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Article

Analysis of OTT Users' Watching Behavior for Identifying a Profitable Niche: Latent Class Regression Approach

Dongnyok Shim [1], Changjun Lee [2] and Inha Oh [1,*]

[1] Department of Advanced Industry Fusion, Konkuk University, Seoul 05029, Republic of Korea
[2] Media and Social Informatics, Hanyang University, Ansan 15588, Republic of Korea
* Correspondence: inhaoh@konkuk.ac.kr; Tel.: +82-2450-0446

Abstract: Over-the-top (OTT) firms must overcome the hurdle of the competitive Korean media market to achieve sustainable growth. To do so, understating how users enjoy OTT and analyzing usage patterns is essential. This research aims to empirically identify a profitable niche in the Korean OTT market by applying market segmentation theory. In addition, it investigates an effective content strategy to convert free users into paying customers belonging to profitable niche segments. The latent class regression model was applied to Korean Media Panel Survey data to divide Korean OTT customers into submarkets. According to an empirical analysis, Korean OTT users can be divided into three submarkets based on their OTT usage patterns, with the third segment serving as a profitable niche market. An additional analysis of the profitable niche market revealed that bundling content, such as foreign content, original content, and movies, is a crucial content strategy for increasing paying subscribers in a profitable niche segment.

Keywords: market segmentation; Korean OTT market; niche; content preference; latent class model; paying subscribers

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1. Introduction

The over-the-top (OTT) market has been growing rapidly every year. According to Statista [1], the total revenue of OTT providers recorded 106.48 billion U.S. dollars in 2020, and the figure is expected to reach over 210 billion by 2026. As of January 2021, the global online streaming service Netflix had more than 207 million subscribers worldwide. According to a report published by the Korea Communication Commission, as of 2020, 66.3% of Koreans had used OTT services [2]. These figures are interesting because just 10 years ago, it was expected that global OTT providers would have trouble foraying into the Korean market due to the moderate price of conventional pay-TV platforms and the preference of Korean media users for Korean content [3,4]. However, the opposite was observed. A dozen OTT companies successfully run their own services in Korea, and the competition is now extreme [2]. Terrestrial, mobile, broadband, cable TV, Internet portal, start-up, and individual companies are now entering the OTT market.

In general, OTT is understood as content, a service, or an application that is provided to end-users over the open Internet. This means that there is no integration, affiliation, or any other joint ownership with content, broadband, or Internet service providers [5,6]. Hence, its business models have transformed the way consumers enjoy media, allowing them to freely access whatever content they want [7]. Similarly, academic studies have considered OTT as an innovative service based on cutting-edge technology, and scholars have employed the diffusion of innovation theory or technology acceptance framework to understand consumers' OTT adoption behavior [8,9]. In other words, research on OTT user behavior has attempted to understand user behavior—adoption or non-adoption—in a dichotomous way [10]. Some studies have focused on OTT service design issues related to consumers' willingness to pay for certain attributes of OTT services when global OTT services were introduced in the Korean market [11,12]. These studies provided practical implications when OTT was perceived as a novelty in the media market and many people had not experienced such a service.

However, the media environment in Korea has changed dramatically over the last few years [13]. More than a dozen OTT providers, including global and domestic companies, deliver services in Korea, and many people are aware of and enjoy OTT. Unsurprisingly, the biggest global OTT provider, Netflix, terminated its 30-day free trial for new subscribers as of April 2021 in Korea [14]. At the same time, Disney+ removed its free week trial in the U.S. and other parts of the world, while Apple TV+ had a free trial for only one week in the U.S. [15]. The fact that these organizations' policies have changed implies that their strategic goal is to recruit paying customers among OTT users, rather than increasing attention.

In a situation where market competition grows expeditiously, it is strategically important for OTT companies to convert most free users into paying customers, rather than merely introducing services to consumers who are not yet known [16]. Although the proportion of OTT users has increased sharply every year in Korea, the share of paying users is still low compared to the number of conventional pay-TV subscribers [17]. OTT firms have long been concerned with attention-grabbing strategies, but today, they are more concerned with boosting their earnings through paying consumers [18]. In this context, companies must understand and utilize market segmentation and targeted marketing to effectively increase the number of paying subscribers [19–21]. Theoretically, market segmentation and niche marketing are effective approaches that can help OTT service providers when user characteristics are not homogeneous but heterogeneous. Market segmentation divides the addressable heterogeneous market into segments that have consistent and homogeneous characteristics in demographic, psychographic, or usage patterns [22]. As a result of market segmentation, the niche marketing approach, a more narrowly defined attractive market is possible for companies to establish appropriate service development and promotion plans.

However, in the OTT domain, most scholars have thus far paid attention to antecedents of OTT users' behavioral intentions and actual behavior. The theoretical models vary from those that aim to explain consumer behavior in general, such as the theory of planned behavior (TPB) [23], to those that focus on technology acceptance, such as the technology acceptance model (TAM) [24] and the unified theory of acceptance and use of technology (UTAUT) [25]. In an environment where more than half of the Korean population has already experienced and watched OTT, the contribution of adoption behavior studies is limited; rather, classifying the diversified behavior of users into meaningful categories is more important from both academic and managerial perspectives. Unfortunately, the above-mentioned traditional studies did not address market segmentation or targeted marketing for OTT usage behavior. Unlike traditional adoption-based profiling studies, it is vital to understand the unobserved heterogeneity of consumers based on their behavioral and demographic characteristics using market segmentation and targeted marketing theory [26]. Furthermore, information about segmented groups helps firms make better decisions regarding their marketing strategies. Consequently, this paper aims to fill the gap between the limitations of extant studies and emerging research problems in the fast-changing OTT environment.

