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Smartphone preferences and brand loyalty: A discrete choice model reflecting the reference point and peer effect

Junghun Kim, Hyunjoo Lee, Jongsu Lee*

Technology Management, Economics and Policy Program, College of Engineering, Seoul National University, 1, Gwanak-ro, Gwanak-gu, Seoul, 08826, South Korea

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ABSTRACT

Brand loyalty and interest have significant impacts on consumers' smartphone choices. What about brand loyalty and interest of smartphone in South Korea where Samsung originates from? This study investigates brand loyalty and interest and how they are affected by the satisfaction of innovative peers in South Korea. An asymmetric discrete choice model with reference-dependent preferences is applied for the analysis. The estimation results show that in South Korea the brand is the most important attribute of smartphone and Apple is the strongest in brand loyalty. Whether consumers who are currently owners of Apple smartphones continue to maintain the same brand in their next purchasing depends not only on their brand loyalty but also on the satisfaction of their highly innovative peers who currently own the Apple. On the other hand, Samsung's brand loyalty is lower than that of Apple, but the brand interest is the highest. Additionally, in all smartphone brands, satisfaction with smartphone brands owned by innovative peers has a significant impact on consumers' interest.

1. Introduction

The global smartphone market is expanding rapidly, and it is expected that 5.9 billion people will own smartphones by 2025 (GSMA, 2018). This amounts to 71 percent of the total world population, and experts have speculated that smartphone distribution will surpass that of computers due to portability and versatility functions (Deloitte, 2017). In terms of smartphone ownership, South Korea ranks the number one worldwide, constituting nearly 96 percent of the total population (Poushter et al., 2018). Despite the high penetration rate, the number of smartphone users has steadily increased in South Korea (Ministry of Science and ICT, 2018), and smartphone manufacturers are releasing new products at shorter intervals, abbreviating the consumer replacement cycle (Lee, 2014). This results in more intensified competition in the smartphone market. Additionally, smartphone manufacturers have been striving to increase consumer satisfaction regarding products and services in an effort to increase their market share (Chen et al., 2016).

In addition to non-functional attributes like brand and price, smartphones consist of various functional attributes, including screen size and central processing unit (CPU). In the early stages of smartphone production, manufacturers focused on enhancing battery, resolution, CPU, and other core technology that made up the device (Verganti, 2011), which led to smartphones within a similar price range achieving similar functional capacity. Henceforth, manufacturers attempted to gain a competitive edge in the market by offering mobile payments, location-based services, and other added functions, or by enhancing them further (Oliveira et al., 2016), but these added functions could be imitated with ease, and differentiating effects were short-lived. As a result, most of the manufacturers' recent efforts have been on non-functional attributes such as fashionable appearance and after-sales service (Chen et al., 2016).

As it gets more difficult for smartphone manufacturers to gain competitiveness in the functional aspects of the device, subsequently, one could anticipate that interest in a new brand[1] or loyalty to a brand currently own, are going to play a significant role in a consumers' decision. A characteristic of competitive smartphone markets is that consumers are made to choose one out of numerous models available. While it can be confounding to compare their functional attributes in detail, their brands are easily visible and affect consumers' purchase decisions to a great degree. The brand is also related to the device's mobile operating system (OS), a critical functional attribute associated with application, performance, and security.

As the second half of 2018, market shares of Google Android and Apple's iOS operating systems currently dominate the global smartphone market, and are 84.8 percent and 15.1 percent respectively

* Corresponding author.
E-mail addresses: jkim.snu@gmail.com (J. Kim), hlee37@snu.ac.kr (H. Lee), jongsu.lee@snu.ac.kr (J. Lee).

[1] Although brand interest generally includes one's amount of interest in the brand currently owned, for the purpose of this study, the scope was limited to brands other than a consumers' currently owned brand.

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(other OS 0.1%). In addition, market shares among brands that use the Android OS, including Samsung, Huawei, and Xiaomi are 20.9 percent, 15.8 percent, and 9.3 percent, respectively (International Data Corporation, 2018). Thus, understanding brand preferences rather than OS preferences may provide more information on overall smartphone preference of the consumer. In regard this, Apple has strived to convey an innovative and unique brand image through its distinct corporate philosophy and marketing strategies, and consumers associate the brand with modernism, freedom, and youth (Chartrand, 2005). As a result, for some consumers, the brand of Apple stands for outgoing and adventurous while contrarily the Samsung brand emphasizes the ruggedness and functionality (Götz et al., 2017). Furthermore, consumer perception varies among brands running the Android OS. Individual attitude toward a certain brand can be understood as a medium of self-expression, which has been pointed out in marketing and consumer psychology studies (Aaker, 1997; Keller, 1993).

Given these statistical evidences and researches, it is necessary to understand the consumers' brand preference more precisely. However, in reality, there are numerous attributes other than the brand that consumers consider when they purchase the smartphone, such as price and screen size. In order to analyze the actual effect of brand on consumers' preference, the discrete choice model should be applied. It is because the discrete choice model based on random utility framework allows for evaluating the trade-off between attributes (Folta, 1998). The discrete choice model has an advantage that can provide the results such as willingness to pay and relative importance that can be useful to implement in marketing strategies (Lee et al., 2006). In addition, in the case of South Korea, where the majority of consumers already use smartphones, applying a reference point to the model would yield more meaningful results (Kim et al., 2016; Kim et al., 2018). The brand loyalty, which will be discussed in detail in Section 2 of this study, represents a tendency to continuously purchase the same brand of smartphone that one currently uses and prefers. In particular, the marginal utility for brand derived using a standard discrete choice model would be underestimated in comparison with brand loyalty derived using a reference-dependent choice model, which incorporates the reference point effect into the discrete choice model (Kim et al., 2016).

