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Google TV or Apple TV?—The Reasons for Smart TV Failure and a User-Centered Strategy for the Success of Smart TV

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Abstract: Traditional television (TV) has evolved into smart TV in terms of both hardware and software. However, compared with smart phones and tablet PCs, which are huge successes in the market, smart TV has grown more slowly than the market expected and has not really changed the TV market. In this study, we investigate reasons for the failure of smart TV from consumer perspectives. We use conjoint analysis to collect stated preference data from consumers. Our analysis consists of two parts: analyzing consumer preferences for six attributes of smart TVs and examining the effects of socio-demographic and behavioral information on purchase intention for a smart TV. Based on the estimation results from the first part, we find that consumers set a higher value on the traditional characteristics of TV than on the functions of smart TV. Thus, smart TV does not have key functions to encourage its adoption over traditional TV. From the second part of our analysis, we identify which factor is most important to increase purchase intention for a smart TV. Based on our results, we can suggest the direction of market strategies about how to cross the chasm of smart TV.

Keywords: smart TV; consumer preference; mixed logit; binary logit; conjoint analysis; Bayesian estimation

1. Introduction

Since it was developed, television (TV) has been one of the most loved home appliances. Starting from monochrome (black-and-white) TV, it evolved to color and again to 3-dimensional (3D) TV, and the technology still continues to evolve. In terms of hardware, the size of display panel is getting larger while the weight is getting lighter. For example, LG Display recently developed a 55-inch OLED panel that can be stuck to a wall using a magnetic mat. It weighs just 1.9 kg and is just 0.97 mm thick. As another direction of TV evolution, consumers can now enjoy not only traditional broadcasting media but also online interactive media, over-the-top content, and various applications as TV is integrated with software and the internet, so-called smart TV.

Smart TV can be defined as OS (operating system) platform–based TV that provides online video clips and applications such as social network services, emails, and location-based services in addition to traditional broadcasts. That is, smart TV implies the expansion of traditional TV to internet content and web services and represents the evolved form of connected TV and IPTV (Internet protocol television). When smart TV was first launched, many experts forecasted that it would become a main device which controls various content and games in addition to traditional TV services and unite a smart media ecosystem including smart phones and smart pads (e.g., iPad, Galaxy Tab). With such high expectations, Watkins [1] forecasts that the global sales volume of smart TVs would reach up to 220 million units in 2017. Google and Apple, which have led the smart phone market, entered the smart TV market with Google TV and Apple TV, respectively. Both companies had big success in the smart pad market by applying the same business model that was successful in the smart phone market, which makes sense in that smart pads are similar to smart phones but with larger screens. In one sense, smart TVs are just a larger-screen version of smart pads, and that could explain why many forecast the success of smart TV.

Contrary to expectations, however, first generation Apple TV was not a success in the market because of its inconvenient usability, high price, and small amount of content. Likewise, Google failed to achieve user interest even though it uncased its smart TV platform in partnership with Logitech and Sony. Those failures surprised both experts and the public because both companies were so successful in the smart phone and smart pad markets. Of course, Apple continues to upgrade its product, launching second generation Apple TV in 2010 and third generation in 2012, and Google has also expanded its partnership and conducted second generation development. But even though Google got a positive market response to Chromecast, a digital media player released in July 2013, and announced Android TV in 2014, those products are widely seen as unlikely to change the entire TV market.

It is hard to say that smart TV has failed judging from its current sales status. However, several market data sets show that smart TV is not changing the TV market and that consumers are not using the units they do buy as real "smart" TVs but just as new ones. According to the device ratio of consumers using BBC's iPlayer application, the ratio of Internet TV (*i.e.*, smart TV) users is 2%, and the ratio of personal computer users decreased from 47% in May 2013 to 34% in March 2015. On the other hand, the summation of mobile and tablet users increased to 49%. Thus, consumers continue to use smart TVs as simple TVs. Kim [2] analyzed media diary data, and the result shows 99.6% of usage time of smart TVs was watching traditional TV programs. Thus, Kim [2] points out that smart TVs are mostly used as traditional TVs, and consumers barely use the smart functions of smart TVs in Korea.

