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Media channels and consumer purchasing decisions

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Abstract
Purpose – The purpose of this paper is to explore the factors determining which communication mediums influence a given consumer deciding to purchase a specific product.
Design/methodology/approach – Using a consumer survey and a multivariate probit (MVP) model, the authors explore consumer information searches related to purchases in nine categories: milk, instant noodles, shampoo, mobile phones, televisions, cars, mobile communication services, credit card services, and life insurance.
Findings – The media channels that motivate a given consumer to make a given purchase vary depending on both socio-demographic variables and product categories.
Practical implications – As consumers can now obtain product information through different and multiple media channels according to their personal characteristics and the category of the product they seek to purchase, these findings will help companies develop media planning strategies that will effectively target specific market segments.
Originality/value – Unlike previous studies, the authors consider which media channels actually affect a consumer's product purchase decisions, and the authors do so across product categories and media types to provide practical implications for media planning. Furthermore, this is the first application of the MVP model in this context.

Keywords Consumer behaviour, Information search, Marketing communication, Media channels, Multivariate probit

Paper type Research paper

1. Introduction

Consumers once had a limited number of media channels from which to obtain product information and were forced to rely on word-of-mouth (WOM) and print media (e.g. newspapers, magazines) to learn about products in which they were interested. This changed radically in the twentieth century, as the number of media channels increased with the advent of radio and television (TV), revolutionizing the ways in which consumers could access information. Over the past two decades, the advent of the internet has again fundamentally altered the quantity and quality of information

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available to consumers. As a type of "new media," the internet contains all of the information that was available from older media and, when used in conjunction with personal media devices such as smartphones and tablets, allows consumers to obtain information anywhere, at any time.

In tandem with this evolution in information and communications technology (ICT), consumer purchasing behavior and corporate advertising strategies have also changed. Consumers are now able to gather information through various media channels at each stage of the purchase decision-making process (need recognition, information search, alternative evaluation, purchase decision, and post-purchase behavior). Accordingly, companies must determine the appropriate media channels through which to promote their products in order to reach target consumers. Different media channels will generate different marketing and communication results (Chen and Hsieh, 2012).

As world economic growth has accelerated the diversification of consumer preferences and intensified inter-firm competition, companies have engaged in aggressive marketing activities to attract consumers. This is evidenced by global corporations' advertising expenditures: in 2012 alone, these totaled USD 492 billion (Zenith Optimedia, 2013). In addition to changing the amount spent on advertising, companies have gradually changed their marketing approaches. While print media advertising expenditures decreased by 3 percent per year from 2009 to 2012, spending on internet media grew by 18 percent annually over the same time period (Zenith Optimedia, 2013). Many companies have begun using a cross-media advertising strategy, using multiple media channels to market their products. This approach has proven more effective than using any one media channel (Naik and Raman, 2003). Because a consumer's choice of media channel for obtaining product information varies depending on the product category and the consumer's personal characteristics (Bhatnagar and Ghose, 2004; Konuş *et al.*, 2008), companies can take advantage of these factors to develop an appropriate media mix. However, there is little known about the specific factors that influence consumers' choices of media channels for product information. Accordingly, companies develop a media mix for their product based on marketing experts' experience and intuition, and largely fail to optimize their marketing performance. In this context, our study aims to address two research questions. First, how consumers use multiple media channels to gather product information according to their characteristics and the products they want to purchase. Second, how companies should choose from the available media channels to create a media mix to effectively advertise their products and services.

To address the above questions, we quantitatively analyze the differences across consumer segments and products in consumers' use of specific types of media to find product information when they make purchasing decisions. Specifically, we use an econometric model and survey data to demonstrate that consumers' socio-demographic characteristics and the product categories determine which communication mediums influence a given consumer during their purchase decisions for a specific product. We then provide practical advice based on the quantitative analysis to companies interested in effectively planning their media mix to optimize their marketing strategy.

The paper proceeds as follows. Section 2 reviews salient literature concerning media planning and consumer information search behavior across demographic and product categories. In Section 3, we explain the multivariate probit (MVP) model used to estimate the relationship of interest. Section 4 describes the data used in the analysis and presents results. Finally, in Section 5, we discuss the implications of our analysis and offer concluding remarks.

2. Literature review

Recent empirical analyses related to media planning fall into two categories: analyses of cross-media channel synergy and analyses of consumers' choices of various media. Cross-media channel synergy is crucial to understand because firms typically develop media strategies under the assumption that there are synergistic effects among media channels. For example, Naik and Raman (2003) showed that advertising strategies utilizing both TV and print media can positively affect a company's sales. In contrast, Dijkstra *et al.* (2005) found that, while strategies employing multiple media types might be as effective as either TV or print advertising alone, the use of too many media channels may negatively affect consumer attention and advertising effectiveness. Naik and Peters (2009) proposed a model of online and offline advertising to detect within-media and cross-media synergies. Their analysis provided evidence of the within- and cross-media synergistic effects of offline (TV, print, and radio) and online (banners and search) media, demonstrating that these effects influence how consumers value different product brands. Voorveld's (2011) experiment analysis indicated that combining online and radio advertising resulted in more positive affective and behavioral responses than using only one medium. Moreover, Lim *et al.* (2015) demonstrated synergistic effects among TV, mobile TV, and internet advertising. While these studies suggest that cross-media synergies exist, researchers have not yet provided sufficient detail to inform real-world media planning strategies.

Effectively planning a media strategy requires understanding not only the cross-media synergistic effects of various channels but also consumer media choices. There is a significant body of literature showing that these are related to consumer characteristics as well as those of the media. Using a model of consumer TV-viewing habits, Rust and Alpert (1984), Rust *et al.* (1992) and Shachar and Emerson (2000) showed that viewers' preferences for program types vary depending on their demographic characteristics. Moreover, Tavakoli and Cave (1996) used discrete choice modeling to demonstrate that program content significantly affects consumers' viewing patterns. Similarly, Wendel and Dellaert (2005) developed a model explaining consumers' media channel choices as a function of the situation specific to the time and place of usage and the perceived benefits offered by the channels, such as being trustworthy, detailed, time saving, easy to access, personal, stimulating, and informative. This research demonstrated that both the perceived benefits and the usage situation influence consumers' choice of the media channels they use to obtain product information. Lin *et al.* (2013) developed a model to predict consumers' use of multiple media types (print, TV, radio, and internet) within a short time period. Their results suggested that consumers who relied heavily on computers for information were less likely to also use traditional forms of media. Moreover, Woo *et al.* (2014) econometrically analyzed the effects of the internet and smartphones on consumer media use and found that the advent of the internet has negatively influenced consumers' use of print, radio, and TV, though the arrival of mobile internet increased their use of TV. Although these studies have facilitated identification of the media channel preferences of a given consumer, they have not clarified which media channels actually affect that consumer's product purchase decisions.

