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Abstract

With changes in the retail environment due to the development of digital devices and social media, customers can easily obtain appropriate information and purchase products from stores or online, which enables marketers to improve access to their customers. The key issue for designing effective multichannel strategies can be to understand customers' purchase channels and media touchpoints simultaneously under such environment and to provide more seamless connections between advertisement targeting and promotion.

This study provides customer segmentation using Latent-Class Cluster Analysis, which focuses on the purchase channels of bricks-and-mortar stores and online, and the media touchpoints of PC, mobile and social media as well as psychographic and demographic characteristics. This study extends the framework of prior studies from an empirical perspective through 1) providing a behavioral data based approach by using single source panel data, and 2) analyzing uninvestigated products of low-involvement, more frequent purchased category.

The analyses of Japanese panel data revealed seven segments composed of four store-focused customers including two research shoppers, one uninvolved shoppers and two multichannel enthusiasts. The results suggest that differences in psychographics divide the research shoppers into the opinion-seeking type and the time-constrained type. Similarly, the multichannel enthusiasts segment is divided into the price-conscious type who purchased more at online stores using PCs, and the innovator type who shopped with enjoyment using all media actively.

Keywords

Multichannel, Shopping behavior, Segmentation, Latent-Class Cluster Analysis, Single Source Panel Data

1. Introduction

There are many opportunities for customers to shop through a variety of channels owing to developments in digital media in the past ten years. In multichannel, multimedia retailing environments, customers can easily obtain appropriate information and purchase products from stores or online. Under these circumstances, individual differences in purchasing behavior and information search routes are widening due to the diversification of lifestyles and IT literacy levels. On the other hand, for firms, the recent digitalization of marketing is a big change (Leeflang et al., 2014). The firms that take advantage of mobile and social media for promotions to target individual customers are increasing. In this marketing environment, it is useless to capture customer behavior on average. Neslin and Shanker (2009) addressed the issue of "how firms should segment customers in a multichannel environment" and that is more important now

As the digitalization of marketing evolves, an important challenge is the integration of purchase channels and media touchpoints seamlessly. Purchase channel refers to the place where a product is purchased. Purchase channels such as a bricks-and-mortar store or online are influenced by the kind of media touchpoints the everyday customer uses. In an environment where it is easy to approach individual customers digitally, it is possible for firms

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to implement media advertising plans to easily target and reach customers by their purchasing habits and information consumption patterns. Concerning multichannel, multimedia environments, Dholakia et al. (2010) stated that “It is important to understand how customers utilize the multiple media and channels available to them, manage their complementarities and conflicts, and come to rely on particular media and channels.” For example, it is easy to imagine that a person who almost never uses digital devices would have a hard time purchasing products online. If it is possible for a firm to understand customer characteristics in purchase channels and media touchpoints, it will then grasp the fundamental parts of a customer's activity style, which is a prerequisite to developing policies for individual brands and stores. Hence, it is very important in terms of marketing activities.

Under these conditions, customer segmentation is an effective way for planning channel strategies (Neslin et al., 2006). Konus et al. (2008) presented a clear case study for multichannel customer segmentation and showed its managerial value. They proposed a Latent-Class Cluster Analysis framework that classifies customers based on channel preferences in the stages of information search and purchase, and explain the segments from both a psychographic and demographic perspective. Their analysis, which uses online survey data, resulted in three segments of customers—multichannel enthusiasts, uninvolved shoppers, and store-focused customers. The segmentation framework of Konus et al. (2008) was later refined in several ways by other researchers. For instance, Wang et al. (2014) hypothesized that the effect of psychographic and demographic covariates was different when searching for information and making purchases. Keyser et al. (2015) and Sands et al. (2016) considered the after-purchase process. 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 taking into account the research shopper, who researched online and purchased offline (Verhoef et al., 2007), and differentiated segments by mobile and social media usage.

