source data linked to each individual have evolved rapidly (Taneja and Mamoria, 2012). Over the past five years in the Japanese marketing research industry, multiple large marketing research firms (e.g., INTAGE Inc., Video Research Ltd., the Nielsen Company Japan) have been developing a system to provide single source panel data. In addition, the e-commerce market size in Japan has increased 1.8 times in the past five years, and owing to the increase in online purchase of low involvement, more frequently purchased categories such as groceries, cosmetics, and sundries (Ministry of Economy, Trade and Industry of Japan, 2015). The usage rate of smartphones in Japanese citizens reached 57.9% in 2016, and the proportion of firms using social media for promotions reached 22.1% (Ministry of Internal Affairs and Communications, 2017). Hence, as the usage trends of the purchasing channel and media contacts continue to change, we expect to be able to provide a holistic view of customer behavior by using these new kinds of data.

In summary, this study follows past segmentation studies to understand individual differences based on purchase stage, and expands them by using single source panel data including actual behavioral data and survey data. We assess two types of purchasing channels (bricks-and-mortar and online stores) and three types of media touchpoints for information searches (mobile, PC, and social media). We focus on the market as a whole from a consumer-centric perspective, not focusing on specific firm channels. In this research, bricks-and-mortar stores include supermarkets, convenience stores, drugstores, department stores, and specialty stores, while online stores include Internet supermarkets, e-commerce sites, and direct sales sites of brands. In addition, this study deals with a segmentation case study of a Japanese market never conducted in this way before.

2. Multichannel and multimedia customer segmentation

2.1. Literature review

In this section, we review research streams on multichannel customers and their segmentation studies as well as identify the primary issues.

2.1.1. Multichannel customer behavior in multiple purchase stages

Research related to multichannel customers has been conducted in various contexts. Verhoef et al. (2015) classified these studies into three major topics: (1) impact of channels on performance; (2) shopper behavior across channels; and (3) retail mix across channels. This study falls within the second topic, focusing on the multichannel shopper segmentation and their individual differences. In addition, from the perspective of the multichannel shopper behavior contexts, Neslin et al. (2006) identified six determinants as the customer channel choice drivers: firms' marketing efforts (Valentini et al., 2011; Ansari et al., 2008), channel attributes (Gensler et al., 2012; Chintagunta et al., 2012), social influence (Frambach et al., 2007), situational factors (Chintagunta et al., 2012; Mathwick et al., 2002), channel integration (Falk et al., 2007; Bendoly et al., 2005), and individual differences (Konus et al., 2008; Inman et al., 2004).

Channel integration between purchase channels and communication channels is one research stream. A customer employs multiple channels for either information search or purchase in the decision process (Kumar and Venkatesan, 2005). In early studies, Kim and Park (2005) examined the consumer shopping channel extension. They found that search intention for product information via an online store is a strong positive predictor of online purchase intention. Further, one notable consumer behaviors is the "research shopper" phenomenon (Verhoef et al., 2007). A research shopper is a person who uses one channel for information search and a different channel when making purchases. A generally observed pattern is to search for information on the web and then purchase in bricks-and-mortar stores. These studies show consumers may use the information gained online for both offline purchasing and online purchasing. To capture these kinds of behaviors and achieve appropriate communication, it is thus necessary to distinguish between purchase channel and information search channel.

2.1.2. Customer segmentation studies

Table 1 summarizes past studies of customer segmentation. In terms of offline channel purchase behavior, Gupta and Chintagunta (1994) proposed a Latent-Class Cluster Analysis using demographic covariates to determine segment membership. They showed the validity of the scheme by directly incorporating the effects of the demographic characteristics on segment membership. In terms of online channel purchase behavior, Bhatnagar and Ghose (2004) segmented e-shoppers, finding that consumers are more concerned about web attributes associated with perceived losses (e.g., security of information and vendor reliability). With respect to the multichannel literature, the segments are mostly based on preferred shopping channels with clear definitions assigned, and are expressed in the dependency of the number of channels. For example, comparisons can be made between customers who only use bricks-and-mortar stores (single channel customers) and those who use both bricks-and-mortar and online stores (multichannel customers). Thomas and Sullivan (2005) studied three channels (stores, online, catalogs) of a retailer and identified two segments: the catalog segment and bricks-and-mortar segment. Because these distinctions are easy to comprehend, they are often employed not only in segmentation research but also in general research dealing with channel choice behavior (e.g., Kushwaha and Shankar, 2013).

However, it is difficult to capture individual differences by only focusing on the number of channels customers use. Konus et al. (2008) identified the need for research that develops a segmentation scheme that incorporates covariates and multiple purchase stages. They proposed the Latent-Class Cluster Analysis scheme that classifies customers based on channel preferences in the stages of information search and purchase, and explains the segments from both a psychographic and demographic perspective. Their analysis resulted in three segments of customers: *multichannel enthusiasts, uninvolved shoppers,* and *store-focused customers*.

The concepts clarified by Konus et al. (2008) evoked a number of studies (Wang et al., 2014; Keyser et al., 2015; Sands et al., 2016). This study contends that the approach of Konus et al. (2008) will become an important scheme in customer segmentation as the multichannel and multimedia retailing environment develops (Dholakia et al., 2010). Table 2 summarizes the key findings of past studies. Wang et al. (2014) extended the concepts by exploring the possibility of perceived values being different between the information search stage and purchase stage. They identified two customer segmentations: *innovative consumers* and *conventional consumers*. Keyser et al. (2015) and Sands et al. (2016) considered the after-purchase stage. Sands et al. (2016) also captured media channels more finely and expanded the scope by including mobile and social media. Their research made a new contribution by considering the segment of *research shoppers*.