Additionally, there are several studies examining the factors affecting consumer's information search behavior and product purchases. Moorthy *et al.* (1997) developed a model to identify the factors affecting a consumer's information search behavior, which suggests an inverse parabolic relationship between the amount of consumer's product purchase experiences and the amount of search activity. While this work showed how the amount of search activity varied by consumer characteristics, it did not consider how these characteristics might affect consumer choices of media channels for obtaining product information. More recently, May So *et al.* (2005) found out that internet shopping intentions are directly affected by internet search behavior and internet shopping adoption decisions, and are indirectly affected by internet shopping attitudes, past internet experiences by using principal components analysis, structural equations, and survey data. Bhatnagar and Ghose (2004) applied a discrete hazard model to survey data to investigate internet information search termination patterns and relate variations in these to differences in product categories and consumer characteristics. They demonstrated that internet search patterns vary depending on both consumer characteristics (age, education, gender, and internet experience) and product category (software, apparel, music, recreational equipment, or travel package). In the context of women's fashion, Vernette (2004) used a survey to identify "opinion leaders" and measure their affinities for different media types. He discovered that opinion leaders tend to discuss and hold positive attitudes regarding advertising media; furthermore, relative to others, opinion leaders read more women's fashion magazines and feel significantly more favorably toward them. Although this study expanded understanding of media preferences, it focussed only on a single product type (women's fashion) and a single media channel (magazines). Although these studies offer useful information on consumers' product information search patterns, these deal with a limited number of product categories and media channels, so could not provide practical implication for media planning. These findings must be validated empirically for other product categories and media types to be useful for a wider audience.

Despite providing a strong foundation on which to conduct further research, these studies provide little insight into our research questions. That is, they fail to provide sufficient guidance to inform the development of media planning strategies across product categories, a gap that our research aims to fill.

3. Methodology

As ICT has become more advanced and diversified, consumers generally obtain product information through different and multiple media channels. Therefore, in this study, we employed a MVP to model consumers' choice of media channels for obtaining product information, because it can allow consumers' multiple choices (Baltas, 2004; Chib and Greenberg, 1998; Edwards and Allenby, 2003; Rossi *et al.*, 2005; Zhao and Harris, 2004). Specifically, the MVP model allows us to consider multiple media channels simultaneously as we aim to identify key consumer demographic characteristics that influence choices of media for obtaining product information. In addition, the MVP model does not assume the independence of irrelevant alternatives, so we can examine substitutionary or complementary relationships among media channel choices. While this is the first application of an MVP model in this context, Koo *et al.* (2014) used an MVP model to similarly analyze the effects of user characteristics, such as the main objective of using social network services (SNS) and socioeconomic background, on the choice of multiple SNS services.

The MVP model is based on the random utility model in which each consumer seeks to maximize his or her utility through the decisions he or she makes. There are two parts to a consumer's utility, deterministic and stochastic; the former is determined by contextual and personal characteristics, whereas the latter captures random variations.

The utility that consumer i derives from media channel alternative j, U_{ij}, is expressed as follows (McFadden, 1974):

$$U_{ij} = V_{ij} + \varepsilon_{ij} = \alpha_j + \sum_k \beta_{ijk}{}' X_{ik} + \varepsilon_{ij} \tag{1}$$

In Equation (1), V_{ij} is the deterministic portion of the consumer's utility and ε_{ij} is the stochastic component. V_{ij} contains alternative-specific constant α_j, and explanatory variables X_{ik} and their coefficients β_{ijk} The stochastic term $\boldsymbol{\varepsilon}_\mathbf{i}$ follows a multivariate normal distribution with mean 0 and variance Σ, that is, $\boldsymbol{\varepsilon}_\mathbf{i} = (\varepsilon_{i1}, \ldots, \varepsilon_{iJ}) \sim MVN[0, \Sigma]$. Because the variance-covariance matrix Σ contains a potential correlation between unobserved effects, the approach is appropriate for analyzing patterns of substitution and complementarity among alternatives (Edwards and Allenby, 2003).

The utility function cannot be directly observed and hence the model does not estimate utility directly; rather, it estimates parameters based on the choice, which is observed. If the expected utility of alternative j is greater than zero, then consumer i chooses j; the dependent variable Y_{ij}, representing whether or not j is chosen, is then 1. Otherwise, consumer i does not select alternative j, and $Y_{ij}, = 0$. Therefore, the choice function is:

$$Y_{ij} = \begin{cases} 1 & if \quad U_{ij} > 0 \\ 0 & if \quad U_{ij} < 0 \end{cases} \tag{2}$$

Further, the probability of consumer i choosing alternative j is given by:

$$P_{ij} = \Pr\left(U_{ij} > 0\right) = \int I\left(V_{ij} + \varepsilon_{ij} > 0\right) \Phi(\boldsymbol{\varepsilon}_\mathbf{i}) d\boldsymbol{\varepsilon}_\mathbf{i} \tag{3}$$

Because the MVP model can be applied to multiple-choice situations, the choice probability must be adjusted, as shown in the following equation (4) (Chib and Greenberg, 1998):

$$\Pr\left(\mathbf{Y_i} | \beta, \Sigma\right) = \int_{S_J} \cdots \int_{S_1} \Phi\left(\boldsymbol{\varepsilon}_\mathbf{1}, \ \ldots \ , \boldsymbol{\varepsilon}_\mathbf{J} | 0, \Sigma\right) d\boldsymbol{\varepsilon}_\mathbf{1} \ \ldots \ d\boldsymbol{\varepsilon}_\mathbf{J} \tag{4}$$

$$\text{where: } \mathbf{Y_i} = \left(Y_{i1}, \ldots, Y_{iJ}\right) \text{ and } S_j = \begin{cases} \left(-\infty, \sum_k \beta_{ijk}{}' X_{ik}\right) & \text{if} \quad Y_{ij} = 0 \\ \left(\sum_k \beta_{ijk}{}' X_{ik}, \infty\right) & \text{if} \quad Y_{ij} = 1 \end{cases}$$

It is difficult to estimate the parameters shown in Equation (4) using maximum likelihood estimation (MLE) because the likelihood function is too complicated to find the global maximum value. In addition, MLE is sensitive to the starting values chosen. To overcome these problems, we implemented a Bayesian estimation technique using a Gibbs sampler (Chib and Greenberg, 1998; Rossi *et al.*, 2005), which does not require maximization. In this study, we estimated parameters via the *R* package *bayesm*; full details of estimation procedures are given in Rossi *et al.* (2005).