However, there are certain limitations to these studies because the results are based on self-reported surveys. Attitudes reported in self-reported surveys do not necessarily match actual behavior (cf. Presser, 1990; Prior, 2009). The problem of common method bias pertaining to survey data has been pointed out, and additional validation based on behavioral and longitudinal data has been recommended as a future study issue (Konus et al., 2008; Wang et al., 2014). Considering the recent data utilization environment, the processes of collecting behavior logs and then turning these data into single source data linked to each individual, have evolved rapidly (Taneja and Mamoria, 2012). Single source panel is an example, in which survey monitors collect media contact logs at the same time as they collect purchase scan panel data. The advantages of single source panel are that they capture customers on a behavioral basis as well as at an individual level. In addition, because it is longitudinal panel data, it can capture the entire picture of a market, including competitive products. Furthermore, the findings obtained from the behavioral data are suitable for digital marketing. Targeting methods are incorporated directly into the behavioral history data existing on the data management platform and the findings can also be applied to marketing actions. In this context, this study proposes new segmentations using single source panel data.

We focus, also, on product categories that have not been studied in our analysis. Past studies on multichannel customer segmentation analyzed high involvement products such as clothing, electronics, holiday travel, computers, books, mortgages, and insurance. 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 the low involvement, more frequently purchased categories such as groceries, cosmetics, and sundries. In fact, in the Japanese market, according to the results released by a 2015 Ministry of Economy, Trade and Industry survey[1)], the online purchase rate of growth from the previous year, in descending order, were as follows: groceries, beverages/alcoholic beverages, clothing/accessories, office supplies/stationery, and cosmetics/drugs. Accumulation of knowledge on low involvement, more frequently purchased categories is a challenge under this changing business environment (Sands et al., 2016), and this study focuses on these categories for analysis.

This study proposes a customer segmentation method that focuses on purchase channels and media touchpoints. We assess types of purchasing channels—bricks-and-mortar stores and online stores—and three types of media touchpoints used for information search—mobile, PC, and social media. This research extends frameworks proposed by previous research from two viewpoints. The first is to propose a behavior-based segmentation method using single source panel data. The second is to validate the method with the low involvement, more frequently purchased category. In addition, this study deals with a Japanese market whose segmentation in this kind has never been conducted. Therefore, the objectives of this study are to answer the following questions: (1) How can customers be classified on the basis of purchase channel usage and media touchpoints? (2) What is the relationship between customer's psychographic and demographic covariates and segment membership?

The organization of this paper is as follows: Section 2 presents a review of previous studies concerning multichannel customer segmentation. Section 3 outlines the concepts and methods of this study. Section 4 presents the analysis results, and Section 5 discusses and summarizes the results and raises issues for future study.

2. Multichannel Customer Segmentations

2.1 Literature Reviews

In prior empirical studies, a number of segments were identified for multichannel customers. These segments have a basis on preferred channels of shopping and clear definitions assigned. For example, Keen et al. (2004) derived four segments of *Generalists*, *Formatters*, *Price sensitives*, and *Experiencers*. *Generalists* are average people for whom psychographics and demographics do not really influence channel selection. *Formatters* only shop at bricks-and-mortar stores. *Price sensitives* tend to select low-price channels. *Experiencers* tend to select channels where they have had a satisfying experience in the past. Thomas and Sullivan (2005) used the corporate database of a U.S. retailer that operated through three channels (stores, online and catalogs) and identified two characteristic segments: 1) the catalog segment, and 2) the bricks-and-mortar segment. Further, Ganesh et al. (2010) derived a number of shopper types from their differences in motivation in relation to online or offline shopping.

However, most of the previous studies focused only on segmentation based on purchase channel preference. Stages in the purchasing process, such as the information search stage and the purchase stage, were not taken into account. To rectify this, Konus et al. (2008) proposed a method of customer segmentation using purchase channels (stores, online and catalogs) and purchase stages. They used Latent-Class Cluster Analysis, which can help identify segments and encompass psychographics and demographics that influence segment membership for segmentation. In their study, they surveyed Dutch customers regarding multichannel purchasing using stores, the Internet, and catalogs to purchase several product categories such as mortgage, health insurance, holidays, books, computers, electronics, and clothing. They identified three clear segments: 1) *Multichannel enthusiasts* who have a high tendency to use all channels and have a high level of innovativeness and shopping enjoyment; 2) *Store-focused customers* who have a high tendency to use stores and have a high level of brand and channel loyalty; and 3) *Uninvolved shoppers* who have a low tendency to use any channel and low purchasing involvement.