In summary, two important perspectives on developing multichannel customer segmentation research exist. First, the examination of the device/media characteristics of communication channels enables us to capture the characteristics of multichannel customers, including research shopper characteristics (Sands et al., 2016). Business managers are increasingly demanding the development of communication strategies in response to the spread of mobile devices. In particular, because screen size and portability differ between PCs and mobile devices, it is important to reach customers by devising different ways of extracting information depending on the device used in mobile marketing (Strom et al., 2014). However, while Sands et al. (2016) addressed mobile devices, they did not mention the differences between PCs and mobile devices. Therefore, this study bridges the gap in past studies by taking device characteristics into account. Second, another key factor for capturing individual differences is to understand *innovative* and *loyalty* customers. Past studies have suggested that multichannel customers have an innovative tendency, seeking pleasurable shopping experiences and trying to reduce time, effort, and cost (Konus et al., 2008; Wang et al., 2014). On the contrary, store-focused customers retain loyalty and tend to seek service quality. These tendencies are, however, further divided within the same segment in reference to communication channels; customers who prefer mobile channels are more innovative but anti-mobile customers are less innovative (Sands et al., 2016). It is thus a challenge to examine and generalize the characteristics of channel use as well as the relationship between them and individual differences.

2.1.3. Actual data studies and related issues

One of the issues recognized by researchers in multichannel customer segmentation is the problem of common method bias pertaining to survey data. In other research context, there are several studies based on actual behavioral data. In the channel synergy research context, actual purchase data on online and offline have been used to verify the effect by combining different purchase channels (Avery et al., 2012; Fornari et al., 2016), in which no information search channel is considered. In the recent channel synergy research context, Wagner et al.

Table 2
Key findings of multichannel customer segmentation that incorporates covariates and multiple purchase stages.

	Products	Segmentation result	Key findings
Konus et al. (2008)	Books, Mortgage, Electronics, Holidays, Clothing, Computers, Insurance	Three segments Uninvolved shoppers (40%) Multichannel enthusiasts (37%) Store focused customers (23%)	• Multichannel enthusiasts tend to be more innovative. • Store-focused consumers generally are more loyal. • Multichannel enthusiasts consider shopping a pleasurable experience than do the other two segments and uninvolved shoppers do not consider shopping a pleasurable experience at all.
Wang et al. (2014)	16 types of products including apparel, computers, television sets, jewellery, toys, books, MP3/MP4 players, headphones, cars, etc.	Two segments Innovative consumer (52%) Conventional consumer (48%)	• Most of the innovative consumers tend to choose the online channel for information search and product purchase. • Innovative consumers placed more emphasis on reducing the time/effort cost in the information search. • Conventional consumers devoted more attention to information service quality.
Keyser et al. (2015)	Mobile solutions which are sold by a Dutch telecom retailer by such as devices, their accessories, and subscriptions	Six segments Research shoppers after-sales: store (34%) Web-focused shoppers (22%) Store-focused shoppers (18%) Research shoppers after sales: Internet/store (11%) Web-focused shoppers after sales: store/call center (9%) Call center-prone shoppers (6%)	• Identification of the research shopper segment. • Customer loyalty is an important covariate predicting segment membership. In contrast, innovativeness is not a significant covariate.
Sands et al. (2016)	Consumer electronics, Clothing, Holiday travel	Six segments ROPO anti-mobile/social media (36%) ROPO multichannel enthusiasts (22%) ROPO social media enthusiasts (16%) Internet-focused anti-mobile enthusiasts (14%) Internet-focused multichannel enthusiasts (12%)	• Identification of the research shopper (ROPO: Research Online, Purchase Offline) segment. • Demonstrated individual differences occur by the use of the mobile devices and social media among the ROPO consumers and Internet-focused customers.

(2013) evaluated multiple e-channel strategies including mobile, considering the information search channel based on survey data. They suggested that synergy and complementarity are relevant antecedents of consumer behavior to use multiple e-commerce system. In the communication research context, several studies capture the effects of coupons distributed for each channel by using actual data (Chiou-Wei and Inman, 2008; Ansari et al., 2008). These studies use actual purchase data to evaluate a firm's promotional activities.

Both Konus et al. (2008) and Wang et al. (2014) stated that it is necessary to generalize the findings by validating with actual behavioral data. This study raises two points on the necessity of validation based on actual behavioral data and the kinds of common methods bias. First, there is a discrepancy between intention and actual behavior. Referring to the hierarchy of communication effects theory (Barry, 1987) in consumer behavior research, purchase intention is an important predictor that causes actual purchase, but they are not the same. Second, even when an attempt is made to capture actual behavior by survey data, the survey results will be divergent from actual behavior. In the literature on survey quality research, researchers use different survey methods with the same person (e.g., collection of log data and surveys) and examine the degree of discrepancy between them (Abeele et al., 2013; Boase and Ling, 2013). When there is such a discrepancy, it could lead to a problem of mis-prediction of consumers' tendency and communication effects (Abeele et al., 2013).

Our segmentation research may also contribute to channel synergy research. Synergies derive from similarities between channels, whereas complementarity derives from the heterogeneity (Avery et al., 2007). Wagner et al. (2013) implied that distinctive customer capabilities for each channel with their technology acceptance (e.g., mobile) is an important element on the basis of resource-based theory (Zhu, 2004). The customer segmentation in this study can allow us to understand customers' similarity and heterogeneity in terms of purchase channel and device/media capabilities. However, no research has thus far integrated actual information search and purchase behavior with the psychological differences behind actual behavior in multichannel settings.

Therefore, this customer segmentation study aims to give a basis for a holistic integration of customers' actual information search and purchase behavior and their psychological differences. The objectives of this study are to answer the following questions: (1) How can we validate the findings from segmentation based on actual behavioral data? (2) What evaluation of the individual differences among segments can be made by using a customer's psychographic and demographic covariates? (3) How can we connect purchase channels with information search device/media that could lead to channel synergies for the future integration of the two?