4. Empirical analysis

4.1 Survey data

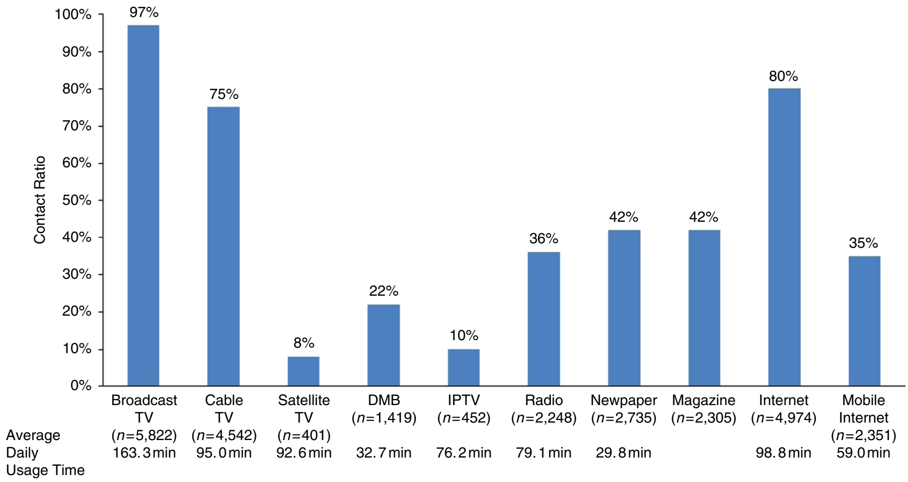
We applied this model to data provided by Media and Consumer Research (MCR), a large-scale marketing research project conducted by the Korea Broadcast Advertising Corporation (KOBACO) to identify patterns in consumers' media usage and purchasing behaviors. The survey consisted of face-to-face interviews with 6,000 respondents (aged 13-64) in 41 South Korean cities in October and November 2011. To obtain a representative sample of the entire South Korean population[1], KOBACO used purposive quota sampling to identify respondents according to geographic region, gender, age, and income. The MCR data includes consumers' demographic information, lifestyle factors, and media usage behavior as well as purchasing behavior in various product categories. Table I provides descriptive statistics of the sample, and Figure 1 summarizes the contact ratios (i.e. the proportion of people who use a specified medium more than once a week) for ten significant media channels.

We analyzed consumers' information search behavior for nine different product categories: milk, instant noodles, shampoo, mobile phones, TVs, cars, mobile communication services, credit card services, and life insurance. To address the specific goals of the study, we used participants' responses to the question: "What kinds of media channels for product information influenced you to make a purchase decision?" As independent variables in our analysis, we used socio-demographic characteristics, including age, gender, education level, and household income, as well as lifestyle variables related to early-adoption, brand-loving, and impulse-buying tendencies.

	Respondents	Portion of respondents (%)
Total respondents	6,000	100.0
Gender		
Male	3,053	50.9
Female	2,947	49.1
Age		
13-20	898	14.9
21-30	1,160	19.3
31-40	1,391	23.3
41-50	1,429	23.8
51-64	1,122	18.7
Education level	712	11.87
Less than middle school	2,453	40.88
High school	2,671	44.52
University/college	164	2.73
Above graduate school		
Average household monthly income (*in thousand Korean Won*[a])		
< 1,990	529	8.8
2,000-2,990	952	15.9
3,000-3,990	1,496	25.0
4,000-4,990	1,138	19.0
5,000-5,990	1,084	18.1
6,000-7,990	562	9.4
8,000	228	3.8

Notes: [a]According to the Bank of Korea (www.bok.or.kr). 1 USD = 1,062 Korean Won in November 2013

Table I. Respondent demographics



Note: Contact Ratio: the ratio of people who uses certain media more than once a week

Figure 1.
Contact ratios and average daily usage time for ten media types

4.2 Results

To analyze how consumer demographics and product categories affect consumers' choice of media to assist with product purchase decisions, we modeled utility functions for respondent *i*'s choice of media channel alternative *j* for nine different product categories, as shown in the following equation:

$$U_{ij} = \alpha_{ij} + \beta_{ij,Early}X_{i,Early} + \beta_{ij,Loyalty}X_{i,Loyalty} + \beta_{ij,Impulse}X_{i,Impulse}$$

$$+ \beta_{ij,Gender}X_{i,Gender} + \beta_{ij,Edu}X_{i,Edu} + \beta_{ij,Age}X_{i,Age} + \beta_{ij,Income}X_{i,Income} + \varepsilon_{ij} \quad (5)$$

The media channels included broadcast TV, subscription-based TV (cable and/or satellite), radio, newspaper, magazine, internet advertising, internet search, WOM, and other. The variables $X_{i,\ Gender}$, $X_{i,\ Edu}$, $X_{i,\ Age}$, and $X_{i,\ Income}$ respectively represent gender, education level, age, and average monthly household income. To model gender, we used a dummy variable that was equal to 0 if the subject was female and 1 if the subject was male. $X_{i,\ Early}$, $X_{i,\ Loyalty}$, and $X_{i,\ Impulse}$ depict the variables associated with the respondent's lifestyle. $X_{i,\ Early}$ denotes a tendency for early-adoption, $X_{i,\ Loyalty}$ denotes a brand-loving tendency, and $X_{i,\ Impulse}$ denotes an impulse-buying tendency. All of the lifestyle variables are index variables formed from survey responses that were extracted using principal component analysis (PCA). PCA reduces a large set of variables to a smaller set that captures the important dimensions of variability (Jolliffe, 2002, 2005). Table II summarizes the results of the PCA of the lifestyle variables.

We classified nine product categories into three different groups to identify patterns across product categories:

(1) Non-durable goods: milk, instant noodles (ramen), shampoo.

(2) Durable goods: mobile phone, TV, car.

(3) Services: mobile communication services, credit card services, life insurance.

Rotated component Matrix[a]	Early-adoption tendency Factor 1	Brand-loving tendency Factor 2	Impulse-buying tendency Factor 3
I tend to buy new technologies and digital products without hesitation	*0.849*	0.077	0.134
I tend to buy newly released products more quickly than others	*0.874*	0.071	0.146
I tend to get information about new products faster than others	*0.844*	0.145	0.085
My friends tend to buy things after I buy them	*0.756*	0.154	0.162
I tend to care about brands when I buy things	0.099	*0.784*	0.036
I tend to repurchase brands that I have bought before	0.012	*0.818*	0.051
I tend to consider company image when I buy things	0.089	*0.804*	0.080
I tend to buy products from famous brands even though they are expensive	0.247	*0.676*	0.140
I tend to regret purchases after I get them home	0.098	0.097	*0.794*
I tend to buy things on impulse, that are unplanned	0.165	0.114	*0.844*
My opinion tends to be influenced by others	0.155	0.041	*0.786*
Reliability – Cronbach's α	*0.872*	*0.788*	0.765

Notes: [a]Extraction method: principal component analysis; Rotation method: Varimax with Kaiser normalization, converged in four iterations

Table II. Principal component analysis of lifestyle variables

We estimated nine different MVP models for each product category. To compare the estimates, we classified and reorganized the results according to a sort of variables. Table III outlines the alternative-specific constant (ASC) estimation results for the nine product categories.