The concepts clarified by Konus et al. (2008) evoked a number of studies. Wang et al. (2014) extended the concepts by exploring the possibility of perceived values being different between the information search stage and the purchase stage. Their results indicate the existence of two segments: *innovative customers* and *conventional customers*, from the channel usage standpoint of online vs. offline. The results of their analysis were based on surveys of Chinese consumers that asked their preferences in apparel, computers, television sets, jewelry, toys, books, MP3/MP4 players, headphones, and cars. Keyser et al. (2015) surveyed information search, purchase, and after-sales preferences in stores, the Internet, and call center channels, with customers of a Dutch telecom retailer that sells mobile devices and their accessories. They included after-sales aspects in its scope. The results of the analysis revealed six segments: *Research shoppers after-sales-store*, *Web-focused shoppers*, *Store-focused shoppers*, *Research shoppers after sales-Internet/store*, *Web-focused shoppers after sales-store/call center*, and *Call center-prone shoppers*. Their major finding is the identification of research shoppers. Research shoppers are customers that use one channel for information search and a different channel when making purchases (Verhoef et al., 2007). A general pattern in this case would be to search for information on the web and then purchase at bricks-and-mortar stores. Verhoef et al. (2007) posited that there are three forces in the background of research shopping behavior. These are *attribute differences* (e.g., the web offers the convenience of flexible searches for a variety of information; bricks-and-mortar stores allow shoppers to actually see and feel the product, and their privacy is protected), *customer lock-in* (e.g., it is much easier to leave a website than to leave a store while being waited on by a salesperson), and *cross-channel synergy* (e.g., it is much easier to purchase a product in a store if you have already compared products online and decided which one to purchase). Sands et al. (2016) took media characteristic differences into account when classifying these research shoppers. They extended their scope of inquiry to the Internet, mobile, and social media contact behavior. They surveyed Australian customers on clothing, consumer electronics, and holiday travel. Their results identified two groups using two purchase channels, *the ROPO (Research Online, Purchase Offline) segment* and *the Internet-focused segment*. Furthermore, they demonstrated that each of these could be divided into five subgroups based on the differences in their media usage: *ROPO anti-mobile/social media*, *ROPO multichannel enthusiasts*, *ROPO social media enthusiasts*, *Internet-focused anti-mobile enthusiasts*, and *Internet-focused multichannel enthusiasts*.

Konus et al. (2008), in their initial research, took purchasing stages into account. However, their output was expressed in a way that depended on the number of channels; that is, the concern was about “Which channels are preferred?” and whether the preference is for “Single channel or multichannel?” Recent studies by Keyser et al. (2015) and Sands et al. (2016) identified people who use different channels for information search and for purchase as research shoppers. Moreover, Sands et al. (2016) demonstrated that suggested approaches to customers who obtain information from media channels that also include mobile and social media, can be segmented at the fine granular level.

2.2 Conceptual Framework

Figure 1 shows the conceptual framework for this study. This study uses single source panel data, where purchase scan panel data, media log data, and surveys are associated with the same ID to materialize this framework. The novelty of the present study is that it adopts the approach of integrating behavioral data and surveys.