2.2. Conceptual framework

Fig. 1 shows the conceptual framework for this study. The segmentation concept is based on the past segmentation research of Konus et al. (2008) and Sands et al. (2016), which is derived from the theoretical background on multichannel customer behavior in multiple purchase stages (Verhoef et al., 2007; Kumar and Venkatesan, 2005). We expand the concept by using single source panel data (including actual behavioral data and surveys) and aim to give a basis for a holistic view. In the proposed conceptual framework, the channel utilities that customers obtain from purchasing and information contact, are measured by the usage rates of purchase channels and media touchpoints. There are two types of purchase channels (bricks-and-mortar stores and online stores) in the purchase process and three types of media touchpoints (mobile, PC, and social media) in the information search process. Specifically, for low-involvement, more frequently purchased categories, we use overall purchase volume from scan panel purchase data for each purchase channel and overall usage frequency of each media from media log data for each media touchpoint. Although past multichannel customer segmentation studies (Konus et al., 2008; Wang et al., 2014; Keyser et al., 2015; Sands et al., 2016) were analyzed for a few product categories, we aim to analyze the whole market in low-involvement, more frequently purchased categories.

After segmenting customers by channel utility, we identify the psychographic and demographic covariates contributing to those segment memberships. For this purpose, we use the demographics of gender, age, marital status, number of family members, number of children, education, and household income, as well as the six psychographics proposed by Konus et al. (2008). The first psychographics is *Innovativeness*. This variable expresses the propensity to try new and different products and to seek new experiences (Midgley and Dowling, 1978). The second is *Brand/Retailer Loyalty*. This variable expresses the tendency to continue using specific brands and channels (Ailawadi et al., 2001; Klemperer, 1995). The third is *Motivation to Conform (Opinion Seeking)*. This variable expresses the extent to which consent from others is required when making a purchase decision (Ailawadi et al., 2001; Chandon et al., 2000). The fourth is *Shopping Enjoyment*. This variable expresses the extent to which entertainment and emotional benefit is sought (Babin et al., 1994). It expresses the hedonic value of shopping. The fifth is *Time Pressure*. This variable expresses the scarcity of the customer's time resources, as people who lack time tend to shop in a planned way (Kleijnen et al., 2007). The final variable is *Price Consciousness*. This variable expresses the degree to which customers focus on paying low prices (Lichtenstein et al., 1990). Customers have particular perceptions of the prices of products in particular channels, and this influences their channel selection (Verhoef et al., 2007).

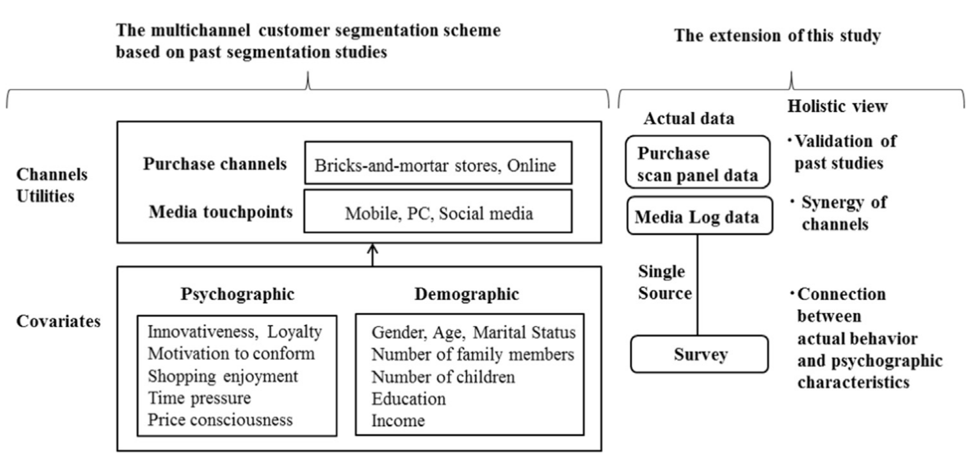

Fig. 1. Conceptual framework.

Table 3
Summary statistics in demographic covariates.

Gender		Marital status	
Male	55.4%	Married	66.7%
Female	44.6%	Not married	33.3%
Age		Household income (million yen)	
15–24 years	4.7%	Less than 3.99	25.7%
25–34 years	20.6%	4.00–5.49	20.6%
35–44 years	30.6%	5.50–6.99	17.7%
45–54 years	27.6%	7.00–8.99	16.9%
55–69 years	16.4%	More than 9.00	19.2%
Number of family members (mean)			2.94
Number of children (mean)			0.59
Education (mean)			14.43

This study also focuses on product categories that have not been studied before. Past studies of multichannel customer segmentation have analyzed high-involvement purchased categories such as clothing, electronics, holiday travel, computers, books, mortgages, and insurance. The online marketplaces for these categories matured relatively early. Therefore, they were suitable categories for research at that time. However, in recent years, there has been remarkable growth in low-involvement, more frequently purchased categories such as groceries, cosmetics, and sundries. In fact, in the Japanese market, according to the results of a 2015 Ministry of Economy, Trade and Industry survey, the online purchase rates of growth from the previous year for the top 5 categories in descending order were as follows: groceries, beverages/alcoholic beverages, clothing/accessories, office supplies/stationery, and cosmetics/drugs. Hence, the accumulation of knowledge on low-involvement, more frequently purchased categories is a challenge in this changing business environment (Sands et al., 2016).

3. Method

3.1. Data collection

We used the single source panel data (*i-SSP*) obtained from INTAGE Inc., one of the largest Japanese marketing research companies. The *i-SSP* consists of a purchase scan panel data set (*SCI*) and log data of mobile/PC media contacts. These are linked by the same individual monitor ID as the key. The subjects of the panel are sampled by assigning gender, age and area to comply with the composition of the Internet user population, assuring market representation. A total of 2595 individuals (males and females) between the ages of 15 and 69 living in Japan were collected, and the data period was the six months between April 1, 2016, and September 30, 2016 (183 days).