The ASC analysis shows consumers' preferences for media channels in each product category when socio-demographics and lifestyle variables are held constant. The estimates for broadcast TV and WOM are relatively larger, and those for newspapers and magazines are relatively smaller; this suggests that consumers' product purchase decisions are affected most by broadcast TV and WOM and least by newspapers and magazines.

Table IV reports the estimation results by age group, wherein columns contain product categories and rows contain media channels. The estimate in the milk column and newspaper row shows a statistically significant positive value, meaning that older consumers are more affected by newspapers than younger consumers in decisions

	Non-durable goods			Durable goods			Services		
	Milk	Instant noodles	Shampoo	Mobile phone	TV	Car	Mobile communication	Credit card	Life insurance
Broadcast TV	−0.2882*	−0.1907	−0.2543	−0.4554**	−0.1378	−0.2251	−0.3290**	−0.3806*	−0.9884**
Subscription TV	−0.9707**	−1.5383**	−1.0894**	−1.3360**	−1.4956**	−1.0528**	−1.0401**	−1.0167**	−1.5216**
Radio	−1.9109**	−1.8209**	−1.3819**	−2.3497**	−2.5236**	−1.8552**	−2.2365**	−1.0120**	−1.4416**
Newspaper	−2.1455**	−3.2664**	−1.8732**	−2.9547**	−2.8557**	−3.0009**	−2.8107**	−1.6729**	−2.6575**
Magazine	−1.7460**	−2.9026**	−2.1086**	−2.1936**	−1.9537**	−2.2312**	−1.6176**	−1.8277**	−1.8881**
Internet Ad.	−1.9635**	−1.3398**	−1.3495**	−1.3582**	−1.7641**	−1.4931**	−1.0309**	−0.7519**	−1.5311**
Internet search	−1.3450**	−1.8662**	−1.0355**	−1.0617**	−2.3847**	−0.9468**	−1.1047**	−0.6095**	−0.9073**
Word-of-mouth	−0.5978**	−0.7662**	−0.4669**	−0.2704**	−0.5858**	0.0822	−0.3858**	−0.2726*	0.1682
Other	−0.2755	−0.2018	0.1279	−0.4541**	−0.2611	−0.5718**	−0.1485	0.3423	−0.1308

Notes: $^*p < 0.05$; $^{**}p < 0.01$

Table III. Estimation results: alternative-specific constant

Table IV. Estimation results: age

	Non-durable goods			Durable goods			Services		
	Milk	Instant noodles	Shampoo	Mobile phone	TV	Car	Mobile communication	Credit card	Life insurance
Broadcast TV	0.0032	−0.0021	−0.0046	−0.0070**	0.0042	−0.0029	−0.0042*	0.0020	0.0075*
Subscription TV	0.0038*	0.0015	−0.0010	−0.0017	0.0033*	−0.0022	−0.0007	0.0028	0.0019
Radio	0.0081*	0.0066**	0.0056	0.0095*	0.0108**	0.0044	0.0170**	−0.0014	−0.0020
Newspaper	0.0144**	0.0138**	0.0052	0.0131**	0.0097**	0.0103**	0.0199**	0.0061	0.0140**
Magazine	0.0016	0.0026	−0.0011	−0.0046	−0.0016	−0.0013	−0.0037	0.0081	0.0036
Internet Ad.	−0.0231**	−0.0140**	−0.0111**	−0.0267**	−0.0220**	−0.0283**	−0.0216**	−0.0204**	−0.0111*
Internet search	−0.0091**	−0.0102**	−0.0260**	−0.0241**	−0.0320**	−0.0182**	−0.0256**	−0.0145**	−0.0168**
Word-of-mouth	0.0052**	0.0054*	0.0089**	0.0040**	0.0051*	0.0100*	0.0046**	0.0057*	0.0038
Other	−0.0034	−0.0023	−0.0084*	0.0033*	−0.0068**	−0.0038	−0.0027*	−0.0096*	−0.0108**

Notes: $*p < 0.05$; $**p < 0.01$

related to buying milk. By contrast, the estimate in the milk column and internet ad row shows a statistically significant negative value, meaning that younger consumers are more affected by internet ads than older consumers when making decisions to buy milk. Other estimation results in the table can be interpreted like these as follows.

In Table IV, the estimates for internet ads and searches have statistically significant and negative values in all product categories, while the estimates for newspapers, magazines, and WOM have statistically significant and positive values in most product categories. This suggests that internet ads and searches are more effective marketing channels for attracting younger consumers, while newspapers, magazines, and WOM are likely to be more useful for targeting older consumers. This result rejects Bhatnagar and Ghose's (2004) empirical finding that older consumers spend more time seeking product information on the internet than younger consumers. However, the effect of broadcast TV varies across product categories, tending to effectively attract younger consumers who are purchasing mobile phones (−0.007) and mobile communication services (−0.0042) and older consumers interested in life insurance (+0.0075). The findings also suggest that subscription-based TV is useful for advertising some non-durable (+0.0038 for milk) and durable goods (+0.0033 for TVs) to older consumers, though the patterns are somewhat inconclusive. There were no differences with respect to age in terms of magazine usage for product-research purposes. Table V outlines the estimation results associated with gender.

The analysis of gender-based differences shows a statistically significant positive value for newspapers in all product categories, and the estimates for magazines have

Table V. Estimation results: gender

	Non-durable goods			Durable goods			Services		
	Milk	Instant noodles	Shampoo	Mobile phone	TV	Car	Mobile communication	Credit card	Life insurance
Broadcast TV	0.0648	−0.1209*	−0.4543*	−0.0201	−0.0665	0.0340	0.0432	−0.1185	0.1441*
Subscription TV	0.0440	0.0217	−0.0172	0.0397	0.0229	0.0685	0.0079	0.0251	0.1224
Radio	0.1277	0.0884	0.2720**	0.1558	0.1600*	0.2092*	0.1272	−0.0908	0.1545
Newspaper	0.3251**	0.4877**	0.3971**	0.2435**	0.2245**	0.1426*	0.3581**	0.2128**	0.3734**
Magazine	−0.1276	−0.1431	−0.7043**	−0.2014**	−0.1847**	−0.2850**	−0.1103	−0.1270	−0.1707
Internet Ad.	0.0342	−0.0124	−0.1209	0.0444	0.0239	0.1607*	0.0857*	0.0987	0.0422
Internet search	−0.0183	−0.0551	−0.0498	0.0903*	0.0139	0.1404**	0.0516	0.0485	−0.0074
Word-of-mouth	−0.1064*	−0.0198	−0.0294	−0.1530**	−0.1230*	−0.0755	−0.1174**	−0.0028	−0.0339
Other	−0.0206	−0.0166	0.0276	0.0671	−0.0274	−0.0341	−0.0877*	−0.0961	−0.0991