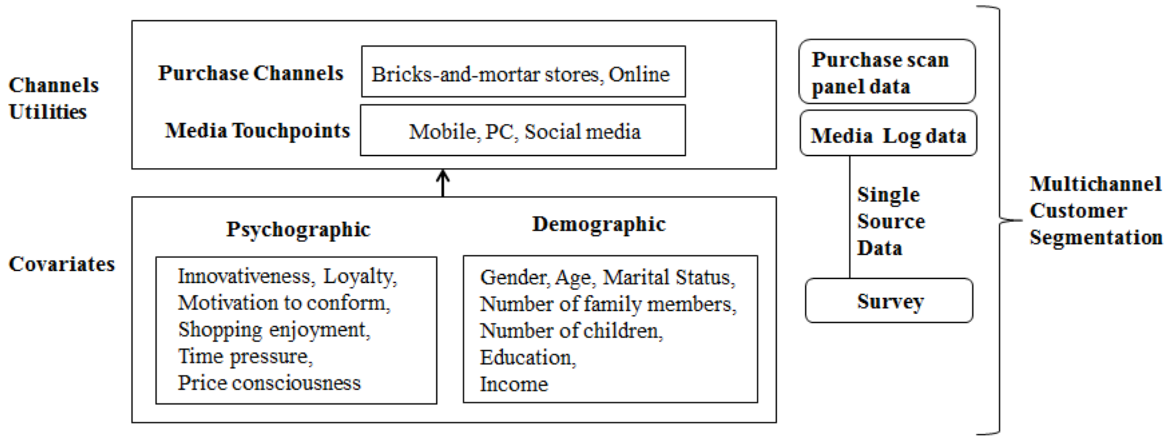

Figure1. Conceptual Framework

The proposed conceptual framework (Figure 1) assumes that the usage rate of purchase channels and media touchpoints depends on the channel utility that the customers obtain from purchasing and information contact. The considered purchase channels are bricks-and-mortar stores and online stores. The media touchpoints used in this study were mobile, PC, and social media similar to the study by Sands et al. (2016). The purchasing frequency at bricks-and-mortar stores and online stores corresponds to the purchasing phase in the purchasing behavior process, and the usage of mobile, PC, and social media to the information searching phase. In this study, to grasp the fundamental parts of a customer's activity style, for the purchase channel, we used overall purchase volume by each purchase channel in low involvement, more frequently purchased categories, and overall usage by each media for media touchpoints.

After segmenting the customers from channels utilities, we identify the psychographics and demographics 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, and 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 while making a purchase decision (Ailawadi et al., 2001; and 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. It is known that people who lack the 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 regarding the prices of products in particular channels, and this influences channel selection (Verhoef et al., 2007).

3. Method

3.1 Data collection

We used the single source panel data (*i-SSP*) obtained from Intage Inc.[2)], one of the largest Japanese marketing research companies. The *i-SSP* consists of a purchase scan panel data set called *SCI*, and log data of mobile/PC media contacts. These are linked with the same individual monitor ID as the key. The population of this panel is Internet users. Internet users cover 82% of the Japanese population in 2016, according to Intage Inc.'s survey[3)]. The subjects of the panel are sampled by assigning gender, age and area to comply with the composition of the Internet population, assuring market representation. A total of 2,595 individuals (males and females) between the ages of 15 and 69 living in Japan were collected, and the data period was six months between April 1, 2016, and September 30, 2016 (183 days).

The *SCI* contains behavioral data that were retrieved by panel monitors who record purchased products by barcode scanners that have been distributed to them. We use all products data of transected categories in *SCI* except perishable categories. Those are groceries (staple foods, seasonings, and processed foods, but did not include fresh fish, vegetables, or prepared box lunches), beverages (milk-based drinks, soft drinks, and alcohol), sundries (household good, paper goods, personal care items, baby-related goods, and pet-related goods), cosmetics, and drugs. The mobile/PC data are retrieved automatically as log data that supplement monitors' behavior constantly via an application in the installed monitors' terminals. Furthermore, psychological attributes are obtained by an online survey administered collaterally to the monitors in October 2016.

3.2 Definition and measurement of covariates

This section describes the variables used in this study in detail. First, purchase frequency in bricks-and-mortar stores and online stores is used as the indicator of purchase channels. Purchase frequency is the number of purchase days in bricks-and-mortar stores and online stores, respectively, during 183 days. The bricks-and-mortar store channel includes supermarkets, convenience stores and drugstores, department stores, and specialty stores. The online channel includes Internet supermarkets, e-Commerce sites, and direct sales sites of brands. Second, media usage duration is used as the indicator of media touchpoints. Media usage duration is the average number of daily usage duration (minutes) of mobile and PC. For the touchpoint of social media, media usage duration (minutes) is used as the indicator of social media touchpoints of 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 PC, we categorized their usage duration as time spent on social media.

For 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 represents “male” or “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.

To create psychographic variables, we first surveyed the panel monitors using a questionnaire same to the one used by Konus et al. (2008) (as detailed in Table 1). Measurements were obtained by using a 5-point Likert scale (1 = fully disagree; 5 = fully agree). The results of the reliability analysis showed that Cronbach’s alpha for multi-item scales were all greater than 0.7 except for motivation to conform (see Table 1). Although the value for “motivation to conform” was 0.63, it was adopted for this study, in the same way as the adoption by Konus et al. (2008) with the value of 0.64 for “motivation to conform.” Next, we carried out principal component analysis (PCA) on each of the questions making up the structural concept (see Table 1). The principal component scores extracted here were used as psychographic variables.