Although market analysis for overcoming a current bottleneck in the smart TV market is needed, most previous literature related to smart TVs focused on technological improvement of smart TVs. A few studies analyze consumer preference for smart TV, but these studies did not provide why diffusion of smart TVs has a gap with market expectation. Hence, this paper investigates reasons for the failure of smart TV from the viewpoint of consumers. People share a TV in the living room with their family, contrary to smart phones and smart pads, which are private devices. People watching TV do not want to actively input or find information but want rest comfortably while they watch. Accordingly, we categorize the characteristics of smart TVs into traditional ones and the others to use smart TV to be smart, and find which attributes consumers regard as most important. We consider definition and screen size as the characteristics of traditional TVs and possibility of 3D service, number of applications, and OS platform as the characteristics of smart TV. In addition, we divide smart TVs into television sets with integrated Internet capabilities (*TV set type*) and set-top boxes for any television (*set-top box type*) and investigate how consumers' preferences change with the attributes of smart TVs. By doing so, we analyze why smart TV has failed in terms of consumer preference and suggest a user-centered strategy for the success of smart TV.

Existing Research on Smart TV

In our review of the previous literature related to smart TVs, we found that most studies suggested ways to improve smart TVs in terms of technology [3–6] or services [7–10]. For instance, Jeong and Lee [3] introduced a new content search method that minimizes the consumer effort needed to use multimedia content in a smart TV environment. Similarly, Park *et al* [6] suggested a way to increase the performance of voice recognition by decreasing noises and then tested the performance of their method. In terms of services, Pyo *et al*. [7] proposed a scheme that automatically recommends TV programs to consumers using sequential pattern mining. Linda *et al*. [8] conducted a case study of European video-on-demand (VOD) services to analyze the success factors of VOD applications to smart TVs and the obstacles in diffusing VOD applications. In addition, Ko et al. and Shin *et al*. [9,10] analyzed factors for the successful introduction of smart TVs and applications.

Several studies have investigated consumer preferences in adopting smart TVs, but they simply analyzed the effects of particular functions and consumer characteristics in the adoption of smart TVs [11–16]. Prabhala and Ganapathy [14] analyzed consumer perceptions of smart TVs from the viewpoint of artificial intelligence, and Shin and Kim [15] investigated the effect of interactions between users and smart TVs on consumers' perceptions, attitudes, and willingness to use. Lee [13] introduced six main factors (perceived usefulness, perceived ease of use, *etc.*) that affect smart TV adoption using the technology acceptance model and diffusion of innovation theory. To the best of our knowledge, however, no study has yet proposed a user-centered strategy to analyze why smart TVs have failed to meet expectations.

Although there is a gap between the market expectation and actual sales of smart TVs, a market analysis for explaining this gap has not yet been conducted. Therefore, this study analyzes the reasons for smart TV failure from consumer perspectives. According to [17], TV manufacturers did not provide attractive smart TV features to consumers. Anthony [18] mentioned that the 3D function, which is one feature of smart TVs, did not leave an impression on consumers because consumers only focused on brand new models, not the 3D function. Based on the literature review, we develop the following research hypothesis to figure out the gap between the market expectation and actual sales of smart TVs:

(i) Even if consumers prefer brand new models in the TV market, consumers do not attach high value to smart TV features.
(ii) Although smart TVs have differentiated functions from traditional TVs, consumers still have "lean back" characteristics regarding smart TVs.

The remainder of this paper is structured into four sections. Section 2 briefly explains the research models, and Section 3 provides a description of choice experiments and data. Section 4 presents our results and the reason for smart TV failure. We present our conclusions in Section 5.

2. Model

We use discrete choice models based on random utility theory to analyze consumer preference. A discrete choice model assumes that each consumer i has its own utility function for each product j in choice set t [19,20]. This utility function can be stated as Equation (1).

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} = \sum_k \beta'_{ik} X_{jkt} + \varepsilon_{ijt} \tag{1}$$

In Equation (1), a random utility model is divided into effects from deterministic factors (V_{ijt}) and random factors (ε_{ijt}). The deterministic part consists of the marginal utility of each attribute k of product j (β_{ik}) and the vector of each attribute (X_{jkt}). Models are differentiated by the specification of β_{ik} and ε_{ij}. Among various discrete choice models, we adopt two models: a binary logit model to learn why a consumer did not adopt smart TV, and a mixed logit model to analyze consumer preference for the characteristics of traditional and smart TV.