With the expansion and growing competitiveness of the smartphone industry, understanding brand loyalty has become an important issue among academics and practitioners. This study will begin with a preliminary evaluation of the most important attributes of brands, analyzing consumer preferences for smartphones using a standard discrete choice model, then deriving marginal utility and relative importance for each attribute in relation to one another. This study will then use the discrete choice model with consideration of reference-dependent preferences to analyze consumers' asymmetric preferences for attributes, using the attribute levels of smartphones currently owned by consumers as reference points. The absolute value of losses coefficient for the brand, which will be used synonymously with giving up the brand of the smartphone one currently owns and prefers, would indicate levels of brand loyalty, which will be the focus of this study. Lastly, this study will analyze how the satisfaction of peers with higher innovativeness influences on consumers' brand loyalty and interest, in order to deepen the understanding of consumer preferences for smartphones.

This study consists of five sections. Section 2 includes a literature review of existing studies regarding consumers' smartphone choices, and then specifically covers brand loyalty, brand interest, and peer effects. It also discusses which reference-dependent preferences should be considered to overcome the existing limitations of the discrete choice model by examining past studies of consumer preferences for smartphones. Section 3 proposes a discrete choice model, which reflects the reference point and peer effect. Section 4 presents the data collected on smartphones for empirical analysis, as well as the estimated results of the proposed models. Section 5 discusses the results and, concludes this study and its implications.

2. Literature review

There are various studies regarding consumers' smartphone choices, specifically questioning about what makes consumers purchase smartphones. One of the approaches is to identify the factors affecting consumers' purchasing behavior of smartphones. According to the study of Filieri et al. (2017), brand-related socio-cultural, aesthetic, and utilitarian factors are three major factors affecting the consumers' smartphone choice. These three factors are synopsized the factors that also treated in other papers (Kim et al., 2014; Petruzzellis, 2010; Seva and Helander, 2009). Among these factors, brand-related factors play an important role in consumers' smartphone choices. In particular, the study of Kim et al. (2014) identifies the factors that can distinguish smartphone adopter and non-adopters. As a result, the brand is considered to be a comprehensive indicator of the factors that affect consumers' smartphone choices.

Furthermore, as a part of the socio-cultural factor, peer influence is an important factor influencing consumers' choice behavior. Studies on peer influence are based on the theory of planned behavior (Ajzen, 1991). The theory of planned behavior indicates the individual's intention to perform a given behavior, and this intention is influenced by three explanatory variables: attitude toward the behavior, subjective norm, and perceived behavioral control. Here, the subjective norm represents the peer influence. In addition to the theory of planned behavior, numerous scholars have emphasized the importance of peer influence on consumers' purchasing behavior (Hahn and Kim, 2013; Lee, 2014).

In order to identify these factors, various methodologies can be applied. Mainly, structural equation models (SEMs) and discrete choice models are used in numerous studies. Although both methods are applied for investigating the effectiveness of factor on consumers' choice in real markets, the prediction of the discrete choice models is consistently better than those of the SEMs (Wang et al., 2007). In addition, the discrete choice model allows the trade-off between attributes, which are influential factors in consumers' smartphone choice (Folta, 1998).

2.1. Brand loyalty and interest for smartphone

The brand is the most valuable asset of the manufacturer. The brand value recognized by the consumer is formed around the manufacturer's products and services. The brand is considered to play an important role in the relationship between manufacturers and consumers (Kotler and Armstrong, 2010). Status quo bias (SQB), which indicates a tendency of people to maintain the current state, preference or behavior (Samuelson and Zeckhauser, 1988), leads consumers to maintain the incumbent brand rather than switching to a new brand. Ganesan and Sridhar (2014) analyzed consumer preferences for smartphone attributes with a focus on the association between brands and key attributes in the process of a consumers' purchase decision. Their analysis revealed that brand preference enhances consumers' purchase intentions, and smartphone owners tend to continue purchasing the same brand of the smartphone as the one they already own.

Brand loyalty, defined as an amicable attitude and commitment toward a particular brand, builds around consumer satisfaction and leads to continued maintenance and purchasing of that brand (Ballantyne et al., 2006). Brand loyalty consists of attitudinal and behavioral loyalty, and all of which contribute to brand performance (Yeh et al., 2016). Specifically, behavioral loyalty can increase brand market share and profit. The attitudinal loyalty positively correlates with the acceptance of word of mouth and premium price (Shankar et al., 2003). Lee and Park (2016) pointed out that brand loyalty plays a more significant role in the purchase decisions of smartphones compared to other products. With the smartphone market dominated by a handful of brands such as Apple and Samsung, consumers are likely to have a strong loyalty to certain brands, which may significantly influence their purchase decisions when purchasing new smartphones.

The level of interest in brands other than the one currently owned is another factor that should be considered in the purchasing decision of smartphones. This is because the concept of brand preference, generally speaking, encompasses not only brand loyalty but one's interest towards other brands as well. In this respect, Chen et al. (2016) analyzed which factors affect consumers' repurchasing intentions and identified brand-related qualities (experience with the brand, service quality, trust, satisfaction, and commitment) as influencers. Price, function, appearance, social influence, and brand perception were set as external variables that affect brand-related qualities. The analysis revealed that some consumers made their purchasing decisions because they were convinced by other people. When consumers were satisfied with the quality of the service of a certain brand, they encouraged people around them to make similar purchasing decisions through word of mouth (Azad and Safaei, 2012). In sum, consumers can develop an interest in a new brand of smartphone under the influence of their peers, which can affect their intention to switch to a new brand.

Peer effect refers to the phenomenon in which one's purchasing decision is influenced by the purchasing actions of others, and it is observed in consumer behaviors (Bursztyn et al., 2014). As demonstrated, the peer effect can motivate consumers to develop an interest in smartphone brands other than the one they currently own. This is augmented by the fact that consumers continuously exchange information with one another on their smartphones (Kim et al., 2015) and smartphone use can serve as an indicator of one's social inclusion (Park et al., 2013). Furthermore, consumers are more likely to try out a new brand of the smartphone when they are influenced by peers with high levels of innovativeness (Hoffmann and Soyez, 2010).