The *SCI* contains behavioral data retrieved by panel monitors who record the products purchased by using barcode scanners. We used all the data on the products from the following categories in the *SCI*: groceries (staple foods, seasonings, and processed foods, but not including fresh fish, vegetables, or prepared box lunches), beverages (milk-based drinks, soft drinks, and alcohol), sundries (household goods, paper goods, personal care items, baby-related goods, and pet-related goods), cosmetics, and drugs. The mobile/PC data were retrieved automatically as log data that supplement monitors' behavior constantly via an application in the installed monitors' terminals. Psychological attributes were obtained by carrying out an online survey to the monitors in October 2016.

3.2. Definition and measurement of the covariates

This section describes the variables used in this study. First, purchase frequency in bricks-and-mortar stores (i.e., supermarkets, convenience stores, drugstores, department stores, and specialty stores) and online stores (i.e., Internet supermarkets, e-commerce sites, and direct sales sites of brands) was used as the indicator of the purchase channel. Purchase frequency was calculated as the number of purchase days in these stores, during the study period. In the context of RFM analysis, there are monetary values and recency besides purchase frequency. In our research, we adopt purchase frequency to give a clear definition to capture purchase channel usage because we deal with the general purchasing behavior of low-involvement, more frequently purchased categories including products of various price ranges. When dealing with purchasing behavior of a specific firm or category in the future, it would be meaningful to extend variables such as monetary values. Second, media usage duration was used as the indicator of media touchpoints. Media usage duration was calculated as the average daily usage of mobile and PC (minutes). Social media included Facebook, Twitter, Instagram, and Mixi, which are most often used in the Japanese market. Regardless of whether these sites were accessed via applications on mobile devices or PCs, we categorized their usage duration as time spent on social media.

As demographics, we used gender, age, marital status, number of family members, number of children, education, and household income. Gender and marital status were expressed by dummy variables where 1 represented "male" and "married," respectively. Age and income were expressed by categorical variables. Number of family members, number of children, and education (the term of study) were expressed by continuous variables. Table 3 presents the summary statistics in demographic covariates.

To create the psychographic variables, we surveyed the panel monitors by using the same questionnaire used by Konus et al. (2008) (see Table 4). Measurements were obtained by using a 5-point Likert scale (1 = fully disagree; 5 = fully agree). The results of the reliability analysis showed that the Cronbach's alpha values for the multi-item scales were all greater than 0.7 except for motivation to conform (Table 4). Nevertheless, although the value for motivation to conform was 0.63, it was still adopted in this study, following Konus et al. (2008) where the corresponding value was 0.64. Next, we carried out a principal component analysis on each of the questions making up the structural concept (Table 4). The principal component scores extracted were used as the psychographic covariates. These covariates are standardized as mean 1 and variance 0.

3.3. Latent-Class Cluster Analysis

This study employed the Latent-Class Cluster Analysis. In this model, shown in Eq. (1), the number of latent classes corresponding to purchase channels and media touchpoints was specified as K, and the effect of covariate z_i on the membership of each latent class was examined. As shown in Eq. (2), the multinomial logit model was used for the probability of segment membership. Therefore, it is called a latent class multinomial logit model. This is a common method often used in past segmentation studies that have captured segmentation and its covariates (Gupta and Chintagunta, 1994; Bhatnagar and Ghose, 2004; Konus et al., 2008). We used Latent GOLD 5.1 software for the analysis (Vermunt, 2010; Vermunt and Magidson, 2013).

The purchase days used in this study had a discrete value, whereas the media usage duration had a continuous value. Hence, a Poisson distribution was employed to handle the number of times events emerged within the observed period, such as the number of uses of purchase channels. Therefore, this study used a mixed distribution, setting a Poisson distribution for g_1, g_2 and a normal distribution for g_3, g_4, g_5. Note that in the latent class model, the sum of the probability of segment memberships π_m becomes 1, as shown in Eq. (3).

The advantage of this method is to indicate a segmentation structure, based on channel utilities, and the impact of active or potential covariates on multichannel orientation (Konus et al., 2008). On the contrary, the setting of this model focuses on the channel usage of customers during the analysis period, and does not take into consideration any change in customers' preferences. However, in the

Table 4
Results of the principal component analysis and reliability analysis.

	Innovativeness	Loyalty	Motivation to conform	Shopping enjoyment	Time Pressure	Price consciousness	Reliability (C. Alpha)
I am one of those people who try a new product firstly just after launch.	0.81						0.77
I like to try new and different products.	0.80						
I always have the newest gadgets.	0.75						
I find it boring to use the same product (for brand) repetitively.	0.67						
I regularly purchase different variants of a product just for change.	0.58						
I have favorite brands that I keep buying frequently.		0.77					0.74
The brand of the product is important for me in my purchase decisions.		0.73					
I generally purchase the same brands.		0.70					
The place where I do my shopping is very important to me.		0.69					
I generally do my shopping in the same way.		0.61					
I find it very boring when other people criticize my behavior.			0.79				0.63
Being accepted by other people is very important to me.			0.73				
I like to have some problems that I can solve without much thinking.			0.70				
I like shopping.				0.87			0.81
I like shopping for groceries and commodity goods.				0.86			
I take my time when I shop.				0.83			
I am always busy.					0.92		0.81
I usually find myself pressed for time.					0.92		
I compare the prices of various products before I make choice.						0.86	0.76
It is important for me to have the best price for the product.						0.84	

context of marketing automation, which is the purpose of using this segmentation, it is necessary to change marketing actions according to a customer's circumstances (Jarvinen and Taiminen, 2016). Hence, we use a short analysis period (six months from the time of conducting the survey) and this preference is not easily changed.