Hence, the purpose of our paper is to identify and characterize OTT user segments based on their usage patterns, such as OTT usage frequency, video-watching time, and paying for the service experience, and to find profitable niches from the OTT provider's perspective. To accomplish this purpose, we use latent class regression analysis to simultaneously identify the number of unobservable latent classes of OTT users and describe the characteristics of each of the segments. As a result of empirical analysis, we discover a profitable niche segment that includes a meaningful portion of paying subscribers, whereas others do not. Finally, we analyze the impact of content preference on the paid service experience in a profitable niche segment to discuss the positioning strategy from the content perspective. The main contribution of this study is the identification and characterization of three OTT user segments based on their usage patterns.

2. Literature Review

We reviewed the previous literature to understand the research stream and to find some limitations from the user behavior perspective. While extant studies have contributed to increasing the understanding of new media diffusion in the early stages of OTT introduction, the media environment has changed rapidly over the years and faces new market situations [13,14]. The studies on OTT consumers can be broadly classified into three categories, depending on the main research question. The first concerns how user attitude and usage intention are shaped regarding the use of OTT services. When OTT services first appeared in the media market, scholars were interested in whether OTT could be successfully diffused over the traditional media ecosystem and studied users' behavioral intention using an innovation diffusion model. This was because OTT was considered a novelty or an innovation in the media market. The second topic was to evaluate the competitiveness of OTT services compared to conventional pay-TV, such as cable TV, IPTV, and satellite TV, which are based on real-time broadcasting. These studies focused on measuring the level of competition between pay-TV and OTT services to predict whether OTT services can substitute pay-TV in the future. Finally, many studies have employed quantitative analysis to evaluate consumers' willingness to pay (WTP) by reflecting consumer preferences and to suggest optimal OTT service configuration.

Specifically, in the studies related to the first research topic, OTT was regarded as a result of ICT innovation. The underlying assumption of these studies is that technological innovation allows users to experience video services that can seamlessly use any content desired by the user at any time on any device if an Internet connection is available [27]. From this perspective, TAM and TPB were theoretically applied to understand users' behavior in the OTT market [28,29]. TAM is an information systems theory that proposes two essential factors of behavioral intent toward the usage of technology: perceived ease of use and perceived usefulness of the technology [24]. Cebeci et al. [8] analyzed the determinants of intention to use Netflix based on the TAM. They collected survey data from 251 respondents and found that perceived usefulness influenced the intention to use OTT by formulating positive attitudes, whereas perceived ease of use did not. Similarly, Bhattacharyya et al. [10] utilized a modified UTAUT2 model and supported the explanatory strength and predictability of UTAUT2 as a model to explain the motivation of OTT usage. Recently, Basuki et al. [30] analyzed the effects of perceived ease of use, usefulness, enjoyment, and intention to use on behavioral intention in online movie watching during the COVID-19 pandemic era. They found that the TAM model successfully explains users' behavior in online video streaming. Kim and Park [31] demonstrated the influence of participants' innovativeness, subjective norms, and reputation motives on satisfaction and the intention of continued use within the frameworks of uses and gratifications. They also used the TAM model and expectation–confirmation model on an online survey sample of 315 respondents in Korea. These studies contributed to the literature by presenting an empirically tested theoretical model that demonstrated the determinants of intention to watch OTT services when the service was just introduced in the market and most consumers did not have enough knowledge of it. However, the media market has changed dramatically over the past few years. In many developed countries, including Korea, OTT services have penetrated and are now ahead of existing broadcasting services.

In studies related to the second research topic, where scholars focused on competition between pay-TV and OTT services, Dimmick's niche theory [32] was frequently applied. Dimmick's niche theory assumes that consumers have limited time and money. Accordingly, when new media with superior functions become available, customers will be more inclined to utilize them. This will result in less time and money being spent on old media [32,33]. Using niche theory, Li [34] examined the competitive relationships among three television media, OTT, IPTV, and digital cable, and concluded that OTT was the most competitive while digital cable and IPTV were almost equally competitive. In Korea, Kim et al. [35] adopted niche theory to explain the competitive dynamics in video platforms and argued that competition between conventional pay-TV and OTT services was not severe in Korea.

Meanwhile, the U.S. indicated a different trend. Chen [36] conducted a similar competition study in Taiwan using niche theory and found that OTT services and conventional TV shared a high level of similarity in amusement and ease of use. In addition, he also discovered that OTT services' competitive superiority surpassed that of conventional TV in all dimensions. When OTT services initially entered the market, these studies were useful in determining the worthy attributes of OTT services compared to traditional media and their direct competitiveness with conventional TV series providers. However, one of the main limitations of the niche analysis is that it ignores the complementary relationship between the old and new media by only focusing on the concept of displacement. In other words, viewing OTT services and pay-TV as a battle between new and old media is no longer a viable approach.

