Master Thesis in Engineering

Understanding consumer decisions in media content using the multivariate probit model

다변량 프로빗 모형을 이용한 미디어 소비 행태 분석

June 2022

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이 논문을 공학석사학위 논문으로 제출함

2022 년 7 월

서울대학교 대학원

협동과정 기술경영경제정책 전공

오수민

오수민의 공학석사학위 논문을 인준함

2022 년 6 월

위 원 장 _____(인)

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Abstract

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Media content distributors and producers should understand consumer choices and patterns regarding media content to effectively create and present content that satisfy the consumer's interest. This study analyzes the effects of demographic characteristics, subscription service motivation, and subscription status on the consumer decision making process in choosing media content using a multivariate probit model. The empirical model allows us to review the multiple choices consumers make, starting from the location, device, content distributor, and up to the content genre. Our analysis suggests different user scenarios and strategies targeting various customer profiles based on the characteristics of consumer preferences in choosing media content. We propose how digital media services can select content and improve content delivery to retain viewers.

Keywords: Consumer Preference; Media Content; Simultaneous Choice; Multicategory Choice; Multivariate Probit Model
Student Number: 2020-23704

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Chapter 1. Introduction

1.1 Research Background

Netflix announced it lost about 200,000 subscribers in the first fiscal quarter of 2022. Accompanying this disappointing news on performance, the company also expects to lose another two million subscribers in the second quarter, which sent the share price sliding down more than 35% the day after Netflix released the report earnings. The streamer attributed its subscriber loss to a number of possible causes, including password sharing among viewers and a drop-off in the adoption of broadband and smart TVs (Sperling, 2022). However, arguably one of the most attributable factors is the hyper-competitive media market. Netflix faces harsh competition from emerging streaming services like Disney+, Apple TV, HBO Max (Gleiberman, 2022).

This phenomenon is not unique to the US market. While Netflix has managed to lead in the South Korean market, Disney+ and Apple TV are struggling to retain and attract users (Hong, 2022; Donga, 2022). They also face intensified competition with Paramount, Amazon Prime, and HBO Max preparing to enter the South Korean market. Given the challenges unique to the Korean market and increasing competition, there is need for foreign OTT services to understand Korean consumers and their media selection behavior.

For media companies like Netflix, data is used to make informed decisions in betting on content. Kevin Spacey, the star of “House of Cards,” said Netflix approached him with these words, “We’ve run our data and it tells us that our audience would watch this series…How many do you wanna do?” (Wu, 2015). However, both Ted Sarandos, Netflix’s

Chief Content Officer, and Chris Kelly, CEO of Fandor, an indie-film streaming service, suggest content curation also requires human judgement. Intuition is no stranger to studios and television networks as they have relied on approval from a handful of executives and depending on the budget, a greenlight from the chairman him/herself (Lang & Shaw, 2013). Therefore, this study presents a means for content distributors and producers to analyze consumer preferences to make informed decisions in regards to partnerships and content creation. Our analysis aims to dissect the consumer's decision in video content by considering the multi-category choices that are made in the decision process. Understanding consumer choices and patterns allow content distributors and producers to effectively create and present content according to consumer behavior and their interest.

1.2 Study Scope and Research Goal

An independent market research group identified about a quarter of streaming subscribers to be 'hoppers' who frequently switch services (Thomson, 2022). Despite access to big data, OTT service providers have struggled to retain customers. Digital media distributors are limited to audience behavior data collected from users using their services. This study aims to identify the effects of demographic characteristic, subscription motivation, subscription status, and the relationships in consumer choices between different categories when deciding on what to watch. Taking inspiration from past studies that review consumer decisions in media content, this study considers categories more fitting for the present day using the multivariate probit model. This empirical model reveals whether the choices consumers make, starting from the location, device, content distributor, and content genre,

are complementary or coincidental by nature in its variance-covariance matrix.