$$f(U_{ic}|z_i) = \sum_{m=1}^{K} \left[\prod_{c=1}^{4} g_c(U_{ic}|z_i, s_i) \right] p(s_i = m|z_i) \tag{1}$$

$$p(s_i = m|z_i) = \frac{\exp(z_i{}'\gamma_m)}{\sum_{l=1}^{K} \exp(z_i{}'\gamma_l)} \tag{2}$$

$$\sum_{m=1}^{K} \pi_m = \sum_{m=1}^{K} \left[\prod_{c=1}^{4} g(U_{ic}|z_i, s_i) \right] = 1 \tag{3}$$

U_{ic}	Customer i's perceived utility of purchase channel and media touch points c. c = {1:store purchase, 2:online purchase, 3:mobile usage, 4:PC usage, 5:social media usage}
s_i	Indicator of customer i's segment, equal to 1,2,…,K, where K is the number of segments.
z_i	Customer i's covariate vector of the psychographic and demographic.
$f(U_{ic}\|z_i)$	Probability distribution for customer i's perceived utility of purchase channel and media touch points c, given the customer's antecedent variables.
$g(U_{ic}\|z_i, s_i)$	Probability distribution for customer i's perceived utility of purchase channel and media touch points c, given the customer's antecedent variables and given that the customer is in segment s_i.
$p(s_i = m\|z_i)$	Probability that customer i is in segment m, given the customer's antecedent variables.

4. Results

4.1. Multichannel customer segmentation

Table 5 shows the log-likelihood statistics for model selection including the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and the Consistent Akaike Information Criterion (CAIC). We obtained the minimum BIC value and CAIC value for the seven-cluster model, while the AIC value was minimized in the nine-cluster model. The BIC is considered to be more effective than the AIC for Latent-Class Cluster Analysis because it performs consistently well, while the AIC overestimates the correct number of components (Vermunt and Magidson, 2013; Collins and Lanza, 2009; Provencher and Bishop, 2004). Therefore, we selected the seven-cluster model as the best model from the perspective of the BIC and CAIC.

Table 6 shows the cluster profiles of purchase days and media usage

Table 5
Log-likelihood statistics for model selection.

		LL	AIC	BIC	CAIC
Model 1	1-Cluster	− 5588.7	11,205.4	11,287.5	11301.5
Model 2	2-Cluster	− 5056.1	10,184.2	10,395.3	10,431.3
Model 3	3-Cluster	− 4676.6	9469.1	9809.1	9867.1
Model 4	4-Cluster	− 4393.8	8947.5	9416.4	9496.4
Model 5	5-Cluster	− 4185.4	8574.9	9172.8	9274.8
Model 6	6-Cluster	− 4061.6	8371.1	9097.9	9221.9
Model 7	**7-Cluster**	**− 3957.7**	8207.5	**9063.2**	**9209.2**
Model 8	8-Cluster	− 3894.3	8124.5	9109.2	9277.2
Model 9	9-Cluster	− 3858.2	**8096.5**	9210.1	9400.1

Table 6
Cluster profiles of purchase days and media usage duration for each cluster (n = 2595).

		Cluster1 21.3%	Cluster2 19.0%	Cluster3 15.7%	Cluster4 15.7%	Cluster5 15.4%	Cluster6 6.5%	Cluster7 6.4%	The Overall Mean 100.0%
Purchase channels	Store	**101.3**	58.2	71.1	**143.2**	27.9	58.7	**123.8**	82.3
	Online	1.1	0.9	0.7	0.4	0.8	**16.5**	**11.8**	2.5
Media touchpoints	Mobile	137.8	139.2	**223.8**	**176.5**	164.1	148.0	**176.2**	164.8
	PC	55.5	46.7	**130.5**	**102.0**	80.3	**90.2**	**99.5**	81.8
	Social Media	2.9	2.4	**58.3**	**19.1**	18.4	12.1	**27.3**	18.6

These are the total number of purchase days during the six months and the average number of minutes of media usage per day.
The values in bold font are higher than the overall average.

duration. In terms of purchase channel preferences, we grouped customers into store-focused customers, uninvolved shoppers, and multichannel enthusiasts, following Konus et al. (2008). The final clusters were obtained by further classification into subgroups based on their level of media usage. Cluster 5 is the only one that can be categorized as uninvolved shoppers (15.4%) with a low frequency of purchase channel use. The media usage of uninvolved shoppers was close to the overall mean. Clusters 1–4 can be categorized as store-focused customers who use bricks-and-mortar stores often. Clusters 1 and 2 are "anti-digital" customers who have a media usage below the overall mean. Therefore, we named cluster 1 (21.3%) store-focused/anti-digital customers and cluster 2 (19.0%) store-focused light/anti-digital customers. Clusters 3 and 4 comprise multimedia customers whose media usage is above the overall mean. Cluster 3 has the highest usage of all the media among all segments, and they also used social media for almost one hour per day. Thus, we named cluster 3 (15.7%) store-focused light/multimedia social customers. Media usage by cluster 4 was found to be lower than that by cluster 3, but it was higher than the overall mean in all media. We named cluster 4 (15.7%) store-focused/multimedia social customers. Clusters 6 and 7 can be considered to be multichannel enthusiasts who purchase from both bricks-and-mortar and online stores. The online store usage frequency of cluster 6 was the highest among all segments, exceeding six times the overall mean. Further, their PC usage was above the overall mean, although their usage of mobile and social media was lower than the overall mean. We named cluster 6 (6.5%) online-favored multichannel enthusiasts/PC customers. The bricks-and-mortar store usage frequency of cluster 7 was 1.5 times the overall mean, and their online store usage frequency was also 4.7 times the overall mean. Their usage of all media was higher than the overall mean. We named cluster 7 (6.4%) store-favored multichannel enthusiasts/multimedia social customers. Table 7 summarizes the cluster names.