A binary logit model considers a binary choice situation that is adopted or not adopted. In this study, we consider whether or not consumers have purchase intention for a smart TV. Because a binary logit model assumes that ε_{ij} follows i.i.d extreme value distribution and β_{ik} is equal to all consumers, the likelihood function can be derived as Equation (2).

$$L = \left(\prod_{i=1}^{N} \frac{e^{\sum_k \beta_k' X_{jkt}}}{1 + e^{\sum_k \beta_k' X_{lkt}}} \right) \tag{2}$$

where, N represents the number of consumers, which is the total number of respondents in this study.

We also adopt a mixed logit model to analyze consumer preferences for each attribute of smart TV and compare those results with preferences for the characteristics of traditional TV. Unlike other discrete choice models, a mixed logit model allows the marginal utility β to be stochastic to consider consumer heterogeneity. Thus, β_{ik} is defined as a coefficient vector and follows the multivariate normal distribution, $\beta_{ik} \sim N(b_k, \Sigma_k)$, which consists of mean b_k and covariance matrix Σ_k. Moreover, a mixed logit model can define different distributions for each attribute's coefficient depending on the effect of the attribute on consumers [20]. For instance, coefficient vectors generally follow the normal distribution. However, when all consumers have the same direction of preference, the normal distribution is unsuitable. Therefore, another distribution must be assumed for certain coefficients, such as cost [21]. To assume that some coefficient β follows a log-normal distribution, a transformation process converts the equation $C(\beta) = \exp(\beta)$. From those assumptions, the likelihood function for each consumer can be derived as Equation (3).

$$L(d_n | \beta_n) = \left(\prod_{t=1}^{T} \frac{e^{C(\beta_n)' x_{jt}}}{\sum_{k=1}^{J} e^{C(\beta_n)' x_{kt}}} \right) \tag{3}$$

where d_n represents that each consumer n chooses T-times among a total of $T \times J$ alternatives in each choice set.

To estimate the coefficients of our mixed logit model, we use the Bayesian estimation method because it is too complicated to calculate the maximum likelihood by classical methods. The Bayesian estimation method has some advantages in addition to avoiding computational complexity, such as integration of a multivariate density function and overcoming the initial point problem [22–24].

Based on the results of the mixed logit model, we provide the marginal willingness-to-pay (MWTP) and relative importance (RI) of each smart TV attribute to provide economic value. The background of MWTP is compensation value in microeconomic theory, so MWTP is the amount of payment to compensate for a 1-unit change in attribute k. MWTP and RI are derived through Equations (4) and (5), respectively.

$$\text{Median } MWTP_k = \text{Median}_i \left[-\frac{\partial U_i / \partial x_i}{\partial U_i / \partial p_i} \right] = \text{Median}_i \left[-\frac{\beta_{ik}}{\beta_{i(price)}} \right] \tag{4}$$

$$(\text{Average Relative Important Percent of Attribute } k) = \frac{1}{N} \sum_{n=1}^{N} \left(\frac{\text{part-worth}_{nk}}{\sum_k \text{part-worth}_{nk}} \times 100 \right) \tag{5}$$

where, part-worth_{nk} = (interval of attribute k's level) $\times \beta_{nk}$.

3. Survey and Data

We conducted a survey to collect data on consumers' usage patterns of smart devices and sampled 1450 consumers in the Seoul area. Because consumers older than 60 have a relatively low usage rate for smart devices and consumers younger than 19 have relatively low purchase power for smart devices, we collected our sample from people aged 19 to 59 using an online survey. In addition, we used the purposive quota sampling method to reflect the characteristics of the actual population. The demographic properties of our sample are shown in Table 1.

Table 1. Demographic properties of sample.

		# of Respondents	Component Ratio (%)
Total		1450	100.0
Sex	Male	810	55.9
	Female	640	44.1
Age	19–29	483	33.3
	30–39	500	34.5
	40–49	344	23.7
	50–59	123	8.5
Education Level	High school	183	12.6
	College	242	16.7
	University	876	60.4
	Above graduate school	149	10.3
Average Monthly Income [a] (10^4 KRW) [b]		483.59	

[a] Because respondents to this study must have at least one smart device, average monthly income in this study is higher than in the general population; [b] KRW represents Korean won, the currency of South Korea. 1 USD is equal to 1171 KRW as of 6 August 2015.