In general, innovativeness represents two perspectives: product category and personal trait innovativeness. This study indicates the innovativeness as consumer innovativeness, which represents the psychological characteristic. Consumer innovativeness represents the consumers' innate tendency to be attracted by new products revealing through their early purchase of new products (Tellis et al., 2009). Thus, the consumer with a high level of innovativeness indicates people who disseminate opinions to others and play an important role in the product's diffusion (Rogers, 2010). In addition, consumers with high innovativeness are experts with broad knowledge and understanding of certain products (Bruner & Kumar, 2007), and those with a high level of innovativeness can influence the decisions of other consumers and play a role as an information provider (Childers, 1986). Therefore, analyzing the correlation between preferences of consumer and satisfaction of innovative peers, for the specific product is highly important for high-tech marketing strategies (Kim and Huarng, 2011). This study will define peers with high innovativeness as "consumers who are highly professional, provide information to others, and influence other people's purchasing decisions regarding high-tech products."

2.2. Discrete choice model considering reference-dependent preferences

Many existing studies have analyzed consumer preferences for smartphones using the discrete choice model. In particular, Park and Koo (2016) used a discrete choice experiment and the hierarchical Bayesian (HB) multinomial logit model to analyze Korean consumers' smartphone preferences. Their model utilized five attributes (OS, screen size, weight, performance, and retail price), and a survey was conducted on 1,370 smartphone users, between the ages of 15–59, who live in South Korea. This study focused on the switching cost of changing one's OS and demonstrated that consumers were inclined to maintain the same smartphone OS as the one they currently. WTP for maintaining the operating system was 202,700 KRW. The intention to retain the current OS can be represented as the loyalty to the OS. However, as mentioned above, using a standard discrete choice model may underestimate loyalty. Given that consumers are largely affected by their experience with their currently owned device when choosing a new smartphone, using a discrete choice model with reference-dependent preferences would be more desirable (Kim et al., 2016).

In general, consumer preference is accepted to be unrelated to the reference point or the status quo in standard consumer choice models concerning consumers' purchase decisions, including the discrete choice model (Hardie et al., 1993; Kim et al., 2019). However, consumers are likely to determine their gains and losses through the comparison of the reference point (Hess et al., 2012). In other words, consumers do not choose their products solely evaluating the presented levels of the product's attributes, but also consider these levels in relation to reference points as well (Kim et al., 2016; Kim et al., 2018). Psychological analysis on values has revealed that reference point is integral to determining consumers' preferences (Tversky and Kahneman, 1991) and the reference-dependent model was found to be superior to standard discrete choice model in explaining consumer behaviors (Bateman et al., 2009).

Models of reference-dependent theory include two characteristics (DellaVigna, 2009). The first characteristic is reference-dependent preferences, where the value (V) is not defined by the presented level of the attribute (x), but by the relative level ($x - r$) in comparison with the reference point (r). The second characteristic is the loss aversion parameter (λ), which is defined in the following Eq. (1) and generally has a measure higher than 1 in studies conducted using the reference-dependent theory. In other words, losses affect consumer utility more than gains (Tversky and Kahneman, 1991).

$$V(x|r) = \begin{cases} x - r & \text{if } x \geq r \\ \lambda|x - r| & \text{if } x < r \end{cases} \tag{1}$$

The most essential step in modeling reference-dependent and loss aversion is assigning a reference point for each respondent (Hardie et al., 1993; Hess et al., 2012). The most widely used reference point is status quo (Hess et al., 2012) and it is regarded as the most realistic reference point for analyzing purchasing decisions (Kim et al., 2016).

Similarly, Kim et al. (2016) analyzed Korean consumers' preferences for smartphones using a mixed logit model that reflects reference-dependent preferences. Six attributes were considered in their discrete choice experiment, including the OS, screen size, availability of 4G, weight, loading time, and price, and data were collected via face-to-face interviews with 1,003 respondents between the ages of 20 and 59. Their results indicated that smartphone owners felt the largest loss aversion with the operating systems. This demonstrated that the OS had the biggest lock-in effect. The loss aversion parameter of iOS was established as the largest among OSs, which provided an empirical demonstration of brand loyalty towards Apple and its iOS. However, their study focused on the OS and did not consider brand loyalty toward other brands besides Apple's iOS. In addition, they did not analyze the relationship between brand preferences and innovative peers.

3. Model specification

This study analyzes the brand loyalty, interest, and decision-making behaviors of customers purchasing smartphones using data obtained via questionnaires and a discrete choice experiment. This data will then be applied to the mixed logit model with consideration to the reference-dependence utility function. Logit or probit models, widely used forms of the discrete choice model, were applied under the unrealistic premise that all respondents have homogeneous preferences for each attribute of the product or service. The mixed logit model, on the other hand, can utilize probability distribution to reflect consumers' heterogeneous preferences for each attribute. The researcher can then also set the coefficient distribution of each attribute (Train, 2009).