Next, we discuss the cluster composition ratios. The results of the research by Konus et al. (2008) showed 23% store-focused customers, 40% uninvolved shoppers, and 37% multichannel enthusiasts; however, in our study, there were 72% store-focused customers, 15% uninvolved shoppers, and 13% multichannel enthusiasts. This difference in cluster composition ratios is related to the different product categories examined. Konus et al. (2008) studied high-priced specialty products, while we studied groceries and sundries. According to the results of the e-Commerce Market Survey 2015 conducted by the Japanese Ministry of Economy, Trade and Industry, the percentage shares of e-commerce in the market scale, are 2% for groceries and 4% for sundries, which are lower than those for household appliances (28%), clothing (9%) and books (22%). Because groceries and sundries are consumed daily and have low e-commerce ratios, our results may therefore be valid. Indeed, it is natural to have more store-focused customers and fewer multichannel enthusiasts compared with high-priced specialty products.

Table 7
Cluster names.

	Purchase channels	Media touchpoints
Cluster1	Store-focused customers	Anti-digital
Cluster2	Store-focused Light customers	Anti-digital
Cluster3	Store-focused Light customers	Multimedia/social
Cluster4	Store-focused customers	Multimedia
Cluster5	Uninvolved shoppers	Average
Cluster6	Online-favored multichannel enthusiasts	PC
Cluster7	Store-favored multichannel enthusiasts	Multimedia/social

Further, clusters 3 and 4 are close to the research shoppers identified by Sands et al. (2016). Research shoppers actively gather information online, but make purchases in bricks-and-mortar stores. In addition, Sands et al. (2016) identified *Internet-focused/anti-mobile customers*, who actively purchase online, but do not use mobile devices to search for information. Cluster 6 is close to this segment, as these customers mainly use PCs when making online purchases.

4.2. Interpretation of the covariates

Table 8 shows the results of the psychographic and demographic covariates. The results show the impact of each of the covariates on segment membership. A strong positive coefficient means that customers with a high score in that covariate would be more likely to appear in that segment. A large (magnitude) negative coefficient means that customers would not be likely to be in that segment.

According to the entire model, significant psychographic covariates are innovativeness ($p < 0.01$), time pressure ($p < 0.05$), and loyalty ($p < 0.10$). Significant demographic covariates are gender, age, household income ($p < 0.01$), and number of children ($p < 0.05$). On the contrary, the psychographic covariates of motivation to conform, shopping enjoyment, and price consciousness, and the demographic covariates of marital status and education are not significant.

Turning to the results by cluster, shoppers in cluster 5 (uninvolved shoppers) are young married males with many family members and a low income. They have low tendencies towards innovativeness, shopping enjoyment, and loyalty. Konus et al. (2008) suggested that uninvolved shoppers have low loyalty and low shopping enjoyment, which were also observed in this study. Shoppers in cluster 1 (store-focused/anti-digital customers) are elderly females with many children and medium incomes. Shoppers in cluster 2 (store-focused light/anti-digital customers) are married males with medium income. However, their psychographic covariates do not have a strong influence. Shoppers in cluster3 (store-focused light/multimedia social customers) are young females with a relatively large number of children, and there is bipolarization of income from low to relatively high (7.00–8.99 million yen). They have high motivation to conform and a low tendency to loyalty and time pressure. They use social media often, and it is assumed that they are opinion-seekers who tend to follow the opinions of others. Shoppers in cluster 4 (store-focused/multimedia customers) are middle-aged males with a relatively large family size and low income. They are innovative, but do not have time to spare, and have low price consciousness. This resembles the research shopper who often uses mobile devices and social media identified by Sands et al. (2016) in terms of gender and age. They have high innovativeness and low time pressure as well as low price consciousness. Shoppers in cluster 6

Table 8
Parameter estimates.

	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7	Wald	p-value
Intercept	**0.427**	**0.837**	− 0.075	**− 0.818**	**− 1.442**	**0.358**	**0.714**	15.36	**0.02**
Innovativeness	0.008	− 0.082	− 0.076	**0.106**	**− 0.189**	0.013	**0.220**	22.44	**0.00**
Loyalty	0.020	− 0.067	**− 0.120**	− 0.025	− 0.098	**0.126**	**0.164**	11.37	**0.08**
Motivation to conform	0.014	− 0.005	**0.101**	0.027	0.035	− 0.009	**− 0.163**	5.17	0.52
Shopping enjoyment	0.059	− 0.061	− 0.024	0.031	− 0.095	− 0.077	**0.167**	6.68	0.35
Time pressure	0.034	0.041	**− 0.117**	**0.137**	0.085	− 0.078	**− 0.103**	13.52	**0.04**
Price consciousness	0.018	− 0.016	0.019	**− 0.141**	− 0.022	**0.101**	0.041	6.15	0.41
Gender(male)	**− 0.171**	**0.164**	**− 0.105**	**0.826**	**0.754**	**− 0.998**	**− 0.469**	110.94	**0.00**
Age									
15–24 years	**− 0.131**	− 0.003	**1.163**	**− 0.648**	**1.390**	**− 0.110**	**− 1.662**	163.00	**0.00**
25–34 years	**− 0.158**	0.094	**0.192**	**0.138**	**0.369**	**− 0.538**	− 0.098		
35–44 years	**− 0.163**	0.068	**− 0.130**	0.094	**− 0.221**	− 0.018	**0.370**		
45–54 years	0.067	**− 0.142**	**− 0.400**	**0.482**	**− 0.809**	**0.152**	**0.650**		
55–69 years	**0.386**	− 0.018	**− 0.825**	− 0.066	**− 0.730**	**0.514**	**0.739**		
Marital status(married)	0.079	**0.295**	0.017	**− 0.277**	**0.111**	**− 0.155**	− 0.070	9.59	0.14
Number of family members	0.025	− 0.008	− 0.001	**0.175**	**0.269**	**− 0.271**	**− 0.188**	33.81	**0.00**
Number of children	**0.198**	0.011	**0.103**	**− 0.103**	**− 0.154**	**0.130**	**− 0.185**	13.46	**0.04**
Education	0.003	− 0.042	0.036	0.010	0.046	0.016	− 0.069	6.98	0.32
Household income (million yen)									
less than 3.99	− 0.013	0.039	**0.221**	**0.161**	0.014	**− 0.490**	0.069	51.52	**0.00**
4.00–5.49	− 0.016	**0.118**	**− 0.249**	**0.337**	**0.155**	**0.205**	**− 0.550**		
5.50–6.99	**0.115**	0.060	0.007	− 0.050	− 0.018	0.081	**− 0.195**		
7.00–8.99	0.026	− 0.097	**0.105**	− 0.054	**− 0.112**	**− 0.121**	**0.253**		
More than 9.00	**− 0.112**	**− 0.119**	− 0.084	**− 0.394**	− 0.039	**0.324**	**0.423**		

Coefficient values exceeding +/−0.1 are shown in bold font.