Notes: $*p < 0.05$; $**p < 0.01$

statistically significant negative values for durable goods, indicating that newspapers are an effective media channel when marketing durable goods to male consumers, whereas female consumers are more likely to respond to magazine advertising. Gender differences in the effects of broadcast TV vary across product categories. For example, it is effective for encouraging female consumers to purchase instant noodles (–0.1209) and shampoo (–0.4543) and male consumers to purchase life insurance (+0.1441). For male consumers purchasing shampoo (+0.2720), TVs (+0.1600), and cars (+0.2092), however, radio is a more effective channel. Moreover, internet advertising appears to be superior to other media for promoting mobile communication services (+0.0857) and cars (+0.1607) to male consumers, and internet searches are more effective for advertising mobile phones (+0.0903) and cars (+0.1404) to males. Therefore, our results support Bhatnagar and Ghose's (2004) empirical results that men are likely to have longer product search times on the internet than women for some product categories.

For female consumers, on the other hand, WOM has more impact than other channels for marketing milk (–0.1064), mobile phones (–0.1530), TVs (–0.1520), and mobile communication services (–0.1174). There were no statistical differences in terms of gender on the impact of marketing via subscription TV.

Table VI provides the estimation results associated with education level and show that the estimates for newspapers and internet searches have statistically significant positive values for durable goods and mobile communication services. Moreover, the estimates for internet advertising and searches have statistically significant positive values for mobile communications and credit cards. These suggest that well-educated consumers are influenced by newspaper and internet searches when purchasing durable goods and mobile communication services. For some product categories, our results are in line with Bhatnagar and Ghose's (2004) finding that consumers with higher levels of education spend more time on internet product searches.

Then, internet ads and searches are also useful channels for persuading better-educated consumers to purchase services related to mobile communications and credit cards. In contrast, WOM appears to be useful for promoting TVs (–0.0666) and life insurance (–0.0535) to less-educated consumers. This demographic is also more likely to be influenced by broadcast TV when purchasing instant noodles (–0.0301) and mobile communication services (–0.0781) and by subscription TV when purchasing milk (–0.0523), instant noodles (–0.0486), cars (–0.0429), and mobile communication services (–0.0330).

	Non-durable goods			Durable goods			Services		
	Milk	Instant noodles	Shampoo	Mobile phone	TV	Car	Mobile communication	Credit card	Life insurance
Broadcast TV	0.0145	–0.0301*	–0.0291	–0.0153	–0.0080	0.0092	–0.0781**	–0.0335	–0.0122
Subscription TV	–0.0523**	–0.0486**	–0.0311	–0.0470**	–0.0372	–0.0429**	–0.0330*	–0.0049	–0.0208
Radio	0.0421	–0.0007	–0.0648	0.0223	–0.1078*	–0.0394	0.0295	–0.0055	–0.0048
Newspaper	0.0392	0.0470	0.0087	0.0794**	0.0512*	0.0768**	0.0649*	0.0221	0.0137
Magazine	0.1332**	0.0317	0.0868	0.0649*	0.0437	0.0490	0.0531	0.0207	0.0345
Internet Ad.	0.0801	0.0303	0.0980**	0.1065**	0.0549	0.0616	0.0761**	0.1163**	0.0551
Internet search	0.0169	0.0688**	0.0295	0.1396**	0.2185**	0.0975**	0.1751**	0.0663**	0.0490
Word-of-mouth	–0.0282	–0.0245	–0.0105	–0.0248	–0.0666*	–0.0547	–0.0110	–0.0474	–0.0535*
Other	0.0216	0.0169	–0.0312	0.0086	0.0577	0.0239	0.0535**	–0.0227	0.0437

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$

Table VI. Estimation results: education level

Table VII provides estimation results related to the effect of household income on the information sources used to make purchases in the nine product categories. The estimates for subscription TV have statistically significant positive values for non-durable goods, services, mobile phones, and TVs, indicating that it appears to be useful for marketing to high-income consumers purchasing non-durable goods and services as well as some durable goods (e.g. mobile phones, TVs). Radio is an effective tool for marketing non-durable goods (+0.0770 for milk, +0.0394 for instant noodles, +0.0380 for shampoo) to higher-income households, who are also likely to turn to newspapers for information when purchasing milk (+0.0498), shampoo (+0.0242), mobile phones (+0.0439), TVs (+0.1049), and various services (+0.0763 for mobile service, +0.0400 for credit cards, +0.0489 for life insurance). Lower-income households, on the other hand, tend to be more affected by internet advertising when purchasing cars (−0.0427) and mobile communication services (−0.0283). internet searches are effective for marketing milk (+0.0374), shampoo (+0.0419), and life insurance (+0.0264) to high-income consumers, while WOM has a greater impact on these consumers when they are considering instant noodles (+0.0333), durable goods (+0.0212 for mobile phones, +0.0277 for TVs, +0.0398 for cars), and mobile communications services (+0.0306). No differences were found between high- and low-income respondents in terms of magazine advertising effectiveness.

Table VIII summarizes estimation results for the effect of early-adoption tendency on use of the nine product categories. The estimates for broadcast TV, subscription TV, and WOM have statistically significant positive values in all product categories,

Table VII. Estimation results: household income

	Non-durable goods			Durable goods			Services		
	Milk	Instant noodles	Shampoo	Mobile phone	TV	Car	Mobile communication	Credit card	Life insurance
Broadcast TV	−0.0335	0.0061	0.0366**	0.0247*	0.0237	−0.0255*	0.0609**	0.0312	0.0504*
Subscription TV	0.0383*	0.0620**	0.0394**	0.0448**	0.0469**	0.0171	0.0426**	0.0309*	0.0511**
Radio	0.0770**	0.0394*	0.0380**	0.0369	0.1049**	0.0279	0.0625*	0.0259	0.0259
Newspaper	0.0498*	0.0343	0.0242*	0.0439**	0.0354*	0.0264	0.0763**	0.0400*	0.0489*
Magazine	0.0027	0.0279	0.0265	0.0313	0.0196	−0.0173	0.0268	0.0374	0.0076
Internet Ad.	−0.0109	0.0040	−0.0367	−0.0008	−0.0100	−0.0472*	−0.0283*	−0.0322	0.0031
Internet search	0.0374**	0.0129	0.0419*	−0.0011	0.0298	0.0050	−0.0084	0.0041	0.0264*
Word-of-mouth	0.0180	0.0333*	0.0066	0.0212*	0.0277*	0.0398*	0.0306**	0.0253	0.0172
Other	0.0192	−0.0005	0.0065	−0.0146	−0.0032	0.0133	−0.0201*	−0.0102	−0.0060