This study is organized into five chapters. The first chapter introduces the challenges facing video streaming services and producers and the methodology that can offer stakeholders another perspective in understanding the consumer decision making process in regards to video content. The second chapter reviews existing literature regarding research and analysis on OTT services, multi-platform strategy, and the application of the multivariate probit model. The third chapter on Empirical Model describes the data and methodology used in our study. Our analytical findings from the multivariate probit estimation and the variance-covariance matrices and its interpretation are presented in the fourth chapter, Empirical Results. The fifth chapter Discussion and Conclusion concludes the research with a summary of key findings and suggested strategies for content distributors. Limitations of the study are also discussed.

Chapter 2. Literature Review

2.1 Previous Literatures on OTT Services

There are two major research themes regarding media services. Our review revealed that studies on OTT services use empirical analysis, whereas literature on multiplatform strategy tend to be based on case studies. Among the studies that analyze OTT services, there are two streams. One stream focuses on the macro perspective and the other focuses on consumer preferences of different attributes.

Kim et al. (2016a) analyze competition between traditional pay TV and OTT services through the lens of niche theory and displacement effect of new media on old media. Niche theory stems from ecology but is adapted to examine the competitive dynamics of media industries by measuring niche breadth, niche overlap, and competitive superiority. The authors adopt two different resource dimensions, gratification and time spent on media, which reveal mild competition between traditional pay TV and OTT services in South Korea. Due to the focus on displacement in the measurements of competitive dynamics, the authors are not able to analyze complementary relationship between media. Shon et al. (2021) examine the impact global OTT services like YouTube and Netflix had on the growth of local video content industry through stochastic frontier analysis (SFA) and meta-frontier analysis by comparing efficiency differences. The authors find that while the content production industry was negatively affected by the entrance of YouTube and Netflix in South Korea, the content distribution was not. The study attributes the global expansion of Korean content to the advent of global OTT services.

The second stream of research concerning the analysis of OTT services focuses on consumer preference analysis regarding OTT service attributes. While Shin et al. (2016), Kim et al., (2017) and Kim et al. (2021) use discrete choice experiment to analyze consumers' preferences, the first two publications focus on specific attributes of OTT services, whereas the latter publication shed light on consumer preference for OTT bundled services. Shin et al.'s (2016) study is composed of two parts. The first part uses a mixed rank-ordered logit model with conjoint survey data to estimate consumer preference for each of the five attributes that make up OTT services. Results from this analysis reveal monthly fee to be the most important attribute, followed by real-time broadcasting services, number of VODs, newest broadcasting/movie, and terrestrial television broadcasting. The second part of the study uses a multivariate probit model to analyze the relationship between pay TV and OTT services. The variance-covariance matrix shows significantly negative relationships among pay TV services, which includes cable TV, satellite TV, and IPTV. OTT services also show a significantly negative relationship with cable TV services. The authors recommend further analysis examining the relationships between various types of video content and OTT service. We take this point into consideration by observing consumer choices in content genre and type of distributor. Kim et al. (2017) consider a different set of attributes that characterize OTT services. Using a multinomial logit model, the authors estimate the marginal willingness to pay for the various attributes. Results indicate Korean consumers highly value personalized recommendation systems, followed by a refined recommendation system with a variety of viewing options, and a high resolution. The authors suggest considering attributes regarding content to under consumer viewing behavior. As mentioned, we take various attributes of content into consideration

to understand the relationships of choices consumers make when consuming video media. Kim et al. (2021) use mixed logit model to analyze the marginal utilities of attributes of bundled pay TV and OTT services. The authors' scenario analysis reveal that Korean consumers prefer major TV broadcasting channels, which includes terrestrial and general programming channels. The authors also found a complementary relationship between TV broadcasting channel content and OTT services when they are bundled; this indicates a strong preference for domestic content and real-time terrestrial channels. Studies of this stream focus on specific attributes that attract consumers to subscribe to OTT services. External factors affecting the adoption of OTT services and discussions regarding content are overlooked in these studies.

2.2 Previous Literatures on Multi-Platform Strategies

Rather analyzing consumer preference data, some researchers have focused on identifying multi-platform strategies through case studies or other qualitative research means. Multi-platform strategy research tends to be centered around television migrating onto various distribution channels, hence the "multi-platform" label, and discussions regarding repackaging content for multi-platform distribution.