Using the mixed logit model based on random utility theory, the utility U_{nj} that the respondent n gains from the alternative j is represented by Eq. (2) (Train, 2009).

$$U_{nj} = V_{nj} + \varepsilon_{nj} = \beta_n' x_j + \varepsilon_{nj},\ \beta_n \sim N(b, W) \tag{2}$$

As shown in Eq. (2), the utility U_{nj} can be classified into a deterministic term V_{nj} and a stochastic term ε_{nj}, the latter being uncertain. The deterministic term is a product of vector $x_j' = < x_{j1}, x_{j2}, \ldots, x_{jK} >$, the level of attribute k of the alternative j, which influences the respondent's utility, and coefficient vector $\beta_n' = < \beta_{n1}, \beta_{n2}, \ldots, \beta_{nK} >$, the marginal utility that the respondent assigns to each attribute. Therefore, the evaluation of the attributes of the respondent n varies according to respondents in the population, which has a probability density $f(\beta)$. In sum, a deterministic term refers to predictable aspects such as the smartphone's attributes, and a stochastic term refers to unpredictable elements. As mentioned above, the distribution of attribute coefficients could be set in the mixed logit model, so this study assumed that as shown in Eq. (2), it follows a normal distribution for flexibility. The discrete choice model may also be categorized by the premise of stochastic terms. This study was conducted on the premise that the stochastic term adheres to independent and identically distributed (i.i.d.) Type I extreme value distribution.

When deciding on an alternative, respondents are influenced to a different degree by each attribute, and this is known as relative importance. Part-worth of each attribute is used to derive relative importance of specific attribute k_s, as shown in Eq. (3). Here, the part-worth of the attribute k is calculated by multiplying the difference between the maximum and minimum levels of the attribute with the coefficient value of the attribute.

$$RI_{k_s} = \frac{part - worth_{k_s}}{\sum_k part - worth_k} \times 100 \tag{3}$$

Following this, the characteristics of each attribute must be identified in order to implement the discrete choice model considering reference-dependent preferences. This involved the researcher deciding whether the respondents' preference direction is the same or different for the attribute in question (Kim et al., 2016). Among the studies where the discrete choice model was implemented with consideration of reference points, many considered only attributes for which the respondents' preference direction was the same, such as cost and time. These cases can be straightforwardly represented by using the difference between the level of the attribute presented in alternative and the level of the attribute of the product currently owned, as shown in the first and second lines of Eq. (4) (Hess et al., 2008; Masiero and Hensher, 2010).

Where the study is aimed to focus on the gains and losses coefficients of attributes for which respondents' preference direction is different, reflecting the reference point requires a two-step procedure as demonstrated in lines three and four of Eq. (4). In specific, the individual-level coefficients for attribute derived from a standard mixed logit model and the signs representing the relative level (the difference between the attribute levels of the alternative and the status quo) are used to design the reference-dependent choice model.

$$\begin{aligned} U_{nj} = {} & I(x_{jk_{sg}} \geq x_{rk_{sg}})\beta_{nk_{sg}}^{gains}(x_{jk_{sg}} - x_{rk_{sg}}) + I(x_{jk_{sg}} < x_{rk_{sg}})\beta_{nk_{sg}}^{losses}|x_{jk_{sg}} - x_{rk_{sg}}| \\ & + I(x_{jk_{sh}} < x_{rk_{sh}})\beta_{nk_{sh}}^{gains}|x_{jk_{sh}} - x_{rk_{sh}}| + I(x_{jk_{sh}} \geq x_{rk_{sh}})\beta_{nk_{sh}}^{losses}(x_{jk_{sh}} - x_{rk_{sh}}) \\ & + I\{(\beta_{nk_d}^1 \geq 0 \& x_{jk_d} \geq x_{rk_d})\ or\ (\beta_{nk_d}^1 < 0 \& x_{jk_d} < x_{rk_d})\}\beta_{nk_d}^{gains}(x_{jk_d} - x_{rk_d}) \\ & + I\{(\beta_{nk_d}^1 < 0 \& x_{rk_d} \geq x_{jk_d})\ or\ (\beta_{nk_d}^1 \geq 0 \& x_{jk_d} <_{rk_d})\}\beta_{nk_d}^{losses}|x_{jk_d} - x_{rk_d}| + \varepsilon_{nj} \end{aligned} \tag{4}$$

Variables applied to Eq. (4) can be described as the following. First, x_{jk} is the level of attribute k that makes up the alternative j, and x_{rk} is the level of attribute k for the product currently owned by respondent n. $x_{jk_{sg}}$ and $x_{jk_{sh}}$ represent attributes whose preference directions are the same; for the former, the higher the level, the bigger the preference (like) is (e.g. memory and CPU), while for the latter, a higher level indicates non-preference (dislike) (e.g., price). x_{jk_d} represents level of attributes for which preference direction differs among respondents. Derived coefficients, β's upper subscripts *gains* and *losses*, represent the marginal utility of gains and losses respectively.

In order to reflect the influence of innovative peers on brand loyalty and interest in the model, Eq. (5), used for social network analysis was applied to brand attribute as an interaction term (Wang et al., 2013). Here, S_{BP} represents brand satisfaction felt by all peers for the smartphones they currently own and S_{B_o} represents brand satisfaction felt by a peer with a higher innovativeness.

$$\sum\nolimits_{o=1}^{O} S_{B_o} / \sum\nolimits_{p=1}^{P} S_{BP} \tag{5}$$

This study used the Bayesian estimation method to estimate the individual-level coefficients of each attribute. Bayesian estimation method minimizes the problem of the fluctuation of the maximization result depending on the initial value, which is commonly experienced in conventional estimation methods based on maximum likelihood estimation (MLE) (Edwards and Allenby, 2003). It also creates improved consistency and efficiency under flexible conditions (Train and Sonnier, 2005).

4. Empirical analysis

4.1. Survey design and data description

The discrete choice experiment was conducted on 1,001 citizens who owned a smartphone, resided in Seoul and other large cities[2] of South Korea. In addition, citizens whose ages ranged from 20 to 59[3] were selected by considering their purchasing capabilities and comprehension of the survey (Kim et al., 2016). The survey was conducted by Gallup Korea, a specialized research company, using face-to-face interviews, and the participants were selected by using a purposive quota sampling method. The purposive quota sampling method is based on the respondent's age, gender, and location to maintain a component ratio representative of the large cities in South Korea. A total of 991 responses were analyzed after excluding 10 people who did not answer the questions regarding their current smartphone. The demographic characteristics of the respondents are shown in Table 1, and the characteristics of smartphones currently owned by the respondents are shown in Table 2.