Finally, in studies related to the third research topic, many attempts have been made to quantitatively analyze consumer preference structure on OTT service [11,12,37,38]. For example, Shin et al. [11] and Kim et al. [37] used a discrete choice experiment to capture consumer preference structures for a few noticeable attributes of OTT services. Shin et al. [11] considered real-time broadcasting, terrestrial TV content, the newest broadcasting, the number of VODs, and monthly subscription fees as important features of OTT services. For empirical analysis, they collected conjoint survey data from 1450 Korean respondents. Their analysis results showed that consumers gave the highest priority to real-time broadcasting and the number of VODs was the second most important feature. Kim et al. [37] also gathered conjoint survey data for Korean OTT users. A mixed logit analysis was employed on the data. The analysis results showed that consumers expected an additional discount for pay-TV services when bundled with OTT services, and that the more bundled services consumers currently used, the less sensitive they were to the discount rate. They also found that OTT services and TV broadcasting services had a complementary relationship in Korea. Kim et al. [12] compared the marginal willingness to pay for key attributes of OTT services in China and Korea using conjoint analysis and found that the most important attributes for Chinese consumers were resolution, followed by the recommendation system and viewing option. The recommendation system was ranked as the most valuable attribute, followed by viewing options for Korean consumers. Recently, Shon et al. [38] paid attention to the difference between paid OTT services and free OTT services based on forced advertisement watching since this may cause serious inconvenience, and calculated consumers' willingness to pay for ad-blocking features by ad length, ad location, and the possibility of skipping the ad. Commonly, consumer preference studies on the OTT service used stated preference data through discrete choice experiments because of a lack of market data availability. Despite these studies' contributions to optimal service configuration strategies, they placed less emphasis on OTT users' watching behavior. In other words, they focused on proposing a method for designing an optimal service for the entire market from a product perspective rather than a consumer perspective. However, if an OTT company implements a strategy for transitioning free users to paying users to increase sales, the question of which consumers to target becomes more crucial.

Through a literature review, we found that previous studies have successfully identified (1) antecedents of behavioral intention to watch OTT, (2) the competition level between traditional TV and OTT, and finally (3) the consumer preferences of service attributes. Nevertheless, little research has been attempted to apply market segmentation theory and divide heterogeneous users into meaningful subgroups so far. Given the unprecedentedly fast-growing market and recent highly competitive market situation, it is not desirable to assume OTT users as a single homogeneous group. Obviously, OTT users could be heterogeneous rather than homogeneous in their usage patterns. In this background, an important marketing approach is market segmentation, i.e., dividing the addressable market into segments that have a consistent demographic, psychographic or usage pattern. Particularly, securing paying customers to improve corporate profitability is a challenge for OTT providers. To implement this, OTT service providers can employ customer segmentation to apply various marketing strategies to groups of customers with similar characteristics, achieving increased profits by better satisfying customer requirements. To bridge the gap between the limitations of the previous literature and the rapid change in the media ecosystem, we try to divide a heterogeneous group of customers into smaller, homogenous subgroups that share common characteristics in terms of OTT usage patterns. To do so, this study can answer following research questions.

RQ 1: How many market segments can Korean OTT users be divided into, depending on their usage behavior such as usage frequency, watching time per use and paying for the service experience?
RQ 2: What are the common characteristics of each segment of the market?
RQ 3: Is there a meaningful segment for OTT operators' profit enhancement among the identified submarkets? If yes, what is an effective strategy for conversion to paying customers?

3. Methodology

3.1. Proposed Research Model

As explained, the key purpose of this study is to segment the market into multiple distinctive groups, to find a profitable niche market among them, and to explain the content that influences the paid experience in the niche market we found earlier. To do this, we conduct our research in two steps. First, we conduct market segmentation based on individuals' usage behavior patterns. The most widely used segmentation dimensions are behavioral and demographic variables [22]. Behavioral segmentation focuses on the actual behavior of users, including occasions, benefits, user status, usage rate, loyalty status, readiness, and attitude toward products. Most researchers consider behavioral segmentation as a starting point. Therefore, we adopt OTT usage behavior, which consists of usage frequency, OTT watching time per use, and the experience of paying for the service during the last three months.

In addition to behavioral segmentation, most studies have used demographic segmentation as well. For example, Walsh et al. [39] stated that younger users are more likely to be highly involved with their mobile phones. Castells et al. [40] pointed out that there is a gender difference in mobile phone usage, where women use cell phones to maintain personal intimacy, while men use them for instrumental purposes. Considering the importance of demographic variables, such as gender and age in market segmentation and media service usage, we adopt demographic variables as antecedents to explain distinctive segments by OTT usage patterns. This identification is conducted using a multinomial logit model, and we can profile these segments based on sociodemographic characteristics.

In other words, once class membership has been established using behavioral variables, a multinomial logit model is estimated to determine whether covariates predict class membership, which is the main difference between the latent class model and latent class regression model that we apply in this study. Next, we examine whether there are meaningful differences in usage patterns and demographic characteristics among the different segments and find a meaningful segment.

Second, after identifying the meaningful segment, the so-called profitable niche market, we evaluate how OTT content preferences influence the paid service experience by applying the binary logit model to the identified profitable niche market. This will guide OTT platform companies on the kind of content they should invest more in. Figure 1 provides a simple depiction of the research framework of this study.

3.2. Data and Variables

Korean Media Panel Survey data were used to conduct an empirical analysis and answer the research questions. The Korean Media Panel Survey is a panel survey approved by the national statistical office, designed to accumulate data on the same sample over a long period. This is done to ensure that the data are useful for understanding the Korean media market from a consumer perspective [41–43]. These data are appropriate for analyzing the proposed research framework because the Korean Media Panel Survey aims to track the impact of changes in the media environment on the media use behaviors of households and individuals. It also analyzes their media use behaviors by demographic characteristics. In 2020, 4260 households and 10,302 household members participated in the study.