Notes: $^*p < 0.05$; $^{**}p < 0.01$

Table VIII. Estimation results: early-adoption tendency

	Non-durable goods			Durable goods			Services		
	Milk	Instant noodles	Shampoo	Mobile phone	TV	Car	Mobile communication	Credit card	Life insurance
Broadcast TV	0.1399**	0.1009**	0.1410**	0.2208**	0.0832**	0.1290**	0.2471**	0.3739**	0.3131**
Subscription TV	0.2015**	0.2480**	0.1873**	0.2195**	0.1546**	0.1677**	0.1796**	0.2279**	0.1761**
Radio	−0.0439	−0.1009*	0.0301	0.0994*	−0.0070	0.0073	−0.0250	−0.0417	−0.0411
Newspaper	−0.0414	0.0093	−0.0124	−0.0345	0.0278	−0.1319**	0.0042	0.0426	0.0055
Magazine	−0.1081*	0.0791	−0.0742	0.0264	−0.0202	0.0307	−0.0314	0.0417	0.0660
Internet Ad.	0.0750	0.0581	0.0549	0.0822**	0.0525*	0.1162*	0.0243	0.0230	0.0539
Internet search	0.1430**	0.1413**	0.0735**	0.0979**	0.1404**	0.0775**	0.1115**	0.1059**	0.0426
Word-of-mouth	0.1701**	0.1513**	0.0956**	0.0867**	0.0825**	0.1533*	0.0882**	0.1401**	0.0950**
Other	−0.1483**	−0.0937**	−0.1778**	−0.1568**	−0.1151**	−0.1133**	−0.1172**	−0.2639**	−0.2417**

Notes: $^*p < 0.05$; $^{**}p < 0.01$

suggesting that these are effective channels for reaching early adopters, regardless of product categories. Internet advertising, however, is only effective for targeting early adopters who seek to purchase durable goods (+0.0822 for mobile phones, +0.0525 for TVs, +0.1162 for cars), and internet searches attract early adopters purchasing non-durable goods, durable goods, and some services (mobile communication services, credit card services).

Estimation results for the effects of a consumer's brand-loving tendency on use of the nine product categories are given in Table IX. The estimates for broadcast TV and magazines have statistically significant positive values for all non-durable goods and some durable goods, suggesting that these appear to be the most effective media for promoting these goods to customers with a strong affinity for brands. Newspapers are also an effective channel for marketing some non-durable goods (+0.1685 for milk and +0.0996 for shampoo), durable goods (+0.1327 for mobile phones, +0.1050 for TVs, +0.1482 for cars), and services (+0.0994 for mobile service, +0.1282 for credit cards, +0.1592 for life insurance) to these consumers. On the other hand, subscription TV is a more effective approach for marketing milk (−0.1156), durable goods (−0.0785 for mobile phones, −0.0514 for TVs, −0.0744 for cars), and some services (−0.1507 for credit cards, −0.1068 for life insurance) to consumers with lower brand-loving tendencies. internet-based channels (advertising and search) are effective tools for promoting mobile phones, cars, or mobile communication services to consumers characterized by high brand-loving tendencies. For purchases of milk, instant noodles, and mobile phones, however, consumers with a strong brand-loving tendency are most likely to rely on WOM.

Finally, Table X summarizes the estimation results related to consumers' impulse-buying tendencies. The estimates for broadcast TV and subscription TV have statistically significant positive values in all product categories, suggesting that these are generally effective media for all product categories to target consumers with a tendency to buy items on impulse. In contrast, internet searches tend to be highly effective in persuading consumers with less impulsive purchasing behaviors to buy durable goods (−0.0541 for mobile phones, −0.1268 for TVs, −0.0632 for cars), and mobile communication services (−0.0669). Impulsive consumers are influenced by internet searches when buying milk (+0.1072) and by newspapers for purchases of shampoo (+0.0377), mobile phones (+0.0729), cars (+0.0908), and life insurance (+0.0731). Internet advertising is effective for promoting mobile phones (−0.0574) to consumers who tend to avoid impulse purchases. No significant difference was seen in the impact of WOM between consumers who buy items on impulse and those who do not.

	Non-durable goods			Durable goods			Services		
	Milk	Instant noodles	Shampoo	Mobile phone	TV	Car	Mobile communication	Credit card	Life insurance
Broadcast TV	0.1285*	0.1806**	0.1057**	0.0521	0.0599**	0.1274**	0.0465	−0.1339*	−0.1032
Subscription TV	−0.1156**	−0.0280	−0.0222	−0.0785**	−0.0514**	−0.0744*	−0.0312	−0.1507**	−0.1068**
Radio	0.0203	0.0544*	0.0124	−0.0793	0.0409	0.0282	−0.0675	0.0696	0.0753
Newspaper	0.1685**	0.0542	0.0996**	0.1327**	0.1050**	0.1482**	0.0944*	0.1282**	0.1592**
Magazine	0.0945*	0.0846*	0.1409**	0.0677	0.0586*	0.0796*	0.0707	0.0922	0.0013
Internet Ad.	0.1432*	0.0224	0.0290	0.1421**	0.0435	0.0877**	0.1032**	−0.0376	−0.0084
Internet search	0.0250	0.0504*	0.0244	0.0946**	0.0624	0.0535**	0.0705**	0.0255	0.0722*
Word-of-mouth	0.0645*	0.0493*	0.0296	0.0381*	0.0252	−0.0218	0.0318	−0.0010	0.0229
Other	−0.0288	−0.0746**	−0.0520	−0.0334	−0.0440*	0.0227	−0.0276	0.0456	−0.0069

Notes: $*p < 0.05$; $**p < 0.01$

Table IX. Estimation results: brand-loving tendency

Table X.
Estimation results: impulse-buying tendency

	Non-durable goods			Durable goods			Services		
	Milk	Instant noodles	Shampoo	Mobile phone	TV	Car	Mobile communication	Credit card	Life insurance
Broadcast TV	0.2221**	0.0834**	0.1965**	0.2216**	0.0727**	0.0934**	0.1996**	0.2418**	0.2566**
Subscription TV	0.1301**	0.1013**	0.0693**	0.0956**	0.1193**	0.1468**	0.1326**	0.1222**	0.1349**
Radio	0.0939	0.0094	−0.0044	−0.0406	−0.0302	0.0123	−0.0012	−0.0450	0.0197
Newspaper	0.0312	0.0560	0.0377*	0.0729*	0.0250	0.0908*	0.0543	−0.0082	0.0731*
Magazine	0.0698	0.1269*	0.0061	−0.0126	0.0433	0.0930*	−0.0128	0.0838*	0.0621
Internet Ad.	−0.0137	−0.0138	−0.0085	−0.0574*	−0.0354	−0.0869	−0.0109	0.0231	0.0390
Internet search	0.1072**	0.0207	0.0052	−0.0541**	−0.1268**	−0.0632**	−0.0669**	−0.0152	0.0032
Word-of-mouth	−0.0055	0.0131	0.0019	0.0015	0.0089	−0.0283	0.0343	0.0019	−0.0093
Other	−0.1114*	−0.0963**	−0.1283	−0.1021**	−0.0974**	−0.0998**	−0.1427**	−0.1215**	−0.0809**