Table1. Results of principal components analysis and reliability analysis (psychographic variables)

	Innova- -tiveness	Loyalty	Motivation to conform	Shopping enjoyment	Time Pressure	Price con -sciousness	Reliability (C. Alpha)
I am one of those people who try a new product firstly just after launch.	0.81						
I like to try new and different products.	0.80						
I always have the newest gadgets.	0.75						0.77
I find it boring to use the same product (for brand) repetiively.	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					
The brand of the product is important for me in my purchase dicisions.		0.73					
I generally purchase the same brands.		0.70					0.74
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				
Being accepted by other people is very important to me.			0.73				0.63
I like to have some problems that I can solve without much thinking.			0.70				
I like shopping.				0.87			
I like shopping for groceries and commodity goods.				0.86			0.81
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	

3.3 Latent-Class Cluster Analysis

This study employed the same Latent-Class Cluster Analysis method as the one used by Konus et al. (2008) and Sands et al. (2016). In this model, as shown in Equation 1, the number of latent classes corresponding to purchase channels and media touchpoints was specified as K, and the effect covariate z_i on membership to each latent class is examined. As shown in Equation 2, the multinomial logit model was used for the probability of segment memberships. Therefore, it is called a latent-class multinomial logit model. This method is explained in detail in previous studies like Vermunt (2010), Collins and Lanza (2009), and Hagenaars and McCutcheon (2002). We used Latent GOLD 5.1 software for analysis (Vermunt, 2010; Vermunt and Magidson, 2013).

The purchase days used in this study had a discrete value, and the media usage duration had a continuous value. 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 employed a mixed distribution, setting a Poisson distribution for g_1, g_2 and setting 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 Equation 3.

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

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

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

U_{ic}	Customer *i*'s perceived utility of purchase channel and media touch points *c*. c={1:stores 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 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

This study used the Bayesian information criterion (BIC) for determining the number of segments. BIC is considered to be more effective than other information criteria (such as AIC) for Latent-Class Cluster Analysis (Vermunt and Magidson, 2013; Collins and Lanza, 2009). The results of log likelihood and BIC are shown in Table 2. We obtained a minimum value of BIC for the 7-cluster model, which was selected as the best model in this study.

Table2. BIC for each model

		LL	BIC
Model 1	1-Cluster	-5588.7	11287.5
Model 2	2-Cluster	-5056.1	10395.3
Model 3	3-Cluster	-4676.6	9809.1
Model 4	4-Cluster	-4393.8	9416.4
Model 5	5-Cluster	-4185.4	9172.8
Model 6	6-Cluster	-4061.6	9097.9
Model 7	**7-Cluster**	**-3957.7**	**9063.2**
Model 8	8-Cluster	-3894.3	9109.2
Model 9	9-Cluster	-3858.2	9210.1

Table3. 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
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.

Table 3 shows cluster profiles of purchase days and media usage duration. In terms of purchase channel preferences, we observed similar classifications by having groups of the store-focused customer, uninvolved shoppers, and multichannel enthusiasts proposed by Konus et al. (2008). The final clusters were obtained by further classifications into subgroups based on the level of their media usage. Cluster 5 is only one cluster that can be categorized as uninvolved shoppers (15.4%) with low frequency of purchase channel use. Media usage of uninvolved shoppers was close to the overall mean. Cluster 1, cluster 2, cluster 3, and cluster 4 can be categorized as store-focused customers who use bricks-and-mortar stores often. Cluster 1 and cluster 2 can be anti-digital customers who have less usage of any media than the overall mean in terms of the media usage level. Therefore, we named store-focused/anti-digital customers for cluster 1 (21.3%), and store-focused light/anti-digital customers for cluster 2 (19.0%). Cluster 3 and cluster 4 can be multimedia customers whose media usage is higher than the overall mean. Cluster 3 has the highest usage of all of the media among all segments, and they also used social media for almost one hour per day. We named store-focused light/multimedia social customers as cluster 3 (15.7%). Media usage by cluster 4 was found to be lower than that by cluster 3, but was higher than the overall mean in all media. We named store-focused/multimedia social customers as cluster 4 (15.7%). Cluster 6 and cluster 7 can be considered as multichannel enthusiasts who purchase from both bricks-and-mortar stores and online stores. The online store usage frequency of cluster6 was the highest among all segments, exceeding six times the overall mean. Further, their usage of PC was higher than the overall average, although their usage of mobile and social media was lower than the overall mean. We named cluster 6 as online-favored multichannel enthusiasts/PC customers (6.5%). 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 store-favored multichannel enthusiasts/multimedia social customers as cluster 7 (6.4%). The cluster names are summarized in Table 4.