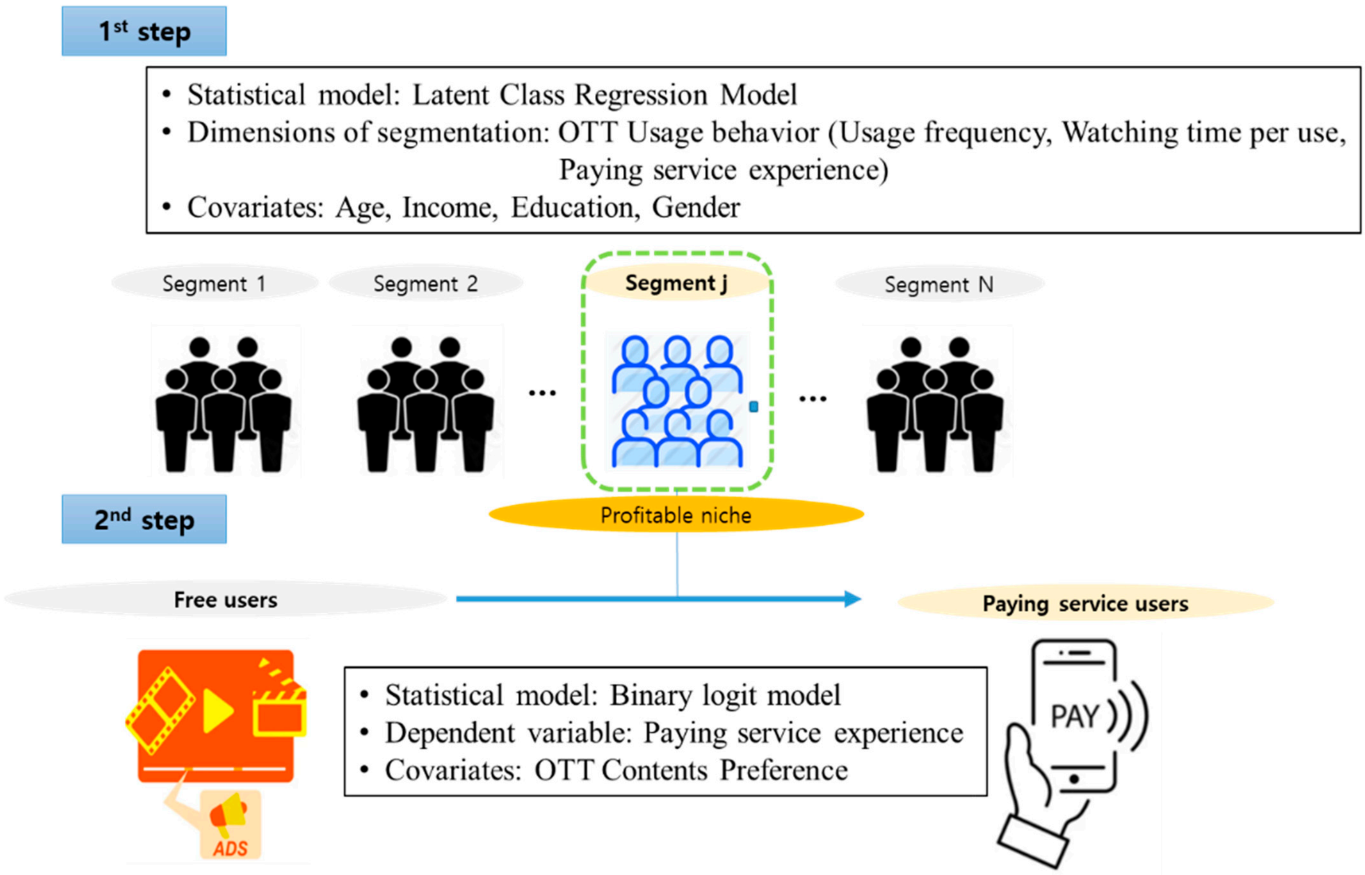

Figure 1. Research Framework.

The Korean Media Panel Survey presented that out of 10,302 respondents, 7024 answered that they had experience watching OTT in the year 2020. Table 1 shows the sociodemographic characteristics of the sample.

The main research variables for market segmentation are those related to the OTT usage pattern. Notably, behavioral-based market segmentation is performed based on the following three variables: OTT usage frequency, average viewing time per use, and use of the paid service. After identifying a niche market, to capture what makes them pay for the OTT service, we analyze the binary logit model based on OTT content preferences. This is because this result informs OTT operators of the kind of content they should invest in and put effort into. Table 2 summarizes the sample characteristics related to the OTT usage pattern.

Based on the OTT usage frequency, 34.97% of OTT users enjoy OTT content several times a day, which shows that many people occasionally access OTT services in their daily lives. Furthermore, the fact that 74.89% of people access OTT at least three times a week indicates that OTT deeply penetrates their lives. Most people spend 20 to 60 min once connected to the OTT platform. These minutes could include watching a couple of short video clips. Interestingly, 10.9% of viewers' viewing time is more than 120 min per use. The proportion of users who have paid services is 12.37%, indicating that there are still fewer paid users compared to the number of OTT users.

Table 1. Sociodemographic characteristics.

Variable		OTT Experience User	
		Respondents	Ratio (%)
Gender	Male	3431	48.83
	Female	3596	51.17
Age	6–19	1052	14.97
	20–29	1170	16.65
	30–39	838	11.93
	40–49	1543	21.96
	50–59	1531	21.79
	Above 60	893	12.71
Education	Less than Middle school	951	13.53
	High school	2453	34.91
	University	3509	49.94
	Above	114	1.62
Income	No Income	2736	38.94
	less than 100	669	9.52
	100–200	1101	15.67
	200–300	1361	19.37
	300–400	655	9.32
	More than 400	505	7.19
Total		71,027	100

Table 2. OTT usage patterns of samples.

Variable		OTT Experience User	
		Respondents	Ratio
OTT usage frequency	Several times a day	2457	34.97
	once a day	1039	14.79
	5–6 times a week	732	10.42
	3–4 times a week	1034	14.71
	1–2 times a week	1260	17.93
	1–3 times a month	368	5.24
	less than once a month	137	1.95
Average watching time per use (minutes)	less than 10	181	2.58
	10–20	1229	17.49
	20–60	3402	48.41
	60–120	1449	20.62
	more than 120	766	10.90
Experience of paid service	Free use	6158	87.63
	Paid service use	869	12.37
OTT content preferences	Real-Time Broadcasting	462	6.57
	TV_VOD	2249	32.01
	American TV Show	76	1.08
	Movie	300	4.27
	OTT original show	484	6.89
	MCN	3265	46.46
	Music & Others	191	2.81

3.3. Statistical Model

One of the essential research objectives of this study is to conduct market segmentation based on consumers' OTT usage patterns and identify meaningful niche markets for OTT providers. To achieve this research objective, we use latent class analysis, which is very popular and frequently applied in market segmentation studies in the ICT field [21,22].