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$

By estimating Σ, we can also calculate correlations among media channels. The correlation results for each product group are shown in Tables XI-XIII. Because of the complexity of identifying differences among product groups across nine different correlation matrices, we present matrixes of the average correlations across items in each product group. Moreover, we present the number of statistically significant (5 percent) correlations for each average correlation in the tables. Individual correlation

Table XI.
Estimation results: average correlation for non-durables

	Broadcast TV	Subscription TV	Radio	Newspaper	Magazine	Internet Ad.	Internet search	Word-of-mouth	Other
Broadcast TV	1.0000***								
Subscription TV	0.5041***	1.0000***							
Radio	0.2340***	0.1872***	1.0000***						
Newspaper	0.2539***	0.2433***	0.5914***	1.0000***					
Magazine	0.1510**	0.1453**	0.4863***	0.6104***	1.0000***				
Internet Ad.	0.1339**	0.3210***	0.3519***	0.3806***	0.4500***	1.0000***			
Internet search	−0.0713*	0.1257***	0.1363*	0.1288**	0.1865***	0.3046***	1.0000***		
Word-of-mouth	−0.4561***	−0.1077***	−0.2088***	−0.1329***	−0.1247**	−0.0404	0.1513***	1.0000***	
Other	−0.5299***	−0.2787***	−0.0368*	−0.0609*	0.0176	−0.1020*	0.1064***	−0.2033***	1.0000***

Notes: *Among the correlations for the three non-durables, only one was at $p < 0.05$; **Among the correlations for the three non-durables, two were at $p < 0.05$; ***Among the correlations for the three non-durables, all reached $p < 0.05$

Table XII.
Estimation results: average correlation for durables

	Broadcast TV	Subscription TV	Radio	News-paper	Magazine	Internet Ad.	Internet search	Word-of-mouth	Other
Broadcast TV	1.0000***								
Subscription TV	0.4955***	1.0000***							
Radio	0.2060***	0.2542***	1.0000***						
Newspaper	0.2158***	0.2457***	0.5761***	1.0000***					
Magazine	0.0983**	0.2037***	0.5751***	0.5782***	1.0000***				
Internet Ad.	0.0742**	0.2042***	0.4142***	0.3849***	0.5153***	1.0000***			
Internet search	−0.0709**	0.0554*	0.0759*	0.2069***	0.0960*	0.2883***	1.0000***		
Word-of-mouth	−0.3164***	−0.0599**	−0.0921**	−0.0963**	−0.1057**	−0.0753*	0.1985***	1.0000***	
Other	−0.4100***	−0.1481***	0.0378*	0.0831**	0.1440**	0.0344**	0.0532**	−0.1340***	1.0000***

Notes: *Among the correlations for the three durables, only one was at $p < 0.05$; **Among the correlations for the three durables, two were at $p < 0.05$; ***Among the correlations for the three durables, all reached $p < 0.05$

	Broadcast TV	Subscription TV	Radio	News-paper	Magazine	Internet Ad.	Internet search	Word-of-mouth	Other
Broadcast TV	1.0000***								
Subscription TV	0.5702***	1.0000***							
Radio	0.2563***	0.2573***	1.0000***						
Newspaper	0.2428***	0.2748***	0.6262***	1.0000***					
Magazine	0.2195***	0.2397***	0.5278***	0.6114***	1.0000***				
Internet Ad.	0.1693***	0.2444***	0.4558***	0.4036***	0.4451***	1.0000***			
Internet search	−0.0396*	0.1238***	0.0379	0.1181**	0.1925**	0.2698***	1.0000***		
WOM	−0.3981***	−0.1801***	0.2136***	−0.1341***	−0.1993***	−0.0919**	0.1180***	1.0000***	
Other	−0.4416***	−0.2419***	0.0568*	−0.0432*	0.0332	−0.0565	0.0053	−0.3153***	1.0000***

Notes: *Among the correlations for the three services, only one was at $p < 0.05$; **Among the correlations for the three services, two were at $p < 0.05$; ***Among the correlations for the three services, all reached $p < 0.05$

Table XIII. Estimation results: average correlation for services

matrices for each product (including the statistical significance of each) are available from the authors upon request.

The average correlation matrices show similar tendencies across all product groups. Traditional media outlets, such as broadcast and subscription TV, radio, newspapers, and magazines – classified as external information sources – are mutually positively correlated but negatively related to WOM (an internal information source). One type of new media, internet advertising, has similar correlational tendencies. Internet searches, however, are positively correlated with WOM and with most technology-based media channels, with the exception of broadcast TV. This is likely attributable to the fact that consumers can perform an internet search to obtain not only basic product information but also reports of previous users' experiences with the product.

By comparing the average correlations across the three groups, we find some interesting results. For example, the absolute values of the negative correlations between WOM and media channels (broadcast and subscription TV, radio, newspaper, magazines, and internet advertising) are smaller than those associated with other linkages. This suggests that when consumers decide to purchase non-durable goods or services, they are more likely to research them via either WOM or external media channels. This tendency is absent when consumers opt to purchase durable goods. Additionally, internet searches tend to be more positively correlated with external media channels for the purchase of non-durable goods and with WOM for purchasing durable goods.

5. Conclusions and implications

As ICT has advanced and diversified, consumers have begun using multiple media channels to gather product information. In turn, companies now use a variety of channels to advertise their products and services. However, companies develop a media mix for their product based on marketing experts' experience and intuition since they lack information about consumers' choices of media channels for product information. This need requires empirical investigations into the varied effectiveness of different media channels in different product categories.

To understand the variety of media channels available to consumers and companies, and to provide advice for effective media planning, we have demonstrated the differences across consumer segments and product categories in consumers' use of specific media to collect information for making purchasing decisions. Specifically, we applied an MVP model and survey data to demonstrate that consumer socio-demographic characteristics and product categories determine which communication mediums influence a given consumer when deciding to purchase a specific product. Table XIV summarizes this study' estimation results.