The attributes and levels used in the discrete choice experiment are explained in Table 3. All attributes besides the five shown in the table (brand, screen size, price, memory and user recognition technology) were assumed to be identical. The selection of the five attributes was determined by considering existing literature (Kim et al., 2016; Park and Koo, 2016), and their levels were determined by smartphones currently on sale.

There were 384 possible combinations of the five attributes and the levels of each attribute ($4 \times 3 \times 4 \times 4 \times 2 = 384$). Since it was not feasible to present all 384 alternatives to the respondents due to fatigue, time, and cost, 16 alternative cards were created using orthogonal design which is one of the fractional factorial designs (Johnson, 2013). For the questionnaire, the cards were grouped into choice sets, each set consisting of four cards. This allowed the respondents to choose one card with the highest utility by answering four choice sets.

In order to reflect peer effect, respondents were told to select a maximum of five peers whom they frequently interact with and then gauge the peers' satisfaction with their respective brand of smartphone. Questions regarding innovativeness were included for determining which peer had a higher level of innovativeness than the respondent. Since innovativeness is a subjective concept and cannot be measured

[2] Five major cities (Busan, Incheon, Daegu, Daejeon and Gwangju) and Gyeonggi (New Town).

[3] Considering the sample of this study, the consumer preferences for the smartphone analyzed in this study should be interpreted to the preferences of those between 20 and 60 years old residing in large cities in South Korea.

Table 1
Demographic characteristics of respondents.

Category		Number of respondents	Ratio
Gender	Male	500	50.5%
	Female	491	49.5%
Age	20s	223	22.5%
	30s	242	24.4%
	40s	268	27.0%
	50s	258	26.0%
Region	Seoul	432	43.6%
	Busan	142	14.3%
	Incheon	132	13.3%
	Daegu	106	10.7%
	Daejeon	64	6.5%
	Gwangju	64	6.5%
	Gyeonggi (New Town)	51	5.1%
Average Monthly Income	~3 million KRW	65	6.6%
	3 million KRW ~ 4 million KRW	165	16.6%
	4 million KRW ~ 5 million KRW	285	28.8%
	5 million KRW ~ 7 million KRW	333	33.6%
	7 million KRW ~	143	14.4%

Note: The following money units are given in USD where USD 1 is KRW (Korean Republic Won) 1,163 (Date: July 1, 2018).

Table 2
Characteristics of smartphones owned by respondents.

Category		Number of Respondents	Ratio
Brand	Samsung	686	69.2%
	Apple	145	14.6%
	LG	154	15.5%
	Others[a]	6	0.6%
Screen size	~5.0 inches	136	13.7%
	5.0 inches–5.5 inches	363	36.6%
	5.5 inches–6.0 inches	403	40.7%
	6.0 inches ~	89	9.0%
Price	~300 USD	298	30.1%
	300 USD ~500 USD	285	28.8%
	500 USD ~700 USD	261	26.3%
	700 USD ~	147	14.8%
Memory	16 GB	172	17.4%
	32 GB	395	39.9%
	64 GB	312	31.5%
	128 GB or greater	112	11.3%
User Recognition Technology	Yes	575	58.0%
	No	416	42.0%

[a] Others include Chinese brands such as Huawei and Xiaomi, as well as Motorola and Blackberry.

Table 3
Attributes and levels of the alternatives (smartphone) of the discrete choice experiment.

Attributes	Description	Level
Brand	Major smartphone manufacturers with sales in South Korea.	Samsung, Apple, LG, and others
Screen size (inches)	Size of the screen; the following are the most common screen sizes. (ex. iPhone 8: 4.7 in., iPhone 8 Plus: 5.5 in., Galaxy S8: 5.8 in., Galaxy Note 8: 6.3 in.)	4.5, 5.5, 6.5
Price (USD 10)	Price excluding carrier subsidy when the device is purchased as a lump sum.	26, 56, 86, 116
Memory (GB)	Built-in smartphone storage capacity excluding external storage such as Micro-SD card.	32, 64, 128, 256
User Recognition Technology	Recognition technology that allows the user to unlock the screen, log into an application, pay, etc. by means of fingerprint or face recognition.	No, Yes

using a single question, this study referred to existing studies (Ailawadi et al., 2001; Goldsmith and Hofacker, 1991; Lam et al., 2010) and derived three questions that were measured on a five-point Likert scale:

- How much technical knowledge of smart devices do you (they) have?
- How interested are you (they) in new products?
- How much advice do you (they) give to other people about purchasing high-tech products?

From these questions, the measuring with a Cronbach's alpha test is 0.7850. Thus, this study analyzes the effect of the peers' satisfaction on the brand preferences of respondents, and these peers are people with higher innovativeness than the respondent.

4.2. Estimation results

In generating the results, the first step of the analysis was a standard mixed logit model. Eq. (6) shows the empirical model in which data obtained from the discrete choice experiment was applied to Eq. (2).

$$U_{nj} = \beta_{n,Sam}d_{j,Sam} + \beta_{n,App}d_{j,App} + \beta_{n,LG}d_{j,LG} + \beta_{n,Scr}x_{j,Scr} + \beta_{n,Mem}x_{j,Mem} + \beta_{n,Int}d_{j,Int} + \beta_{n,Pri}x_{j,Pri} + \varepsilon_{nj} \quad (6)$$

In this equation, $d_{j,Sam}$ $d_{j,App}$, $d_{j,LG}$ are dummy variables which represent Samsung, Apple, and LG, respectively, and other brands are used as the baseline. $d_{j,Int}$ is also a dummy variable that shows whether the device has user recognition technology or not, and will have a value of 1 (yes) or 0 (no) depending on the attribute level reflected in the alternative. $x_{j,Size}$ $x_{j,Memory}$, $x_{j,Price}$ are linear variables that represent screen size, memory, and price, respectively. Numerical attribute levels, as reflected in the alternative, were applied to the model. $\beta_{n,k}$ were estimated through repeated probability sampling[4] under conditional distribution in accordance with the MCMC (Markov chain Monte Carlo). As mentioned above, the mixed logit model has the advantage of setting $\beta_{n,k}$ under various forms of distribution. Normal distribution was used in this study.