Latent class analysis is a statistical technique used to analyze multivariate categorical data. When observed data take the form of a series of categorical responses, it is often insightful to investigate confounding sources between the observed variables, identify and characterize clusters of similar cases, and approximate the distribution of observations across many variables of interest. Latent class analysis is a useful methodology for accomplishing these goals [44].

Suppose we observe J polytomous categorical variables (the observed variables), each of which contains K_j possible outcomes for individuals $i = 1, \ldots, N$. The observed variables may have different numbers of outcomes. Hence, the indexing by j. Denote as Y_{ijk} the observed values of the J observed variables, such that Y_{ijk} = 1 if respondent i gives the kth response to the jth variable, and Y_{ijk} = 0 otherwise, where $j = 1, \ldots, J$. and $k = 1, \ldots, K_j$..

The latent class model approximates the observed joint distribution of the manifest variables as the weighted sum of a finite number, R. R is fixed prior to the estimation based on either theoretical reasons or model fit.

Let Π_{ijk} denote the segment-conditional probability that an observation in segment $r = 1, \ldots, R$ produces the kth outcome for the jth variable. Therefore, within each segment, for each manifest variable, $\sum_{k=1}^{K_j} \Pi_{jrk} = 1$. Further denote as P_r the R mixing proportions that provide the weights in the weighted sum of the component tables, with $\sum_r P_r = 1$. The values of P_r are also referred to as the "prior" probabilities of latent class membership, as they represent the unconditional probability that an individual will belong to each segment before considering the responses Y_{ijk} provided on the observed variables. The probability that an individual i in segment r produces a particular set of J outcomes on the manifest variables, assuming the conditional independence of the outcomes Y given segment memberships, is the product

$$f\ (Y_i;\pi_r) = \prod_{j=1}^{J} \prod_{k=1}^{K_j} \left(\pi_{jrk}\right)^{Y_{ijk}} \tag{1}$$

The probability density function across all segments is the weighted sum.

$$f(Y_i;\pi,p) = \sum_{r=1}^{R} p_r \prod_{j=1}^{J} \prod_{k=1}^{K_j} \left(\pi_{jrk}\right)^{Y_{ijk}} \tag{2}$$

The parameters estimated by the latent class model are p_r and π_{jrk}.

The extended latent class model is applied in this study, which is the so-called latent class regression model. The latent class regression model generalizes the basic latent class model by permitting the inclusion of covariates to predict individuals' latent class membership [45,46]. Covariates are included in the latent class regression model through their effects on the priors, p_r. In the basic latent class model, it is assumed that every individual has the same prior probability of latent class membership. By contrast, the latent class regression model allows individuals' priors to vary depending on their observed covariates. In summary, the latent class regression model allows the latent class prevalence to vary with covariates. However, the meaning of the latent class is still determined by the manifest items.

Let X_i represent the observed covariates for individual i. We arbitrarily select the first latent class as a "reference" segment and assume that the log-odds of the latent class membership priors with respect to that segment are linear functions of the covariates. Let β_r denote the vector of the coefficients corresponding to the rth latent class. With S covariates, β_r has length $S + 1$; this is one coefficient of each of the covariates, plus a constant. Since the first segment is used as the reference, $\beta_1 = 0$ is fixed by definition. Then

$$\begin{aligned} \ln(p_{2i}/p_{1i}) &= X_i\beta_2 \\ \ln(p_{3i}/p_{1i}) &= X_i\beta_3 \\ &\vdots \\ \ln(p_{Ri}/p_{1i}) &= X_i\beta_R \end{aligned} \tag{3}$$

This produces the general result that

$$p_{ri} = p_r(X_i;\beta) = \frac{e^{X_i\beta_r}}{\sum_{q=1}^{R} e^{X_i\beta_q}} \tag{4}$$

The log-likelihood function of the latent class regression model is described as follows:

$$\ln L = \sum_{i=1}^{N} \ln \sum_{r=1}^{R} p_r(X_i;\beta) \prod_{j=1}^{J} \prod_{k=1}^{K_j} \left(\pi_{jrk}\right)^{Y_{ijk}} \tag{5}$$

4. Analysis Results

4.1. Consumer Segmentation and Identifying Profitable Niche

The first step of using latent class analysis for consumer segmentation is to determine the optimal number of submarkets. The optimal model is statistically determined by comparing the model fit for a certain number of latent classes. Table 3 lists several model-fit indices for a given number of segments. The three segments represented the best model fit, which means that CAIC and BIC were the lowest indices among the six models. Accordingly, the result yielded three distinct segments of individuals based on their OTT usage patterns, including usage frequency, usage time, and paying for the experience.

Table 3. Model fit with respect to the number of segments.

Segments	Parameters	Log-Likelihood	AIC	CAIC	BIC
2	27	−22,970	45,993	46,206	46,179
3	**43**	**−22,821**	**45,729**	**46,067**	**46,024**
4	59	−22,811	45,740	46,203	46,144
5	75	−22,970	46,089	46,679	46,604
6	91	−22,970	46,121	46,837	46,746

Tables 4–7 present the item-response probability for the three segments. The item-response probabilities estimated from the latent class regression analysis constitute the response patterns of the observed indicator items and the latent variable for each latent class [47]. An item-response probability means the probability that each segment belongs to an individual category of the given variable.