Next, we discuss cluster composition ratios. Results of the research by Konus et al. (2008) showed 23% store-focused customers, 40% uninvolved shoppers, and 37% multichannel enthusiasts; however, our results indicated there were 72% store-focused customers, 15% uninvolved shoppers, and 13% multichannel enthusiasts. It can be surmised that the difference in cluster composition ratios is related to product categories. 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[1)], the EC ratio, which indicates the percentage share of e-Commerce in the market scale, was 2% for groceries and 4% for sundries, which is lower than household appliances (28%), clothing (9%) and books (22%). Because groceries and sundries are goods that are consumed daily and have low e-Commerce ratio categories, our results can be valid, so that it is natural to have more store-focused customers and less multichannel enthusiasts than those in the results for high-priced specialty products in the prior study.

Further, cluster 3 and cluster 4 are close to the research shopper identified by Sands et al. (2016) and Keyser et al. (2015). These research shoppers actively gather information online, but make purchases at bricks-and-mortar stores. In addition, Sands et al. (2016) identified *Internet-focused/anti-mobile customers*, who actively purchased online, but did not use mobile devices for information search. Cluster 6 is close to this segment. Cluster 6 customers mainly use PCs when making online purchases.

Table4. 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

4.2 Interpretation of the covariates

Table 5 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 other hand, the psychographic covariates—motivation to conform, shopping enjoyment, and price consciousness—, and the demographic covariates—marital status and education—are not significant.

Table5. Estimates of parameters

	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**
Inovativeness	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**		
Martial 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.

Next, let us look at 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, tendencies that are 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, 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 in an inverse U shape, 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 (online-favored multichannel enthusiasts/PC) are female, elderly, large number of children, with a bipolarization of income from low to high, with high loyalty and 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 females, middle-aged to elderly, with high incomes, and tend to have a small family size 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 also obtained similar findings in cluster7. On the other hand, the results indicated that the multichannel enthusiasts, in cluster6, who prefer online purchasing, have low innovativeness tendencies.

4.3 Practical implications

The segmentation in this study has reproducibility of prior studies, and at the same time, obtains deeper insights. This study discovered two subgroups in both the research shoppers and multichannel enthusiasts. Our findings have practical applications for these segments as marketing targets.

Research shoppers were divided into “opinion-seeking type” (cluster 3) and “time-constrained type” (cluster 4) according to those characteristics. The opinion-seeking types make active use of social media, tend to follow the opinions of others, and have low-loyalty tendencies. They are influenced by others. On the other hand, the time-constrained types have innovativeness, do not have time to spare, and have low price consciousness. It is inferred that in addition to feeling that collecting information at bricks-and-mortar stores is a chore, these people are taking 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). The price-conscious types use PCs to carefully select good-quality products and inexpensive products and employ multiple channels to make purchases. In addition, because they have loyalty, it is surmised that it is possible for firms to lock them in by providing products that they like. Because it is possible to provide an abundance of product information on PC websites, it is possible to attract these people by creating websites that focus on high quality. Meanwhile, the innovator type actively uses mobile/social media and seeks 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 that is communicated by mobile screens and by short messages on social networks, which motivates them intuitively.

The key points for the practical application of these results by retailers 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 output information on media and devices. The innovator type multichannel enthusiasts correspond to the people who judge information, and it is critical to acquire this type of customer. These customers become a hub, and if they also post good evaluations such as reviews on the Internet, it becomes possible to attract research shoppers (in particular, the opinion-seeking type). Moreover, for media and devices, it is necessary to understand the characteristics of PC and mobile channels. An important finding of our study is that even though mobile usage has been growing in the recent media environment, a constant number of price-conscious type multimedia enthusiasts exist, who carefully research a wealth of information on PCs. However, one cannot overlook innovator type enthusiasts who are suited for mobile promotions. It is necessary to first get an understanding of the target customers, and then tailor the quality of information on the media and devices to be used.