In the estimated results shown in Table 4, the mean coefficient refers to the consumers' marginal utility in relation to changes in the levels of each attribute. Furthermore, a high standard deviation reflects the heterogeneous preference in the collected samples (Baier, 2014). As expected, consumers preferred Samsung, Apple, and LG over other

[4] Probability sampling was repeatedly performed 20,000 times in the Markov chain using Gibbs sampling, then the 10,000 samples were discarded, and the remaining 10,000 samples were used for analysis.

Table 4
Estimation results for standard mixed logit model.

Variables		Mean	Std. D	Part-worth	RI (%)
Brand (reference: others)	Samsung	6.571***	3.452***	6.505	27.3
	Apple	3.627***	3.622***	3.610	15.9
	LG	3.096***	2.005***	3.109	14.4
Screen size (inch)		0.097*	0.651***	0.446	2.2
Memory (100 GB)		1.151***	1.051***	2.591	10.7
User recognition technology		1.013***	1.533***	1.154	5.2
Price (thousand USD)		−6.431***	5.360***	5.846	24.2
Log-likelihood (AIC, BIC)		−3219.202 (6452.404, 6459.377)			

Note: ***Significant at the 1% level, **Significant at the 5% level, *Significant at the 10% level.

brands, and preferred devices with bigger memory, user recognition technology, and lower prices. The relative importance (RI) of each attribute derived using Eq. (3), illustrated that consumers perceived the brand as the most important factor in their purchasing decision. The RI was found to be the lowest for screen size, which could be attributed to the fact that the discrete choice experiment performed in this study included only the most important attributes of the smartphone and recently released smartphones have similar screen sizes. The price also had a significant influence on consumers' preference and smartphone purchasing decisions.

The marginal utility gained by individual respondents for each attribute which was derived using the standard mixed logit model in the first step and the attribute levels of smartphones currently owned which were the reference points were applied to Eq. (4). The reference-dependent utility by respondents from a choice of the alternative can be represented by Eq. (7), and the estimated results are shown in Table 5. According to AIC (Akaike's Information Criterion) (Akaike, 1998) and BIC (Bayesian information criterion) (Schwarz, 1978) statistics in Tables 4 and 5, the reference-dependent choice model performs better compared to the standard mixed logit model in terms of model fit. In other words, the reference point effect influences the consumer's decision making (Hardie et al., 1993).

Table 5
Estimation results for mixed logit model considering the reference-dependent preferences.

	Variables		Mean	Std. D
Brand	Samsung			
		Gains	4.038***	2.095***
		Losses	−6.632***	2.393***
	Apple			
		Gains	2.305***	2.019***
		Losses	−7.968***	2.223***
	LG			
		Gains	1.951***	1.796***
		Losses	−3.805***	2.009***
Screen size (inch)				
		Gains	0.910***	0.854***
		Losses	−1.073***	0.892***
Memory (100 GB)				
		Gains	0.814***	1.011***
		Losses	−2.068***	1.436***
User recognition technology				
		Gains	0.931***	1.394***
		Losses	−0.976***	1.529***
Price (thousand USD)			−5.820***	5.811***
Log-likelihood (AIC, BIC)	−2674.965 (5375.930, 5388.879)			

***Note: Significant at the 1% level, **Significant at the 5% level, *Significant at the 10% level.

LG in that descending order. On the other hand, Samsung among brands had the highest coefficient related to gains, which indicates the degree of interest in the brand that is not currently owned. This is consistent with the study by Ganesan and Sridhar (2014) that found that Apple has the highest degree of brand loyalty compared to other brands, but may have difficulty in attracting customers who are using other brands due to the complexity of iOS and the higher price of Apple smartphones.

Marginal utility, which gained by consumers from switching their smartphone brands, can be explained by combining the value of the coefficients of the losses (brand loyalty) and the gains (brand interest).

$$
\begin{aligned}
U_{nj} = {} & I(\beta^1_{n,Sam} \geq 0 \& d_{j,Sam} \geq d_{r,Sam})\beta^{gains}_{n,Sam}(d_{j,Sam} - d_{r,Sam}) + I(\beta^1_{n,Sam} \geq 0 \& d_{j,Sam} < d_{r,Sam})\beta^{losses}_{n,Sam}|d_{j,Sam} - d_{r,Sam}| \\
& + I(\beta^1_{n,App} \geq 0 \& d_{j,App} \geq d_{r,App})\beta^{gains}_{n,App}(d_{j,App} - d_{r,App}) + I(\beta^1_{n,App} \geq 0 \& d_{j,App} < d_{r,App})\beta^{losses}_{n,App}|d_{j,App} - d_{r,App}| \\
& + I(\beta^1_{n,LG} \geq 0 \& d_{j,LG} \geq d_{r,LG})\beta^{gains}_{n,LG}(d_{j,LG} - d_{r,LG}) + I(\beta^1_{n,LG} \geq 0 \& d_{j,LG} < d_{r,LG})\beta^{losses}_{n,LG}|d_{j,LG} - d_{r,LG}| \\
& + I\{(\beta^1_{n,Scr} \geq 0 \& x_{j,Scr} \geq x_{r,Scr}) \text{ or } (\beta^1_{n,Scr} < 0 \& x_{j,Scr} < x_{r,Scr})\}\beta^{gains}_{n,Scr}(x_{j,Scr} - x_{r,Scr}) \\
& + I\{(\beta^1_{n,Scr} < 0 \& x_{j,Scr} \geq x_{r,Scr}) \text{ or } (\beta^1_{n,Scr} \geq 0 \& x_{j,Scr} < x_{r,Scr})\}\beta^{losses}_{n,Scr}|x_{j,Scr} - x_{r,Scr}| \\
& + I(x_{j,Mem} \geq x_{r,Mem})\beta^{gains}_{n,Mem}(x_{j,Mem} - x_{r,Mem}) + I(x_{j,Mem} < x_{r,Mem})\beta^{losses}_{n,mem}|x_{j,Mem} - x_{r,Mem}| \\
& + I(d_{j,Int} \geq d_{r,Int})\beta^{gains}_{n,Int}(d_{j,Int} - d_{r,Int}) + I(d_{j,Int} < d_{r,Int})\beta^{losses}_{n,Int}|d_{j,Int} - d_{r,Int}| + \beta_{n,pri}x_{j,Pri} + \varepsilon_{nj}
\end{aligned}
\tag{7}
$$