Table 4. Item-response probability by OTT usage frequency.

	OTT Usage Frequency						
	Several Times a Day	**Once a Day**	**5–6 Times a Week**	**3–4 Times a Week**	**1–2 Times a Week**	**1–3 Times a Month**	**Less Than Once a Month**
Segment 1:	0.3075	0.0732	0.0227	0.1468	0.1908	0.1596	0.0994
Segment 2:	0.2415	0.1438	0.1505	0.1925	0.2167	0.0465	0.0086
Segment 3:	0.5109	0.1822	0.0736	0.0864	0.1248	0.0187	0.0033

Table 5. Item-response probability by OTT usage time.

	OTT Usage Time (Unit: Min)				
	More Than 120	**60–120**	**20–60**	**10–20**	**Less Than 10**
Segment 1:	0.0454	0.0100	0.1736	0.6541	0.1169
Segment 2:	0.0000	0.1407	0.7027	0.1406	0.0160
Segment 3:	0.2797	0.3698	0.3113	0.0356	0.0036

Table 6. Item-response probability by the rate of OTT paid service use.

	OTT Free Use/Paid Use	
	Free Service Use	**Paid Service Use**
Segment 1:	1.0000	0.0000
Segment 2:	0.9979	0.0021
Segment 3:	0.6656	0.3344

Table 7. Market size of each segment.

	Segment 1	**Segment 2**	**Segment 3**
Estimated share	13.74	49.28	36.98
Predicted membership	12.59	54.85	32.56

Based on OTT usage frequency, for all segments, it was found that the probability of belonging to the category of watching several times a day was the highest. This can be attributed to the fact that 34.97% of respondents were included in this category. However, there was a significant difference across segments in the probability of belonging to each of the seven categories. In the case of users of segment 1, the probability of watching OTT services several times a day was 30.75%, which was the highest. However, the probability that they watch OTT 3–4 times a week was 19.08%. The probability of watching OTT 1–3 times a month was 15.9%. We found that occasional viewing also accounted for a significant portion of segment 1. For segment 2 users, the probability of belonging to the category of watching several times a day was 24.15%, which was slightly higher than the probability of belonging to the 1–2 times a week category (21.67%). For segment 2, the probability of watching OTT services several times a day to 1–2 times a week was evenly distributed over the categories. However, for segment 3, more than half (51.09%) were found to belong to the probability of watching several times a day. This was the highest estimated usage frequency portion across the segments. The probability that users of this segment watch OTT services once a day recorded second in this segment. In summary, segment 3 uses OTT services most frequently and habitually so that the probability of watching OTT services at least once a day corresponds to 70%. Meanwhile, most users belonging to segments 2 and 3 are watching OTT services irregularly.

On the basis of usage time per connection, the probability that users in segment 1 spend 10–20 min watching OTT services per connection was 65.41%, which was the highest proportion in segment 2. It is likely that users of this group are watching a short video clip on YouTube. Similarly, 70.27% of respondents in segment 2 spend 20–60 min watching OTT services per connection. Segment 2 respondents spend more time enjoying the OTT than segment 1. In contrast, 36.98% of users of segment 3 spend 60–120 min, and 27.97% of users of this group spend more than 120 min watching OTT.

On the basis of the paid service experience, we found that the probability of users belonging to segments 1 and 2 using paid services was extremely low. No paying customers were found in segment 1. However, the probability that the users included in segment

3 experienced a paid OTT service was 33.14%. In other words, most paying users belonged to segment 3. This fact has important implications. Even for the same free users, the free users in segment 3 were completely different from those in segments 1 and 2. This is a critical reason for conducting customer segmentation and identifying a profitable niche.

According to the results of the latent class analysis, Korean OTT service users can be classified into three segments. For market segmentation, we named the first segment the "occasionally watching group" whose market share is an estimated 13.47%. The key characteristic of this segment is that they occasionally access OTT services, although some watch OTT services multiple times a day (30%). They spend an average of 10–20 min per connection, and most of them are free users, which means that they mainly enjoy short video clips and never pay for them. We named the second segment the "majority group" whose market share in Korea is almost 50%. They spend 20–60 min watching OTT services per connection, but they also do not pay for OTT content. We named the third group "profitable niche" since this is the group we were looking for. In the profitable niche segment, 33% of users pay for OTT services; in both the first and second segments, the ratio of paying users was extremely low. In addition, about half of the users in the third segment enjoy OTT content several times a day, and more than 64% of the third segment watch OTT for more than 60 min when connected once. Meanwhile, 27.9% watch for more than 120 min. Moreover, 30% of this segment pay for OTT services and content. It should be noted that even for the same free service users, the free service users belonging to the first segment differ from those belonging to the third segment. In other words, free service users in the third segment are more appealing to OTT providers when they try to increase the number of paid subscribers because the third segment is sufficiently homogeneous.

Market size is an important factor in determining whether a submarket is sufficiently attractive to companies when implementing targeted marketing strategies. Market size is interpreted as market share in business analysis.

Based on market size, the market share of the profitable niche (segment 3) is 36.98%, ranking second behind the majority group. The largest segment is the majority group (segment 2), representing 49.28% of the sample. Finally, the market share of the occasionally watching group is 13.74%, which is the lowest among the three segments. Even if the submarket is appealing, the costs outweigh the expected advantages if the market is too small. However, our results suggest that the profitable niche (segment 3) is a sufficiently significant market for businesses. Even if it is limited to free users belonging to the profitable niche group (segment 3), it accounts for roughly 24.64% of the total sample, which cannot be neglected by OTT providers. In other words, of the 88% of free users in the market, 24.64% of consumers (profitable niche group) should first be targeted by OTT providers to enhance sales.