At the time the survey was conducted, South Korea ranked second with 58% fiber broadband penetration, and wireless broadband penetration was highest among OECD countries (e.g., see [25]). According to the market research firm, Strategy Analytics, smartphone ownership was also highest in the world; 67.6% of Korean consumers own smartphones while the global average was 14.8% [26]. Since this study analyzed survey data from South Korea that shows a high penetration rate of advanced ICT, such as smartphones, and the sample of this study focused on respondents who possess at least one smart device, we assume that the sample population from South Korea is more technically aware than other countries. Therefore, the results might be different for other countries, and it is important to be aware of this fact when interpreting the analysis results.

Our survey contains four parts. First, we asked screening questions about whether respondents possess at least one smart device in order to improve the understanding of smart TV features, because our goal is to analyze consumers' usage pattern for smart devices, especially for smart TVs. Based on the screening questions, we focused on respondents who have at least one smart device to prevent the misunderstanding of smart TV features. Second, we collected general information about respondents such as age, sex, income, education level, and so on. Third, we asked for respondents' purchase intentions for smart TVs. Last, we collected their preference for smart TV attributes, including TV set type or set-top box type, using the conjoint survey method.

The survey results show that 226 of the 1450 respondents possess a smart TV. Of the 226 respondents who have a smart TV, 84.07% prefer the TV set type. On the other hand, among respondents who do not own a smart TV, only 66.09% said they prefer a TV set type. Taken together, more respondents prefer a smart TV set type (68.9%, $n = 999$) than a set-top box type (31.10%, $n = 451$) (Table 2).

To analyze consumer preferences for the attributes of smart TV, we used conjoint analysis: we collected stated-preference data from respondents by providing alternative cards that each contained several attributes to reflect the properties of actual market products. In other words, respondents choose the alternative they most prefer to maximize their utility, so conjoint analysis can analyze the part-worth of attribute levels based on respondents' stated preferences [27]. Moreover, the results of a conjoint analysis could forecast consumer preferences for various combinations of attributes in products or services [28,29].

Table 2. Preference between TV set type and set-top box type.

		# of Respondents	Component Ratio (%)
Possessors of smart TV	TV set type	190	84.07%
	Set-top box type	36	15.93%
Total		226	100.00%
Non-possessors of smart TV	TV set type	809	66.09%
	Set-top box type	415	33.91%
Total		1224	100.00%

To describe smart TV, we consider several attributes: definition, screen size, possibility of 3D service, number of applications, OS, and price. As mentioned above, we consider definition and screen size as characteristics of traditional TVs and the possibility of 3D service, number of applications, and OS platform as characteristics of smart TVs. Other possible attributes, such as design and weight, are deemed equal in all alternatives. The detailed explanation of the attributes and their levels are described in Table 3.

Table 3. Attributes and attribute levels of smart TV.

Attribute	Level	Explanation
Definition	Regular analog TV	Definition of regular analog TV is 320×240 (=76,800 pixels).
	Standard Definition (SD)	Similar to general DVD resolution, which is 720×480 (=345,600 pixels), SD is 4.5 times higher resolution than regular analog TV.
	High Definition (HD)	HD is 6 times higher resolution than SD, 1920×1080 (=2,073,600).
Screen size	40 inch	TV screen size
	55 inch	
	60 inch	
Possibility of 3D service	Possible	Whether 3D service is possible
	Impossible	
# of Applications	25% of the total number of applications available for smart phones	Number of applications available for download through TV: 100% represents being able to use applications on TV similar in number to those available for a smart phone, and 50% describes being able to use only about half as many applications on the TV as on a smart phone.
	50% of the total number of applications available for smart phones	
	100% of the total number of applications available for smart phones	
OS	iOS	Smart TV operating system made by Apple Inc.
	Android	Smart TV operating system made by Google
	Manufacturer's OS	Smart TV operating system made by a major manufacturer such as Samsung or LG
Price	1/2/3 million KRW for TV type	Price of smart TV
	0.1/0.2/0.3 million KRW for set-top box type	