Respondents' preferences for attributes can be classified into gains and losses. In particular, the absolute value of losses coefficient for the brand can explain the status quo and brand loyalty illustrating the consumers' tendency to maintain the brand they currently own and prefer, as represented in the literature review section. The loss aversion parameter calculated by dividing the coefficient of losses by the coefficient of gains and the results of asymmetric preference test are also shown in Table 6. This confirmed that consumers have asymmetric preferences for all attributes that take into an account reference point. In addition, the loss aversion parameters for all attributes were found to be greater than one, which is consistent with existing studies.

The estimation coefficients for the brand, the core attribute in this study, are as follows. If consumers convert their existing smartphone brands to other preferred brands, they will gain utility from the new brand but simultaneously lose utility by abandoning the smartphone brand that they own and prefer. Therefore, the absolute value of losses coefficient for a brand can be expressed as loyalty to the brand currently owned, and our analysis revealed brand loyalty was the highest for Apple, Samsung, and

The following example is an illustration of Apple smartphone users switching to Samsung phones. The losses coefficient (−7.968) from discarding Apple smartphone which they prefer and the gains coefficient (4.038) from obtaining a new Samsung smartphone was calculated; adding these together yields a total marginal utility of −3.930, which is negative. In other words, it is very unlikely for this consumer to switch to a Samsung smartphone unless its attributes (screen size, memory, price, etc.) are significantly superior to an Apple smartphone. Another example is LG users switching to Samsung smartphones. The losses coefficient (−3.805) from discarding LG smartphone which they prefer and the gains coefficient (4.038) from obtaining a new Samsung smartphone was calculated; adding these together yields a total marginal utility of 0.233, a positive value. Therefore, if the attributes of the Samsung smartphone are comparable with those of the LG smartphone, it is very likely for the consumers to choose Samsung smartphones in their next purchase. For these consumers, the marginal utility gained from switching to Apple is negative (−1.050), so the probability of them switching to Apple smartphones is low.

Table 6
The results of loss aversion parameters and the asymmetry preference test on each variable.

Variables		Loss aversion parameter	Pr(T < t)	Preference
Brand	Samsung	1.642	0.000	Asymmetry
	Apple	3.456	0.000	Asymmetry
	LG	1.950	0.000	Asymmetry
Screen size		1.179	0.000	Asymmetry
Memory		2.542	0.000	Asymmetry
User recognition technology		1.045	0.050	Asymmetry

This study also examined the influence of peer effect on brand loyalty and interest. In order to reflect peer effect on the discrete choice model in addition to reference point effect, Eqs. (4) and (5) were used to design the model as shown in Eq. (8). Here, $B_{o,Sam}$, $B_{o,App}$, and $B_{o,LG}$ represent the brand of smartphone owned by the respondent's peer with a higher innovativeness, and represent Samsung, Apple, and LG, respectively. S_{B_o} is satisfaction felt by innovative peers toward each brand, and S_{B_p} represents satisfaction felt by all peers, including the innovative peers. The influence of the innovative peer's satisfaction of their smartphone on the respondent's interest in the brand is represented by$\alpha_n^{o,g}$, and its influence on the respondent's brand loyalty is denoted with$\alpha_n^{o,l}$.

$$
\begin{aligned}
U_{nj} = {} & I(B_{o,Sam} = d_{j,Sam} \geq d_{r,Sam})\left\{\beta_{n,Sam}^{gains} + \alpha_{n,Sam}^{o,g}\left(\sum_{o=1}^{O} S_{B_{o,Sam}} / \sum_{p=1}^{P} S_{B_P}\right)\right\}(d_{j,Sam} - d_{r,Sam}) \\
& + I(d_{j,Sam} < d_{r,Sam} = B_{o,Sam})\left\{\beta_{n,Sam}^{losses} + \alpha_{n,Sam}^{o,l}\left(\sum_{o=1}^{O} S_{B_{o,Sam}} / \sum_{p=1}^{P} S_{B_P}\right)\right\}|d_{j,Sam} - d_{r,Sam}| \\
& + I(B_{o,App} = d_{j,App} \geq d_{r,App})\left\{\beta_{n,App}^{gains} + \alpha_{n,App}^{o,g}\left(\sum_{o=1}^{O} S_{B_{o,App}} / \sum_{p=1}^{P} S_{B_P}\right)\right\}(d_{j,App} - d_{r,App}) \\
& + I(d_{j,App} < d_{r,App} = B_{o,App})\left\{\beta_{n,App}^{losses} + \alpha_{n,App}^{o,l}\left(\sum_{o=1}^{O} S_{B_{o,App}} / \sum_{p=1}^{P} S_{B_P}\right)\right\}|d_{j,App} - d_{r,App}| \\
& + I(B_{o,LG} = d_{j,LG} \geq d_{r,LG})\left\{\beta_{n,LG}^{gains} + \alpha_{n,LG}^{o,g}\left(\sum_{o=1}^{O} S_{B_{o,LG}} / \sum_{p=1}^{P} S_{B_P}\right)\right\}(d_{j,LG} - d_{r,LG}) \\
& + I(d_{j,LG} < d_{r,LG} = B_{o,LG})\left\{\beta_{n,LG}^{losses} + \alpha_{n,LG}^{o,l}\left(\sum_{o=1}^{O} S_{B_{o,LG}} / \sum_{p=1}^{P} S_{B_P}\right)\right\}|d_{j,LG} - d_{r,LG}| \\
& + \beta_{n,Scr}x_{j,Scr} + \beta_{n,Mem}x_{j,Mem} + \beta_{n,Int}d_{j,Int} + \beta_{n,Pri}x_{j,Pri} + \varepsilon_{nj}
\end{aligned}
\tag{8}
$$