Additionally, because we adopted a latent class regression model among several latent class models, each category represents a homogeneous segment with an identical regression coefficient per covariate, which is the demographic variable in this study. Table 8 shows the estimation results, which represent the influence of the covariates on the marginal distribution of latent class memberships through a polytomous logistic regression. The results (segment 3/segment 1) indicated that younger people are more likely to become members of a profitable niche. In addition, those who receive higher education are more likely to become members of profitable niches. However, both income level and gender are statistically insignificant when classifying the occasionally watching group (segment 1) and profitable niche group (segment 3). Consequently, OTT service usage behavior can be explained by age and education level.

Table 8. Multinomial logit analysis on latent class classification.

	Segment 2/Segment 1 (Reference)		
	Coefficient	**Std. Error**	***p*-Value**
Intercept	2.5227 ***	0.6693	0.0010
Age	−0.3584 ***	0.0600	0.0000
Income	−0.0438	0.0271	0.1190
Education	0.1506 *	0.0784	0.0660
Gender	0.3765 ***	0.1257	0.0060
	Segment 3/Segment 1 (Reference)		
Intercept	1.4605 **	0.6475	0.0330
Age	−0.8920 ***	0.0665	0.0000
Income	−0.0278	0.0281	0.3300
Education	0.8530 ***	0.0850	0.0000
Gender	0.1826	0.1312	0.1760

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.2. Effect of OTT Content Preferences in the Profitable Niche

Based on an understanding of the common characteristics of each segment and evaluating the attractiveness of segments in order to narrow the firms' choice of which to pursue, the next step in the segmentation and targeting process is to create a meaningful positioning strategy for increasing streaming subscriptions. In the previous section, we found that OTT companies must strategically focus on profitable niches (segment 3) to convert free users to paid customers in order to increase corporate profitability. Consequently, OTT companies must effectively communicate their value propositions to customers to create their desired positioning. In the OTT service context, the positioning strategy is strongly related to service content and genre, which means what content strategy should be implemented to persuade free users in a profitable niche to pay for OTT service is critical. In other words, it is a matter of which content appeals to free service users.

To address this problem, we applied logistic regression to a profitable niche to examine the impact of OTT content preferences on the paid service experience. As various OTT content preferences are categorical variables, we set real-time TV watching through OTT services as a reference. We chose real-time TV watching through OTT services as a reference because there is no difference between real-time TV watching through OTT services and real-time TV watching through conventional pay-TV based on content. We also included the TV watching time as a control variable. Table 9. is the analysis result of logistic regression. The results showed that TV watching time does not influence the paid OTT experience in a profitable niche group. With this result, we cannot conclude that the relationship between the conventional pay-TV platform and the OTT platform are substitutes or complements. OTT content preference, however, significantly influences the OTT payment experience. The results show that users' preferences for foreign content, movies, and OTT original content are strongly associated with the paid experience. Meanwhile, the preference for personal broadcasting designated by MCN (multi-channel network) and music and others negatively impact the paid experience.

The results can be interpreted as follows. First, foreign content in OTT services, such as American TV shows or dramas, nudges individuals to pay for OTT services. Because Korean users who are eager to consume foreign content cannot satisfy their needs on conventional pay-TV, they are willing to subscribe to foreign content. In addition, as many OTT companies are trying to collect foreign content on their platforms, Korean users who prefer foreign content could upend the global mediascape. This phenomenon is similar to that in the U.S. market. Americans consume more foreign content than ever before. The top five international markets in the US by Q4 2020 were the UK (8.3%), Japan (5.7%), Canada (3.2%), Korea (1.9%), and India (1.5%). Second, making original content exclusively available through their services is also a very effective strategy. This result is in line with Palomba's findings [48] that OTT original series are critical for developing OTT brand equity and loyalty. According to Statista [49], in the third quarter of 2021, Netflix released 129 original content titles worldwide, up from the 125 originals released in the same period of the previous year. Netflix has been ramping up its content for several years and will likely continue to do so to hold on to its position as the US market leader amidst fresh competition. In fact, as of January 30, 2016, Netflix provided 1025 pieces of content in Korea; as of May 2018, they provided 3367 pieces of content, consisting of 2614 movies and 753 TV shows. Following Netflix, Korean domestic OTT service platforms are also planning to release their original series to gain a competitive advantage in this competitive industry. OTT providers overcome the problem of local content shortage by focusing on original content distribution, which has resulted in gaining new subscribers. Finally, one of the great advantages of OTT is that one can select a variety of movies according to the consumer's taste and preference in Korea. This is not delivered through traditional pay-TV services. The result implies that collecting the latest and diverse movies can be a content-differential strategy for securing subscribers.

Table 9. Logistic regression results on paid service experience.

		Coefficient	Std. Error	*p*-Value
Intercept		−0.326 *	0.149	0.029
TV watching time		0.000	0.000	0.541
OTT content preference	VOD	0.035	0.159	0.827
	Foreign content	1.341 ***	0.343	0.000
	Movie	0.518 **	0.200	0.010
	OTT original content	0.704 ***	0.207	0.001
	Personal broadcasting	−0.747 ***	0.160	0.000
	Music & Others	−0.724 *	0.340	0.033

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5. Conclusions

5.1. Summary and Discussion

While the consumer segmentation approach has been actively applied in various ICT services, such as mobile services and e-commerce [19–22], few studies have focused on the new media industry called OTT. This is because OTT was considered novel or innovative by scholars. Thus, research topics on OTT consumers were mainly related to the adoption or intention of continued use [50] rather than market segmentation. However, the new media market driven by OTT services has changed dramatically over the last few years. In many developed countries, including Korea, OTT services have penetrated deeply, and most users are aware of and enjoy them. In this competitive media environment, OTT operators are seeking ways to increase profitability [51]. In this context, we applied market segmentation theory to the Korean OTT market, identified profitable niche markets from the OTT platform company perspective, and suggested effective strategies from the content perspective.