Roscoe's (2004) case study on the Australian television show "Big Brother" dissects how content can be repackaged to engage and to be consumed by different audience groups. The author observes a change in consumer viewing habits, from once being controlled through scheduled programming to clustered viewing experiences around events. Instead of imposing on viewers to commit to a long-term viewing schedule, producers of "Big Brother"

found ways to deliver content via modes of communication that are already part of the viewers' everyday lives. To nurture and maintain the relationship with the fan base and the general audience, "Big Brother" created avenues for fans to directly engage with the show by allowing them to vote via telephone, including SMS. The "Big Brother" website also shared exclusive content, such as hidden processes of production, and provided a space for the audience to "live" in the "Big Brother" universe in the form of news, forums, photos, live streaming, etc. While Roscoe (2004) offers a deep dive centered around one TV show, Doyle (2010) presents a wholistic overview in his review of the '360-degree' approach and its financial impact by analyzing financial statements and interviewing with television executives of UK broadcasters. The 360-degree strategy is not too different from what Roscoe (2004) observed in the way "Big Brother" re-versioned its content. The strategy entails making content decisions with the aims to generate consumer value and returns through multiple versions or extensions of that content, from the earliest stages of conceptualization. Doyle (2010) suggests television broadcasters would benefit from economies of scale from extending distribution of a produced content, especially due to its 'public good' quality of which the supply is not reduced by the consumption thereof. Suppliers can reuse and reversion content to cater to the specific wants and needs of audiences active on different platforms. Due to the consumer appeal and financial reward of the multi-platform strategy, UK broadcasters are embracing 'fewer, bigger, better' content.

Although these case studies offer a deep dive into how content can be repurposed and distributed, they offer a perspective specific to these particular cases. Due to the artistic and social characteristic of media, there may be bias in the author's interpretation of the cases

and loss in nuance or detail of the execution from its description.

2.3 Previous Literatures on Multivariate Probit Model in Media

There are already quite a few of studies that use the multivariate probit model to analyze consumer choice behavior in various media channels. Woo et al. (2015) and Park and Lee (2017) both explore consumer purchasing decisions in the omni-channel environment. Woo et al. (2015) examine consumer information searches in nine categories of products and identify corresponding media channels that motivate consumer purchase decisions across product categories and demographic characteristics. Park and Lee (2017) also consider sociodemographic variables, and product categories but expand the study by including communication strategies and time of order as additional variables. Both of these studies the substitution and complementary patterns of alternatives in the correlation of error terms. Koo et al. (2014) and Taneja and Viswanathan (2014) analyze the effects of user characteristics on alternatives within a specific category. Koo et al. (2014) consider main objectives, social network services (SNSs) and internet usage patterns, and socioeconomic background, on the choice of four representative SNSs. All of these studies require analysis of simultaneous choice in multiple categories. Thus, these studies demonstrate the appropriate application of the multivariate probit model, that of which allows researchers to study the observable and unobservable effects on choices of various alternatives within a category and across categories.

2.4 Research Motivation

Existing literature on OTT services miss the opportunity to examine the relationships between various types of video content and OTT services (Shin et al., 2016) and analyze a limited set of attributes that also disregard the type of content consumers seek to watch (Kim et al., 2017; Kim et al., 2021). Interestingly most research on multi-platform strategy have favored case studies or other qualitative research methods (Doyle, 2010; Doyle, 2016; Guerrero et al., 2012; Roscoe, 2004). Among studies that use the multivariate probit model to analyze consumer choices in media content, studies like Park (2008) and Nam (2014) take consumer's decision throughout the media value chain into account providing a broad overview of consumers' choices across various media (e.g. newspaper and radio) and connection types (e.g. wireless and wired networks). However, given the drastic change in the media environment and consumption pattern, this study provides an updated perspective reflective of today's ecosystem with a focus on video content.