(online-favored multichannel enthusiasts/PC) are elderly females with a large number of children, with a bipolarization of income from low to high, with high loyalty and price consciousness. They use PCs to search for good-quality products at low prices online. This cluster resembles the tendencies of Internet-focused/anti-mobile customers identified by Sands et al. (2016) in terms of gender, age, and high price consciousness. Shoppers in cluster 7 (store-favored multichannel enthusiasts/multimedia social) are middle-aged to elderly females with high incomes and tend to have a small family and few children. They have high innovativeness, loyalty, and shopping enjoyment. They have a relative surplus of time, with low opinion-seeking tendencies. It is conceivable that they have their own sense of value and that they are multichannel customers with abundant information contacts. Konus et al. (2008) demonstrated that multichannel enthusiasts have innovativeness and shopping enjoyment. This study obtained similar findings in cluster 7. On the contrary, the results indicated that multichannel enthusiasts who prefer online purchasing, have low innovativeness tendencies (see cluster 6).

Research shoppers were divided into the “opinion-seeking type” (cluster 3) and “time-constrained type” (cluster 4) according to those characteristics. Opinion-seeking types make active use of social media, tend to follow the opinions of others, and have low loyalty tendencies. They are also influenced by others. On the contrary, time-constrained types are innovative, do not have time to spare, and have low price consciousness. It is inferred that in addition to feeling that collecting information in bricks-and-mortar stores is a chore, these people take advantage of the Internet, where it is easier to obtain information (Verhoef et al., 2007).

Among multichannel enthusiasts, we discovered the “price-conscious type” (cluster 6) and the “innovator type” (cluster 7). Price-conscious types use PCs to carefully select good-quality yet inexpensive products and employ multiple channels to make purchases. Because it is possible to provide an abundance of product information on PC websites, firms can attract these people by creating websites that focus on high quality. Meanwhile, innovator types actively use mobile/social media and seek shopping enjoyment. Further, they have low opinion-seeking tendencies. They can judge information by their own sense of value, making it possible to tell that they are people who influence others. We believe that there are advantages to providing information to them via mobile devices and by short messages on social networks, which motivates them intuitively.

Moreover, we assume that shoppers in cluster 6 have a cannibalization tendency between the online and offline purchase channels, while shoppers in cluster 7 have a synergy tendency. While the online purchase frequency in cluster 6 is the highest among all segments, the total purchase frequency in cluster 6 is lower at 75.2 (see Table 6). The total purchase frequency in cluster 7 is 135.6, which is the second highest among all segments. We found that multichannel enthusiasts of the “price-conscious type” (cluster 6) find it easier to focus on online purchasing, whereas the “innovator type” (cluster 7) uses a combination of both online and offline purchasing channels.

5. Contributions and implications

5.1. Theoretical contributions

This study provided customer segmentation by using Latent-Class Cluster Analysis and focusing on purchase channels and media touchpoints. Further, we identified the psychographic and demographic covariates that impact segment membership. We discuss the theoretical implication of our findings below.

5.1.1. Comparisons of segments based on actual behavioral data with past studies

The segmentation based on actual behavioral data in this study has provided results that support the findings from past studies. With regard to the concept of segmentation results, the seven segments obtained in this study are classified into three, just as in Konus et al. (2008) (more precisely, into four store-focused customer segments, one uninvolved shopper segment, and two multichannel enthusiast segments). Furthermore, with regard to media touchpoints, as in the case of Sands et al. (2016), we identified two research shopper segments that used many online information contacts but made actual purchases in bricks-and-mortar stores. Additionally, we obtained findings that are consistent with previous studies with regard to the individual differences between these segments. More concretely, we found among multichannel enthusiasts those with high innovativeness and who seek pleasant shopping experiences (Konus et al., 2008; Wang et al., 2014).

We also found an anti-mobile segment that uses online purchase channels frequently (Sands et al., 2016). Moreover, we found that customers who use PCs relatively more frequently have high price consciousness. These findings can be generalized to conclude that, in multichannel customer segmentation, it is effective to take into consideration (1) the differentiation of purchase stages and (2) device/media characteristics such as PCs, mobile, and social media.

On the contrary, the segmentation of actual behavioral data showed some differences compared with the results of past segmentation studies based on survey data on brand/store loyalty factors. This study found that multichannel customers tend to maintain a high level of loyalty, while single channel customers maintain a low level. This is the opposite finding to that of Konus et al. (2008), which showed that single channel customers (especially store-focused customers) have high loyalty. With regard to the low involvement categories that this study investigated such as groceries and sundries, in which repeat and multi-category purchases take place, previous studies have found that most shoppers tend to revisit the same stores to reduce in-store search and effort costs (Briesch et al., 2009). By contrast, Melis et al. (2015), a recent study based on actual behavioral data, focused on customer experience and behavioral loyalty (Guadagni and Little, 2008), suggesting that when gaining more online buying experience, satisfied online shoppers may develop loyalty to the online store. In this study, the accumulated frequency of purchase channel use is treated as variables of segmentation, which shows the degree to which the experience of using each channel is accumulated. Our study's findings suggest that among those with considerable experience of using online channels, customers have not only high behavioral loyalty but also high psychological loyalty to the brand or store.