Summarizing the empirical findings, it can be said that the Korean OTT market can be divided into three sub-segments based on users' behavioral patterns such as usage frequency, usage time per connection and the paid service experience. The common characteristics of the first segment are that only approximately 30% of them watch OTT content numerous times per day, and their average viewing time lasts between 10 and 20 min with no one likely to pay for OTT. The second segment has the traits of having a daily OTT viewing frequency of approximately 38%, with viewing time per connection ranging from 20 to 60 min, with the proportion of individuals who watch for a fee being only 0.2%. Lastly, the third segment has an estimated 70% of people watching OTT at least once a day, more than half of them spend more than 60 min per connection, and 33% of them have the experience of paying for OTT service. The application of market segmentation with a latent class model for OTT users showed that segmentation works successfully, and such an approach can explain users' behavior and leverage the targeting in product and marketing strategies by avoiding generic and vague marketing messages. In our analysis, we found that the third segment was the profitable niche where firms can narrow their strategic choice for profitability because their proportion over total OTT users was approximately 36% and most paying customers were in the third segment. Lastly, to create a meaningful positioning strategy to convert free users to paying customers in a profitable niche, we analyzed the impact of content preference on the paid service experience. This is because content genre is directly associated with OTT brand and service characteristics.

5.2. Academic and Managerial Implications

The results of this study provide several academic implications. First, it is worthwhile to expand the scope of the existing OTT research by introducing market segmentation and targeted marketing theory into the Korean OTT market, which has not been widely applied in this field. As a result, we demonstrated that the market segmentation approach can be successfully applied in the Korean OTT market, and OTT usage patterns, such as usage frequency, usage time, and paying for the experience, are vital variables for dividing the submarket. In addition, sociodemographic variables such as age and gender explain the differences between segments. Therefore, this study represents pioneering research based on its research framework, which allows us to capture a meaningful, profitable niche. Second, this study successfully applied market segmentation and targeting theory to OTT markets. Market segmentation using a latent class model or other clustering methodologies have been actively applied in the e-commerce market [19–23,52], but this theoretical and applied approach has not been attempted in OTT. In this study, we found that behavioral segmentation and segmented markets explains OTT users better than merely considering OTT users as a homogenous group. Lastly, this study suggests a way to supplement the shortcomings of previous studies using choice experiment data by introducing reliable panel data. Although the conjoint analysis method that asks consumers to select an imaginary service profile is an advantageous way of collecting data, it has a few drawbacks. The data can have only a few attributes by assuming that the others are the same. The data are not based on revealed preferences but rather on stated preferences, which may cause hypothetical bias. Thus, to compensate for the shortcomings of conjoining, this study attempted to obtain reliable panel data that can be considered a randomly selected sample.

Today, the global media industry is in the midst of a digital transformation [53,54]. OTT has empowered consumers to experience content on the move anytime, anywhere, and on any device through digital transformation. In this context, this study offers several managerial implications. First, we identified a meaningful profitable niche from the OTT provider's perspective. According to Smith [55], who first proposed the concept of market segmentation, three criteria must be fulfilled in segmentation: (1) within homogeneity, (2) between heterogeneity, and (3) reaction (i.e., similarity of response towards a marketing strategy, service or offer within a group). From this perspective, the identified profitable niche satisfies all the criteria. Furthermore, we found that depending on the segment they belong to, even the same free users have varied usage behaviors and demographic characteristics. Based on these results, marketers should focus on convincing about 64% of free users in profitable niche segments through targeted marketing with a proper content strategy. Consequently, OTT service providers can increase the transition rate from free users to paying users by effectively targeting OTT users and expecting increasing sales in an intensely competitive environment. Second, we draw strategic implications not only for whom the promotion should be targeted to, but also which service should be designed from a market competition perspective. In contrast, only OTT consumer characteristics or optimal OTT service design was considered in the previous literature. In particular, we focused on addressing consumers' OTT usage patterns and their demographic variables to find a profitable niche market in the first stage. In addition, we paid attention to which service should be designed based on the content implementation in the second stage. Given that most market segmentation studies have focused on identifying significant submarkets, it was worthwhile to investigate the content strategy for transitioning free users in profitable niche groups to paying users in this study.

5.3. Limitation and Future Research

Several limitations still exist in this research. First, we would like to point out the limitation that empirical market segmentation studies share. In this study, Korea's OTT market was divided into three submarkets according to their usage patterns. However, this was merely a result of the analysis of the statistical model. In fact, other types of market segmentation may also exist.

Second, we only used three behavioral variables (how frequently they watch OTT, how long they continue to watch OTT and whether they pay for it or not) for OTT market segmentation, but other behavioral variables such as the benefits desired in a service or the usage occasion are also important and possible variables that divide potential customers into groups. Further studies would be able to include more behavioral variables, which could guide different types of segmentation. For example, OTT watching purposes such as hedonic and functional usages, or watching places such as the home, car and work will provide a deeper understanding of OTT users.

Lastly, this study recognizes the OTT service market as an independent service differentiated from traditional TV services. However, OTT services can also be divided into several categories depending on the type of provider and the method of service delivery. Owing to the lack of rigorous academic definitions of various OTT services and the shortcomings of data availability, OTT was regarded as a single service in this study. For example, there is a wide range of OTT platforms, including YouTube, Netflix, and Disney+. OTT content comes in different forms; classifying them all as the same kind of OTT would be a strong assumption. Future studies could investigate user behavior depending on the type of OTT provider.

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