Additionally, from the results in the average correlation matrices, we find that external information sources (broadcast and subscription TV, radio, newspapers, and magazines) are mutually positively correlated, but negatively related to WOM, across all product groups. Internet advertising has similar correlational tendencies, but internet search is positively correlated with WOM and with most technology-based media channels. Moreover, by comparing the average correlations across the three product groups, we find that when consumers decide to purchase non-durable goods or services, they are more likely to conduct research using WOM or external media channels. This tendency is absent when consumers opt to purchase durable goods. Additionally, internet search tends to be more positively correlated with external media channels for non-durable goods purchases, and with WOM for durable goods purchases.

The results provide useful insight to firm managers seeking to develop an effective media mix for marketing specific types of products. For example, when consumers decide to purchase a car, they generally prefer WOM and broadcast TV to obtain product information. However, considering a prestigious automobile company planning to release a large luxury sedan targeted at high-income, older men who are invested in the brands of the products they purchase, our study suggests that. Our results suggest that newspapers and WOM have the greatest impact on older consumers and that men are most strongly persuaded by radio, newspaper, internet ads, and the results of internet searches. Moreover, our research shows that high-income consumers are influenced by WOM and consumers with strong brand affinities are influenced by broadcast TV, newspapers, magazines, and internet ads and searches. Given this, it would be wise for the company to run long-term newspaper advertisements and attempt to develop positive WOM through experience marketing. Moreover, the strong negative correlation between newspaper advertisements and WOM suggests that the company should differentially market to the customers influenced by each of these mediums in order to reach a wider audience. On the other hand, an automobile company planning to launch a low-cost compact hatchback for female consumers between the ages of 21 and 40 should be aware that younger consumers are positively affected by internet ads and searches, women are more readily persuaded by magazine advertising, and low-income consumers are influenced by broadcast TV and internet ads. Since the latter two are positively correlated, the company could save on advertising costs by selecting just one of these for promoting the car to this customer segment.

Previous studies provide a strong foundation in terms of consumer information search behavior, though they do not provide sufficient practical guidance to inform the development of a media mix across product categories. However, we believe that our study is the first step in filling this gap. Our study's findings indicate that companies should consider both socio-demographic variables and product categories in their marketing plans targeting a particular segment of their market. The novel information provided by this study – how different consumer segments are influenced by various media channels when searching for product information – can help companies plan and develop an appropriate media mix.

However, our study is subject to some limitations. First, as this study used a survey to obtain consumers' information search and purchasing behavior as opposed to observing their actual behavior, this study is limited by its sample-based approach and potentially affected by psychological aspects such as cognitive dissonance

Table XIV. Summary of estimation results

	General preference (ASC)	Age		Gender		Education		Household income		Early-adoption		Brand-loving		Impulse-buying	
		Old	Young	Male	Female	High	low	High	low	High	low	High	low	High	low
Non-durable goods															
Milk	1 > 8 > 2 > 7 > 5 > 3 > 6 > 4	2,3,4,8	6,7	4	8	5	2	2,3,4,7	–	1,2,7,8	5	1,4,5,6,8	2	1,2,7	–
Instant noodles	1 > 8 > 6 > 2 > 3 > 7 > 5 > 4	3,4,8	6,7	4	1	7	1,2	2,3,8	–	1,2,7,8	3	1,3,5,7,8	–	1,2,5	–
Shampoo	1 > 8 > 7 > 2 > 6 > 3 > 4 > 5	8	6,7	3,4	1,5	6	–	1,2,3,4,7	–	1,2,7,8	–	1,4,5	–	1,2,4	–
Durable goods															
Mobile phone	8 > 1 > 7 > 2 > 6 > 5 > 3 > 4	3,4,8	1,6,7	4,7	5,8	4,5,6,7	2	1,2,4,8	–	1,2,3,6,7,8	–	4,6,7,8	2	1,2,4	6,7
TV	1 > 8 > 2 > 6 > 5 > 7 > 3 > 4	2,3,4,8	6,7	3,4	5,8	4,7	3,8	2,3,4,8	–	1,2,6,7,8	–	1,4,5	2	1,2	7
Car	8,1 > 7 > 2 > 6 > 3 > 5 > 4	4,8	6,7	3,4,6,7	5	4,7	2	8	1,6	1,2,6,7,8	4	1,4,5,6,7	2	1,2,4,5	7
Services															
Mobile communication	1 > 8 > 6 > 2 > 7 > 5 > 3 > 4	3,4,8	1,6,7	4,6	8	4,6,7	1,2	1,2,3,4,8	6	1,2,7,8	–	4,6,7	–	1,2	7
Credit card	8 > 1 > 7 > 6 > 3 > 2 > 4 > 5	8	6,7	4	–	6,7	–	2,4	–	1,2,7,8	–	4	1,2	1,2,5	–
Life Insurance	8 > 7 > 1 > 3 > 2 > 6 > 5 > 4	1,4	6,7	1,4	–	–	8	1,2,4,7	–	1,2,8	–	4,7	2	1,2,4	–

Notes: 1 = Broadcast TV; 2 = Subscription TV; 3 = Radio; 4 = Newspaper; 5 = Magazine; 6 = Internet Ad.; 7 = Internet search; 8 = Word-of-Mouth

(Tancer, 2008). The recent emergence of big data and the internet of things could enable a collection of real-time records of consumers' actual behaviors. Therefore, we believe that consumer behavior studies using these data will address the limitations in this study, and enable an analysis of more detailed consumer behavior to provide more detailed media planning implications.

Second, our study takes a broad and synthetic approach to media channels and product categories to determine how companies should combine media channels to more effectively advertise their products. Accordingly, our results cannot provide detailed marketing strategies, such as which web sites a company should use to promote their product, what methods to use, and what information to include. Therefore, we believe that future studies analyzing consumers' information search and purchasing behavior within specific media channels could provide more detailed and readily applicable marketing strategies.

This study could be further extended by, for example, investigating the optimal media mixes for promoting products or services efficiently by combining the consumer preference for media channels estimated in this study, and the unit cost and benefit of each media channel. In other words, it is possible to provide information about how an advertiser finds an optimal combination of advertisement media channels maximizing total advertising effect for a given advertising cost. In addition, as combinations of media channels exponentially increase when considering the advertising time period, optimization tools like the nested partitions method should be used to obtain optimal media mixes.

Note

1. According to the International Telecommunication Union (2013), South Korea ranks first in the world in ICT readiness, usage, and capability as of 2013. In addition, the OECD (2012) reported that South Korea ranked first in terms of Internet penetration (97.2 percent). These figures indicate that South Korean consumers represent the most active group in terms of new media use, and the South Korean case represents a mature media market (Woo *et al.*, 2014). Thus, the analytical results could vary in countries where the Internet and media environment is not fully mature.

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