5.1.2. Types of customers among segments in terms of their psychographic and demographic characteristics

This study provided a finding on the individual differences that emerge when aiming at synergy between purchase and communication channels. It identified individual characteristics that influence those who use different channels for purchase and information search (especially research shoppers who research online and purchase offline). The first customer type is the time-constrained type. These customers tend to dislike transaction costs in terms of delivery time (Chintagunta et al., 2012). On the contrary, because they have innovativeness and low price consciousness and use multimedia, digital communication easily reaches out to them. For those customers, it is effective to carry out promotional activities to invite them to the physical store. Another customer type is the opinion-seeking type. The opinion-seeking type makes active use of social media, tends to follow the opinions of others, and has low loyalty tendencies. In the context of studying the effects of social media, such types are seen as those with a willingness to share knowledge (Rezaei and Ismail, 2014; Zhang et al., 2013). This study's results support previous research showing that customers motivated by social interactions prefer to shop in physical stores as opposed to online (Rohm and Swaminathan, 2004). To satisfy them, it is essential to reflect a good reputation on social media during the information search phase; it is also important for the physical stores to raise the service quality offered by shop attendants. However, because these customers' loyalty is low, they do not necessarily offer a high monetary value to the retailer or manufacturer.

Our study also yielded findings about multichannel customers and their device characteristics. In the device marketing research literature, the value of mobile devices is related to entertainment/hedonic value and efficiency, whereas the value of PCs is related to informativeness (Strom et al., 2014). We found that innovative multichannel consumers seeking pleasure in shopping find it easy to access all media including mobile and social media. In addition, price-conscious multichannel consumers find it easy to use PCs relatively more frequently.

5.1.3. Connection of purchase channels with information search device/media for possible synergies

We summarize the implications of the synergies from two perspectives. First is the synergies between the online and offline purchase channels. We found that for price-conscious online-favored multichannel customers, there is possible cannibalism, as the usage of offline channels decreases as the amount of online channel usage increases. These tendencies are called the “channel lock-in” (Verhoef et al., 2007). In addition to past research, this study suggests that the price sensitiveness characteristics and PC device usage of multichannel customers are involved in the lock-in of online purchasing channel. On the contrary, we found possible synergies between purchase channels for innovator type offline-favored multichannel customers. We assume that “experiential capabilities” (Avery et al., 2012) involved. Since these shoppers have innovativeness and shopping enjoyment and multimedia/social tendencies, both online and offline channels are mutually used to suit the purchase setting.

The second is the synergies between purchase channels and media touchpoints. Synergies derive from the similarity between channels and complementarity derives from the heterogeneity (Avery et al., 2007). In addition, customers' capabilities in each channel are related to their technology acceptance (Wagner et al., 2013). In terms of similarity based on the segments of multichannel customers, PCs can accelerate the search online to purchase online behavior if sufficient information (including price) is provided to customers on websites. Mobile and social media also have the potential for search online to purchase online for innovative customers. These device/ media characteristics lead to synergies for multichannel environments. However, in terms of heterogeneity based on the segments of research shoppers, we found mobile and social media to be used by search online to purchase offline behavior in relation to customers' time resource and opinion-seeking tendencies. We conclude that mobile and social media are also important elements to increase sales in physical stores.

5.2. Managerial implications

Our study yields managerial implications that can be used when designing customer strategies in modern marketing environment.

First, because this study's segmentation is based on actual behavioral data, it has high affinity with digital marketing. More and more actual behavioral data are being accumulated in a firm's integrated databases. The segmentation scheme adopted in this study can be directly used (e.g., the distribution of digital advertisements). This scheme can also accelerate marketing automation, which is the important for firms' data utilization (Jarvinen and Taiminen, 2016). Firm will further be able to design strategies according to the segment's characteristics by creating segments based on behavioral data and interpreting psychological characteristics using survey data.

Second, the key points for the practical application to the firm's customer management are 1) to understand who are “the people who judge information by their own standards” and who are “the people influenced by others” and 2) to consider how to present information on media and devices. Innovator type multichannel enthusiasts correspond to people who judge information, and it is thus critical to acquire this type of customer. These customers become a hub. If they also post good evaluations such as online reviews, it becomes possible to attract research shoppers (in particular, the opinion-seeking type). Moreover, for devices and media, it is necessary to understand the characteristics of PCs and mobile channels. An important finding of our study is therefore that although mobile usage has been growing in the modern media environment, a constant number of price-conscious multichannel enthusiasts exist, who carefully research a wealth of information on PCs. However, one cannot overlook innovator type multichannel enthusiasts, for whom mobile promotions are suitable. It is thus necessary to first understand the target customers, and then tailor the quality of information on the media and devices to be used.

5.3. Limitations and future research

The limitations of this study suggest future research challenges. This study's segmentation considered the entire picture of purchase channel usage and media touchpoints; however, it is necessary to refine the media touchpoint side in the future. The media touchpoints handled in this study were the usage of PCs, mobile, and social media. The limitation is that these media touchpoints were not associated with product categories. When a model is built based on behavior logs, it is extremely difficult to associate all the countless websites and apps that exist globally with product categories. This issue does not occur with models based on self-reported surveys. These circumstances call for a method for aggregating websites and app groups that purchasers of a certain product category are likely to visit. Once such a method exists, it would be necessary to revisit the framework of this study by category. However, the overall picture that emerged in this study remains useful as a context for consumer behavior when analyzed in more detail.

Furthermore, it is necessary to perform customer segmentation in other countries as well. This study performed its analysis for the Japanese market; however, if a validating analysis were to be carried out in other countries with different purchasing, media, and socio-economic environments, it would be necessary to confirm whether different influencing covariates would surface.

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