Despite access to big data, content distributors are struggling to retain users. Evidence suggests that there might be an overwhelming amount of data to digest which breeds analysis paralysis (Germann et al., 2013; Isson & Harriott, 2012). Shamma & Hassan (2013) suggest there may be too much emphasis on precision that stray organizations from finding and implementing practices that improve performance. Germann et al. (2013) also find that the use of marketing analytics can lead to subpar firm performance from missed market opportunities due to analytics myopia (Vollrath & Villegas, 2021). Ransbotham (2016) recommends a need to zoom out to overcome the dilemma that comes with big data. The use of the multivariate probit model in the context of the consumer media selection process

demonstrates how organizations can use a comprehensive statistical model to take a step back from intricate details. This study examines the relationships between the choices consumers make in regards to the location, device, content distributor and content genre.

Chapter 3. Empirical Model

3.1 Overview of Model

The purpose of this study is to understand factors which influence the consumer's choice in media content from analyzing the simultaneous choices they make in the multimedia environment. When consumers watch content, this one action represents the culmination of the consumer's choice in location, device, production entity, and genre. The state of the viewer's environment can influence their decision on the device and type of content to watch, as well as hinder or enhance the viewer's experience depending on the noise level, lighting, and surroundings at a particular location. The choice in device predominates the viewing experience of content in a couple different ways, such as the dimension of the screen and the operating system which predetermines the user experience of the applications consumers use to watch content. The quality and style of editing also varies by the producer, content genre, and content distributor. Choices in these four categories, location, device, content distributor, and genre, epitomize implicit and explicit characteristics of content and its viewing experience. This study observes how the consumer's demographic characteristics, media service subscription status, and location affect consumer's choice in media content. We also review whether the consumer's motivation to subscribe to media services has a significant effect.

When a consumer's choice is affected by the presence of another product from another category that is not substitutable, this can be defined as multiple-category choice (Russell et al., 1999). The paragraph above describes a multiple-category choice as a decision

process aimed to achieve a high-level consumption goal, such as to entertain oneself after a long day of work or on one's commute; this perspective satisfies this study's goal to understand the context in which content choices are made.

3.2 Multivariate Probit Model

The diversification and advancement of the internet has led to the growth of various media services, including OTT and social media platforms that rely on user-generated content. The variety of services in recent years has provided users with numerous options to choose from and to watch video content at user's convenience and preference. The multivariate probit (MVP) model considers situations where more than one category or alternative are selected simultaneously. A similar application of the MVP model has been demonstrated by Park (2008), Koo et al. (2014), Shin et al., (2014), and Park & Lee (2017) to analyze consumer's multiple simultaneous choice in regards to ICT and media. The MVP model can also be applied to multicategory products or services as demonstrated by Seetheraman et al. (2005) in which they identify the MVP model fitting for analyzing cross-category relationships in multicategory choice situations.

The MVP model is a statistical tool that can be used to infer key factors of a latent, multiple category utility function based on the random utility model (Russell et al., 1999; McFadden, 1974). Under the random utility theory, it is assumed each individual maximizes their utility in their adoption decision, which consists of two parts: deterministic and stochastic. When user i chooses alternative j, the utility function U_ij is expressed as follows:

$$U_{ij} = V_{ij} + \varepsilon_{ij} = a_j + \sum_k \beta'_{jk} X_{jk} + \varepsilon_{ij} \qquad (1)$$

Respectively, V_{ij} and ε_{ij} are the deterministic and stochastic terms of the utility function in Eq. (1). The deterministic term consists of alternative-specific constant a_j and the product of marginal utility β'_{jk} and independent variable X_{jk}. The stochastic term ε_{ij} follows a multivariate normal distribution with mean 0 and variance Σ, which can be expressed as $\varepsilon_{ij} \sim \mathrm{MVN}[0, \Sigma]$. The correlation among the unobserved effects of each alternative and the independence of irrelevant alternatives allows us to analyze the substitution and complementary patterns among the alternatives (Edwards and Allenby, 2003). We estimate values of β and Σ. Given the number of alternatives, we estimate Σ from a covariance matrix of $[22 \times 22]$ which consists of correlations between categories as expressed in Eq. (2).