Based on the six attributes and attribute levels, the number of possible combinations for a TV set type smart TV is 486 (=3 × 3 × 2 × 3 × 3 × 3), and the number of possibilities for set-top box type units is 27 (=3 × 3 × 3) because the attributes of set-top box type smart TVs are only number of applications, OS, and price. Because respondents could have difficulty choosing their preferred alternative from among such a large number of options, we used a fractional factorial design to extract optimal alternatives and satisfy orthogonality. We created 18 and 9 alternative cards for TV type and set-top box type units, respectively. We then offered the respondents six alternative sets for TV type units and three alternative sets for set-top box type unit; each alternative set contained three alternative cards. Thus, we asked respondents to choose the card in each set that provides the highest utility. An example of conjoint analysis is shown in Table 4. We provide an example of a conjoint card to improve respondents' understanding of how to state their preference before starting the main survey. In addition, we also controlled for the responding time to prevent survey errors originating from the misunderstanding of discrete choice experiments.

Table 4. Sample alternative set in the survey questionnaire.

- **Question 1 for TV type**

Attributes	Smart TV A	Smart TV B	Smart TV C
Definition	SD	Regular analog TV	HD
Screen Size	55 inch	60 inch	40 inch
Possibility of 3D service	Yes	No	Yes
# of Applications	50% level	50% level	25% level
OS	Android	Android	iOS
Price	3 million KRW	2 million KRW	2 million KRW
I Choose: A _____ B _____ C _____			

- **Question 2 for set-top box type**

Attributes	Set-top box A	Set-top box B	Set-top box C
# of Applications	100% level	25% level	25% level
OS	Android	iOS	Manufacturer's OS
Price	0.3 million KRW	0.5 million KRW	0.1 million KRW
I Choose: A _____ B _____ C _____			

4. Results and Discussion

Our purpose in this study is to examine the reasons for the failure of smart TVs from consumer perspectives. To investigate the main factors of this failure, we did not include an option for not buying a smart TV in the conjoint analysis. To provide more detailed information about the reasons for smart TV failure from a consumer viewpoint, we divided our analysis into two parts. First, we analyzed consumer preferences for each smart TV attribute with a mixed logit model when all respondents were assumed to buy a smart TV. Based on the estimation results from the first part, we compare the consumer preference between characteristics of traditional TVs and smart TVs, and investigate the difference between traditional TVs and smart TVs from consumer perspectives. Second, we used a binary logit model to analyze the main factors explaining why consumers do not have an intent to purchase a smart TV. Based on the estimation results from the second part of our analysis, we investigate how to cross the chasm of smart TVs from the viewpoints of consumers.

4.1. Consumer Preference for Smart TV

In the first part, a mixed logit model is used to analyze the consumer preference for smart TV which consisted of six attributes. Mixed logit model can allow consumers' heterogeneity by assuming the specific distribution of each attribute's coefficient in advance. Generally, because impacts of each attribute on consumer preference are varied depending on socio-demographic information of consumers, normal distribution is used as the distribution of an attribute's coefficient. However, because all consumers have the same direction of preference for some attributes such as price and definition, we assume that these coefficient vectors follow log-normal distribution. Our mixed logit model uses a unit of 76,800 pixels for definition, 10 inches for screen size, 10% level for number of applications, and 1 million KRW for the price of a smart TV. We defined the other attributes (possibility of 3D service, iOS, and Android) as dummy variables with no possibility for 3D service and manufacturer's OS set as reference. Moreover, to provide an economic value for each attribute, we also analyzed the RI and MWTP for each attribute based on 2000 draws generated from the distribution of the estimation results. The results of the mixed logit model are shown in Table 5.

Table 5. Estimation results for smart TV (TV set type).

Attribute	Distribution	Mean	Variation	Average Relative Importance (%)	Median MWTP
Definition	log_normal	2.1698 **	87.1098 **	11.47	137,105.9 (KRW/100,000 pixel)
Screen Size	normal	−0.2321 **	0.2387 **	24.62	201,065.8 (KRW/10 inch)
Screen Size^2	normal	1.7644 **	2.5433 **		
Possibility of 3D Service	normal	1.0511 **	0.9883 **	6.28	293,742.6 KRW
Number of Applications	normal	1.874 **	1.3275 **	9.32	61,649.7 (KRW/10%)
iOS	normal	0.0492	0.6486 **	4.00	5345.9 KRW
Android	normal	1.3673 **	0.5008 **	8.10	461,466.6 KRW
Price	log_normal	−6.9374 **	262.2128 **	36.21	-

Note: ** Significant at 5% level. Screen Size^2 represents the quadratic term of screen size.