5. Conclusion

This study provided customer segmentation using Latent-Class Cluster Analysis that focuses on purchase channels and media touchpoints. Further, we identified psychographics and demographics that impact segment membership. This study extended the framework of prior studies from an empirical perspective through the following two points: 1) eliminating the common bias that exists in a survey method due to the difference between intention and actual behavior by using single source panel data, and (2) providing an empirical analysis of uninvestigated products of low-involvement, more frequent purchased category. Here is a summation of the results from two possible outcomes.

The first question is how customers can be classified on the basis of purchase channels and media touchpoints. This study identified seven segments. From the standpoint of purchase channel use behavior in bricks-and-mortar stores and online stores, the seven segments were consistent with the segments proposed by Konus et al. (2008). The seven segments in our study were composed of four store-focused customer segments, one uninvolved shopper segment, and two multichannel enthusiast segments. Furthermore, from the consideration of media touchpoints, two store-focused consumer segments were identified as research shoppers, who used many online information contacts but made actual purchases at bricks-and-mortar stores. This is consistent with the frameworks of Sands et al. (2016) and Keyser et al. (2015). Further, we found that among multichannel enthusiasts, the people who used the online channel for making purchases more often used PCs and that people who purchased more at bricks-and-mortar stores more often made active use of mobile, PC, and social media. Furthermore, by the analysis of low-involvement, more frequently purchased category in the Japanese market, this study found that percentages of store-focused consumers (72%) were higher compared to those in Konus et al. (2008) and those of multichannel enthusiasts (13%) were lower compared to the same. These results have suitability in light of the purchasing status of these categories in the current Japanese market. However, it can be anticipated that e-Commerce sites will mature, efficiency of logistics systems will improve, and the number of online purchasers for these categories will increase in the future. Therefore, a future increase in multichannel enthusiasts is a point that deserves serious attention.

The second question is what the relationship is between customer's psychographic and demographic covariates and their segment membership based on actual behavior. We observed that demographics differed for all segments. Further, the results suggest that differences in psychographics divide the research shopper into two types: the opinion-seeking type and the time-constrained type. Similarly, the multichannel enthusiasts segment is divided into the price-conscious type and the innovator type. These suggestions would be effective in practical application. First, it is important to discover who "the people who judge information by their own standards" are and who "the people who are influenced by others" are. If a firm could capture as customers the innovator-type multichannel enthusiasts who can judge information, they could earn a positive evaluation from them over the Internet. That will likely exert a positive effect on the opinion-seeking type research shoppers who are influenced by others. In addition, firms need to develop the information that they publish on media and devices. To acquire price-conscious multichannel enthusiasts, it is necessary to publish a wealth of information to prompt judgment on their PC websites. To acquire innovator type multichannel enthusiasts, it is necessary to take advantage of mobile and social media and post-intuitive information that gives the feeling of shopping enjoyment.

There are some limitations of this study and future research challenges. This study performed segmentation that 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 PC, mobile, and social media usage amounts. The limitation of the study is that the 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 is an issue that 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 will be necessary to revisit the framework of this study by category. However, the overall picture that has emerged in this study will serve to be useful as a context for consumer behavior when analyzed in more detail.

Furthermore, it is necessary to perform customer segmentation in the low-involvement, more frequently purchased category in other countries as well. This study performed its analysis for the Japanese market, but if a validating analysis were to be done in other countries with different purchasing, media, and socio-economic environments, it would be necessary to confirm whether different influencing covariates would surface.

Endnotes

1) Ministry of Economy, Trade and Industry, “e-Commerce Market Survey (2015)” (in Japanese), http://www.meti.go.jp/press/2016/06/20160614001/20160614001.html (accessed March 10, 2017)
2) INTAGE Inc. official web site (in Japanese), https://www.intage.co.jp/english/ (accessed March 10, 2017)
3) INTAGE’s multi-device usage surveys (in Japanese), http://www.intage.co.jp/library/20160601/ (accessed March 10, 2017)

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