$$\Sigma = \begin{bmatrix} \sigma_{location-location} & \sigma_{location-device} & \sigma_{location-distributor} & \sigma_{location-genre} \\ \bullet & \sigma_{device-device} & \sigma_{device-distributor} & \sigma_{device-genre} \\ \bullet & \bullet & \sigma_{distributor-distributor} & \sigma_{distributor-genre} \\ \bullet & \bullet & \bullet & \sigma_{genre-genre} \end{bmatrix}$$

(2)

Since the utility function cannot be directly observed, the model uses consumer's observable choice in binary form to estimate parameters; this study uses survey data to observe respondent's choice in four categories: location, device, production entity, and genre. If the expected utility of alternative *j* is greater than 0, consumer *i* chooses alternative *j*, in which the dependent variable Y_{ij} becomes 1, or otherwise 0. Therefore, the choice function is described as follows:

$$Y_{ij} = \begin{cases} 1 & if \quad U_{ij} > 0 \\ 0 & if \quad U_{ij} < 0 \end{cases} \qquad (3)$$

The probability P_{ij} of consumer *i* choosing alternative *j* can be represented as below:

$$P_{ij} = \Pr\left(U_{ij} > 0\right) = \int I(V_{ij} + \varepsilon_{ij} > 0)\Phi(\boldsymbol{\varepsilon_i})\, d\boldsymbol{\varepsilon_i} \qquad (4)$$

Considering the multiple-choice situation, the choice probability is adjusted as follows:

$$\Pr(Y_i|\beta, \Sigma) = \int_{S_J} \cdots \int_{S_1} \Phi\left(\boldsymbol{\varepsilon_i}, \dots, \boldsymbol{\varepsilon_J}\middle|0, \Sigma\right) d\boldsymbol{\varepsilon_i} \dots d\boldsymbol{\varepsilon_J}, \qquad (5)$$

where $Y_i = (Y_{i1}, \dots, Y_{iJ})$ and $S_J = \begin{cases} (-\infty, 0) \;\; if \;\; Y_{ij} = 0 \\ (0, \infty) \;\; if \;\; Y_{ij} = 1 \end{cases}$

This study uses R Programming to run the parameter estimation using a package called *bayesm*. Due to difficulty in estimating the likelihood function Eq. (5) using maximum likelihood estimation (MLE), this study implements a Bayesian estimation method using a Gibbs sampler, an MCMC algorithm (Chib and Greenberg, 1998; Rossi et al., 2005). This allows us to overlook two problems that arise with estimating the likelihood function: one is the complication in finding the global maximum value from the likelihood function and the second is MLE's sensitivity to starting values.

Since the model analyzes both observable and unobservable effects on the multiple-category choice situation through various explanatory variables, we are able to differentiate choices of complementarity from choices made in coincidence, where insights regarding consumer's choice behavior are unobservable (Koo et al., 2014; Russell et al., 1999). The MVP model allows us to identify key factors that help us understand how and why consumers select and watch content.

3.3 Survey Design

The survey consists of several sections regarding demographic information, currently subscribed services (i.e. OTT and pay TV), motivation for opting in to subscription

television, and average portion of time spent on watching on a specific device, location, and content per week. The section pertaining to video consumption behavior is designed as a table which consists of five rows and four columns. The first column responds to the device consumers use to watch content. The portion of time is recorded as a percentage of time spent in a week. The summation of time spent on each device adds up to 100%. The following columns respond to the location, content distributor, and genre watched using the pertaining device of that row. Since respondents indicate their consumption as a percentage of time, we assume any usage greater than 0% as having utility greater than 0; thus, usage is coded as 1 ($Y_{ij} = 1$) and 0 otherwise, as indicated above.

This survey does rely on stated preference with respondents' consent. Although it is ideal to use revealed preference method to derive utility and estimate models of consumer's demand of products and services, stated preference methods allow researchers to put questions in behavioral choice context and analyze correlations to personal characteristics (Kroes and Sheldon, 1988). It has been used to directly examine consumers' choice processes. However, individuals' stated preferences may not correspond to their actual behavior and preferences (Wardman, 1988). (Refer to Appendix 1 for a copy of this section of the survey.)