The results show that all attributes are statistically significant at the 5% level. For screen size, which is a characteristic of traditional TV, we assumed that consumer preference is non-linear, so we used a quadratic form. Based on our estimation results, consumer preference for screen size follows a U-shape and can be divided into two consumer groups: those who prefer a relatively small screen and those who prefer a relatively large screen with a reference of 65.7 inches. In addition, the results show that in general, consumers significantly prefer a large number of applications and prefer 3D service. As for OS, consumers prefer Android to both iOS and a manufacturer's OS at the 5% level. Compared with the results of [30], who analyzed consumer preference for tablet PCs, consumer preference for OS could vary depending on the smart device. Our results suggest that Android could have an advantage over other OSes in the smart TV market.

On the other hand, when we analyzed the RI for each attribute, we found interesting results. Among the attributes, consumers consider screen size (RI = 24.62%) and definition (RI = 11.47%) as the main factors, behind only price. In other words, consumers set a higher value on the characteristics of a traditional TV than on the characteristics of a smart TV when making a purchase decision for a smart TV. Therefore, we can conclude that the failure of smart TV stems from the small value and hedonism consumers give characteristics of a smart TV such as applications, OS, and 3D. When asked why they do not want to purchase a smart TV, 50.5% of respondents answered that they do not need a smart TV because they have enough smart devices. Thus, consumers do not perceive smart TV to have unique features compared with other smart devices. According to [10], three important factors in adoption of new technology are usability, utility, and hedonism. Therefore, smart TV makers should consider utility and hedonism in promoting smart TV.

To provide an economic value, we analyzed the MWTP of each attribute. The results show that for a smart TV that can use 3D service, consumers' MWTP is 293,742.6 KRW. In addition, if the number of applications increases by 10%, consumers' MWTP is 61,649.7 KRW, on average. Information about consumers' MWTP can be used to establish pricing policies for smart TVs, depending on technological improvement.

To compare consumer preferences by smart TV type, we also analyzed consumer preference for set-top box type units. For this analysis, we used the 451 respondents who said they preferred a set-top box type. The estimation results are shown in Table 6 and are consistent with those for TV set type smart TVs except for OS preference. The consumer preference for OS in a set-top box type is Android, manufacturer's OS, and iOS in descending order.

Table 6. Estimation results for smart TV (set-top box type).

Attribute	Distribution	Mean	Variation	Average Relative Importance (%)	Median MWTP
Number of Applications	normal	2.3867 **	8.6353 **	29.53	37,587.19 (KRW/10%)
iOS	normal	−0.9964 **	2.5182 **	20.10	−111,419 KRW
Android	normal	0.7045 **	3.531 **	20.70	52,456.9 KRW
Price	log_normal	−0.2996 **	2.0742 **	29.66	

Note: ** Significant at 5% level.

4.2. Purchase Intention for Smart TV

In our second analysis, we used a binary logit model to analyze the main factors for smart TV failure. We consider socio-demographic variables (sex, age, income, and education level) and behavioral information (daily average internet use time, daily average time watching TV, ratio of watching VOD to watching TV, recognition of cloud computing services, number of smart devices owned, and experience using a second screen) as explanatory variables. We define education level as a continuous variable and set graduate from high school as 1. Male, recognition of cloud computing services, and experience using a second screen are defined as dummy variables. For instance, if consumers know what cloud computing service is, we set this variable to 1.

In our data set, 226 of the 1450 respondents already possessed a smart TV. We assumed that 226 respondents have purchase intention for a smart TV. In addition, we asked purchase intention for a smart TV from the 1224 remaining respondents. Survey results show that 642 of 1224 respondents (52.5%) do not have purchase intention for a smart TV. In particular, respondents who are female and in their 20s show relatively low purchase intention for a smart TV. Due to the missing data for explanatory variables, we used 1421 samples for analysis. Based on the purchase intention data and explanatory variables, we estimate the effects of the different variables on purchase intention (Table 7).

Table 7. Estimation results for purchase intention of smart TV.