The estimated results for the coefficients are shown in Table 7. They also demonstrate that the average consumer has the highest level of interest in Samsung and the highest level of loyalty in Apple, similar to the results shown in Table 5. Additionally, consumers had a higher interest in brands that they do not own when their peers with a high level of innovativeness expressed satisfaction with that brand of smartphone. However, brand satisfaction felt by peers with higher innovativeness was found to be a statistically significant influencer of brand loyalty only for Apple.

5. Conclusion

The discrete choice experiment that used in this study reflects the multiple attributes of the product and can be used to analyze the consumers' preferences. In addition, the results obtained through the discrete choice model can be used for the strategic development of corporate marketers. However, a standard discrete choice model does not consider consumers' reference-dependent preferences. In more reality, consumers are significantly affected by their reference point when they purchase new products. Therefore, in this study, consumers' preference of smartphone is analyzed by applying the asymmetric discrete choice model with reference-dependent preferences. Especially, this study analyzed the loss aversion parameter and asymmetric preferences for each attribute of the smartphone. Reflecting the consumers' reference-dependent preferences in the model improved the performance of the empirical analysis, and provided a better understanding of consumers' purchasing behavior.

As a result of the empirical analysis, the brand has been found to be the most important attribute in consumers' purchasing decisions for smartphones. In related to the brand attribute, our findings revealed that respondents had the highest level of interest for Samsung when it came to brands other than the one they currently own. This result may be resulted from the country of origin effect of the brand, Samsung. The percentage of respondents who own the Samsung and LG smartphone is 69.2 percent and 15.5 percent, respectively. That means seven out of ten consumers use the Samsung smartphone, leading Korean consumers to have the strongest brand interest for Samsung. However, the interesting point is that despite the country of origin effect, Apple had the highest brand loyalty, even though only 145 (14.6 percent) of the respondents were Apple users. Given that a critical characteristic of Apple is its small pool of highly loyal consumers, it is suitable to apply the discrete choice model considering reference-dependent preferences in analyzing brand loyalty (Kim et al., 2016).

In addition, the level of interest in other brands increased with satisfaction felt by peers with higher innovativeness toward their respective smartphones. In other words, consumers develop more interest in brands that their peers express high satisfaction for, and view that brand in a positive light. However, in related to brand loyalty, brand satisfaction felt by peers with higher innovativeness was found to be statistically significant only for Apple's brand loyalty. According to the respondents in the survey, the number of respondents aged 20–30 who have an Apple smartphone was 116, indicating that about 80% of Apple smartphone owners are young. Therefore, this result could be featured to Apple user's tendency to project Apple's innovativeness image onto themselves, given the youth are more susceptible to the opinions of their peers and dislike falling behind others. In sum, it would be in a smartphone manufacturers' best interest to focus on enhancing the satisfaction felt by their existing customers as well as attracting new ones in order to expand their market share and remain competitive in the industry.

One of the limitations of this study is the generalizability of the sample. Since brands such as Samsung and LG are originated in the Korean market before they have become global brands, it is difficult to generalize the results of this study to other countries. The findings of this study are also limited because it only considered circumstances when a consumer chose a new smartphone based on their experience with the device they already own. Considering that the current average global smartphone replacement cycle is 21 months (Lu, October 2017), consumers' purchasing decisions should be understood as a reflection of their cumulative purchasing experience with several devices. Although this study limited the scope of analysis to make data collection more efficient, future studies will use the data of real purchase history, which

Table 7
Estimation results for mixed logit model with reference point and peer effect.

Variables			Mean	Std. D
Brand	Samsung			
		Gains	3.815***	1.993***
		Losses	−6.451***	2.489***
	Apple			
		Gains	2.415***	1.510***
		Losses	−7.991***	2.729***
	LG			
		Gains	1.952***	1.603***
		Losses	−3.746***	1.868***
Innovators' brand satisfaction	Samsung			
		Gains	0.803**	1.699***
		Losses	0.267	2.223***
	Apple			
		Gains	1.007***	1.578**
		Losses	−1.240***	1.515***
	LG			
		Gains	1.948***	2.554***
		Losses	0.807	2.262***
Screen size (inch)			0.090	0.814***
Memory (100 GB)			0.924***	0.999***
User recognition technology			1.036***	1.420***
Price (million KRW)			−5.978***	5.496***

Note: ***Significant at the 1% level, **Significant at the 5% level, *Significant at the 10% level.

would allow for the analysis of changing preference over the course of multiple purchases. In addition, the difference in preference according to demographic characteristics (gender, age, etc.) was not reflected in our model. Future studies could employ a hierarchical Bayesian logit model with reference points, which would enable the analysis of differences in preference among different demographic groups.

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