A consumer's media activity is reflected in their choice of location, device, production entity, and genre; multiple decisions are simultaneously made to actualize a viewing experience. These decisions can be expressed as dummy variables. The survey data for the dependent variables is reformatted to binary data of 1s and 0s to satisfy the MVP model. If respondents recorded spending more than 0% of their time on any particular alternative, we interpret this as a selection of the alternative, thus attributing the response to 1 ($Y_{ij} =$

1) and 0 if not selected ($Y_{ij} = 0$). Alternative j represents the consumer's choice in four facets that make up a viewing experience, which makes each alternative of the four categories a dependent variable as listed in Table 1.

In addition to the reformatting, some alternatives are rearranged or excluded from the analysis. While the survey was constructed to analyze respondents' choices in five different locations, two of the original alternatives, "Workplace/School, etc" and "Indoor Public Place," are consolidated into one new alternative, "Indoor Public," in this study. *Indoor public space* has been defined as somewhere accessible to the public, which includes spaces used by employees or patrons and any other enclosed public spaces (World Health Organization, n.d.). Unlike "Indoor Public" and "Home," which are *destinations*, "Transit" is a *mode* to reach a destination. Few respondents selected "Other Places" and it is unknown where those other places are. Given the sample size of the respondents who selected this alternative and the lack of context of the location, we choose to focus on "Home," "Indoor Public" and "Transit" as alternatives for where consumers choose to watch content. For this same reason, an alternative, "Etc," under genre is also removed.

Table 1. Dependent variables

Category	Alternative	Dependent Variable
Location	Home	HOME
	Indoor Public	INDOOR
	Transit	TRANSIT
Device	Smartphone	SPHONE
	Tablet	TABLET
	Desktop	DESKTOP
	Laptop	LAPTOP
	TV	TV
	Terrestrial Channel (KBS, SBS, MBC)	PUBLIC

Content Distributor	Alternative Terrestrial Channel (KBSN, SBS Golf, MBC+)	PUBLICT
	Cable Channel	CABLE
	OTT	OTT
	User Generated Content	UGCT
Content Genre	Press Coverage	PRESS
	Documentary	DOC
	Korean Drama	KDRAMA
	Foreign Drama	FDRAMA
	Movie	MOVIE
	Music	MUSIC
	Entertainment (variety show, game show)	ENT
	User Generated	UGCG
	Sports (includes e-sports)	SPORTS
	Educational	EDU
	Shopping	SHOP

Independent variables include ASC, and variables representing demographic characteristics, subscription status, and motivation for subscription TV. To analyze the effect of user characteristics on the consumer's media viewing experience, the utility function for respondent i choosing alternative j in four different facets of the content viewing experience is expressed below:

$$U_{ij} = a_j + \beta_{j,AGE}X_{i,AGE} + \beta_{j,GENDER}X_{i,GENDER} + \beta_{j,OTT}X_{i,OTT} + \beta_{j,PAY}X_{i,PAY} + \beta_{j,P\_CHAN}X_{i,P\_CHAN} + \beta_{j,RES}X_{i,RES} + \beta_{j,N\_CHAN}X_{i,N\_CHAN} + \beta_{j,CABLE}X_{i,CABLE} + \beta_{j,VOD}X_{i,VOD} + \beta_{j,BUNDL}X_{i,BUNDL} \quad (5)$$

The variables $X_{i,AGE}$ and $X_{i,GENDER}$ represent demographic characteristics of respondents, respectively the age and gender of the respondent. The variable $X_{i,AGE}\cdots$, whereas $X_{i,GENDER}$ is a dummy variable. The dummy variables $X_{i,OTT}$ and $X_{i,PAY}$ indicate whether the respondent is subscribed to at least one OTT service and one pay TV

service respectively. The question regarding consumer's subscription status for OTT service offered three multiple choice options; responses corresponding to "pay usage" and "free and pay usage" were assigned 1, and otherwise "free usage" as 0. The variables X_{i,P_CHAN}, $X_{i,RES}$, X_{i,N_CHAN}, $X_{i,CABLE}$, $X_{i,VOD}$, and $X_{i,BUNDL}$ depict the motivations that positively encouraged respondents to pay for subscription TV. As the section of the survey regarding the user's motivation was a five-point Likert scale question, answers indicating "4: very influential" and "5: absolutely influential" were converted to 1; answers indicating "1: not influential at all," "2: not very influential," and "3: indifferent" were converted to 0.