Variables	Mean	Relative Importance (%)
Constant	−3.7962 **	28.65%
Male	0.2846 **	2.15%
Age	0.0333 **	9.80%
Education level	0.0156	0.35%
Income	0.0005	3.74%
Daily average internet use time	−0.0196	2.81%
Daily average time watching TV	0.2638 **	21.90%
Ratio of watching VOD to watching TV	0.0066 **	4.99%
Recognition of cloud computing services	0.2932 **	2.21%
Number of smart devices owned	0.2366 **	19.65%
Experience using a second screen	0.4963 **	3.75%

Note: ** Significant at 5% level.

The estimation results show that female and younger consumers have significantly lower purchase intention than male and older consumers. Most of the behavioral variables affect purchase intention for smart TV, except for daily average internet use time. When we analyzed the RI for each explanatory variable, we found that daily average time watching TV and number of smart devices owned are the most critical factors for purchase intention for a smart TV. According to [31], the daily average traditional TV viewing time in the U.S. has decreased since 2012 because of the diffusion of smart devices and over-the-top video services. Thus, it will be difficult to improve purchase intention for smart TV by increasing traditional TV consumption. An effective way to increase purchase intention for smart TV is thus to promote the diffusion of smart devices. Therefore, in order to improve the possibility of success for smart TV, stakeholders should try to encourage the sales of smart devices firstly.

5. Summary and User-Centered Strategy for the Success of Smart TV

Since smart phones were first released in the mobile market, various smart devices have been developed and released in related markets, such as TV, automobile, home, and so on. Although many previous cases, such as smart phones and tablet PCs, have been huge successes in the market, smart TVs have grown relatively slowly [32], and the ratio of TV set type to set-top box type smart TVs is expected to decrease by 2018 [33]. Therefore, this paper has investigated the reasons for the failure of smart TVs from the viewpoint of consumers and here suggests a direction for market strategies to improve the diffusion of smart TVs.

The analysis consists of two parts: the first part is to use the mixed logit model to identify the difference of consumer preference between a characteristic of traditional TV and smart TV based on the stated-preference data collected from conjoint analysis, and the second part is to use binary logit model to analyze the impact of consumers' socio-demographic and behavioral information on purchase intention for smart TV. The results of the first part of our analysis show that consumers set a higher value on the characteristics of traditional TV (definition, screen size) than on the specific functions of smart TVs (applications, 3D, OS). Therefore, the key reason for the failure of smart TV is that it lacks key functions to encourage its diffusion. The results of the second part of our analysis show that younger and female consumers have significantly lower purchase intention for smart TVs than older and male consumers. On the other hand, consumers with a large number of smart devices, higher TV/VOD consumption, and experience using a second screen have higher purchase intention. Among the various factors we analyzed, the most practical way to improve purchase intention for a smart TV is encouraging the diffusion of smart devices.

In the age of 2G mobile networks, consumers could not freely access social network services, search engines, e-commerce, or entertainment through their mobile devices. Accordingly, it was necessary to evolve from 2G to 3G networks and from feature phones to smart phones. Apple and Google both applied the business model that was successful in smart phones to smart TV. However, whereas users actively input their intentions into cell phones and tablet PCs, which have the characteristic of making consumers "lean forward", TV is a device with "lean back" characteristics. Users want to control a TV simply with a remote control. To secure a specialty and make it different from other smart devices, smart TV should maintain the property of traditional TV and be linked with smart devices consumers already use. If a smart TV provider offers an environment in which consumers can use a smart TV in a traditional "lean back" way and use other "lean forward" devices linked to the smart TV as a second screen, it could satisfy both users who want to watch TV comfortably on the couch and those who want to find information while watching TV.

In an ever-changing environment, the competitive advantage of a firm is not sustainable over the long term [34], and resisting change presents more risks for firms. Accordingly, firms reposition themselves, change current processes, and create new products or services to increase the probability of business success and sustainability. However, such attempts by firms are not always successful, and to sustain their business competitiveness, user-centered strategies based on the analysis of target consumers are necessary. In the case of the TV industry, the number of technologies being used in newer TV sets is increasing and the product life becomes shorter. Therefore, it is getting harder for firms to sustain their market power and business competitiveness. In that sense, the results of this paper suggests the direction of market strategies to cross the chasm of smart TVs. Even though this paper is limited in that the estimation results are from the stated preference data, which are responses to a hypothetical situation, the advanced methodology and the unique data set shed light on the sustained growth of the TV industry.

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