Table 2. Independent variables

Category	Independent Variable	Description
Alternative-specific	ASC	Captures the average effect of each alternative on utility. The corresponding alternative is assigned a value of 1 if selected, 0 otherwise.
Demographic Characteristic	AGE	Respondent's age
	GENDER	Respondent's gender. 1 for male, 0 for female.
Subscription Status	OTT	Respondent's pay status for an OTT service. 1 for subscribing[1], 0 if not.
	PAY	Respondent's pay status for pay TV. 1 for subscribing, 0 if not.
Motivation for Subscription TV	P_CHAN	1 for when a respondent feels strongly motivated[2] to pay for subscription TV to access terrestrial channels, 0 if not.
	RES	1 for when a respondent feels strongly motivated to pay for subscription TV for

[1]"Free usage" = 0, "Free and pay usage" = 1, "Pay usage" = 1 for OTT subscription status.
[2]"1: not influential at all" = 0, "2: not very influential" = 0, "3: indifferent" = 0, "4: very influential" = 1, "5: absolutely influential" = 1.

		higher resolution of terrestrial channels, 0 if not.
	N_CHAN	1 for when a respondent feels strongly motivated to pay for subscription TV to access alternative terrestrial channels, 0 if not.
	CABLE	1 for when a respondent feels strongly motivated to pay for subscription TV to access cable channels, 0 if not.
	VOD	1 for when a respondent feels strongly motivated to pay for subscription TV to watch VOD, 0 if not.
	BUNDL	1 for when subscription TV is included in a bundle offered by their current telecommunications company, 0 if not.

Chapter 4. Empirical Results

4.1 Descriptive Statistics

This study uses data collected from a consumer survey conducted by Gallup Korea, a specialized survey agency, for three weeks, between June 28th and July 18th, 2019. The survey was carried out in eight major cities (i.e. Busan, Bundang, Daegu, Daejeon, Gwangju, Ilsan, Incheon, and Seoul) which contain about half of South Korea's population. 665 respondents between the age of 20 and 60 were selected for this study using purposive-quota sampling to reflect the age and gender balance of the country's population. However, 2 respondents were eliminated due to inconsistencies and errors in their response. Thus, 663 respondents (99.7%) were selected to be analyzed. The statistics representing the demographic characteristics of survey respondents can be found in Table 3 below.

Table 3. Demographic characteristics of survey respondents

Sample Group		No. of Respondents	Ratio (%)
Total		663	100.0%
Gender	Male	337	50.8%
	Female	326	49.2%
Age	20 to below 30	171	25.8%
	30 to below 40	147	22.2%
	40 to below 50	179	27.0%
	50 to below 60	166	25.0%
Region	Seoul	270	40.7%
	Ilsan	33	5.0%
	Bundang	33	5.0%
	Incheon	85	12.8%
	Busan	91	13.7%
	Daegu	69	10.4%
	Gwangju	41	6.2%
	Daejeon	41	6.2%

The characteristics of subscription TV services used by the survey respondents are shown in Table 4. Nearly a majority of respondents (46.9%) receive their telecommunication services from SK Broadband, followed by KT (28.7%) and LG U+ (24.1%). A vast majority of respondents (92.8%) subscribe to Pay TV, while 8.1% and 12.5% of respondents identify themselves as a premium user of some kind of OTT service or a user who uses both paid OTT services and free options.

Table 4. Characteristics of subscription services used by respondents

Category		No. of Respondents	Ratio (%)
Total		663	100.0%
Telecommunication Provider	SK Broadband	331	46.9%
	KT	190	28.7%
	LG U+	160	24.1%
	Other	2	0.3%
Pay TV	Yes	615	92.8%
	No	48	7.2%
OTT Service	Not a user	119	17.9%
	Free	407	61.4%
	Premium user	54	8.1%
	Free & Premium user	83	12.5%
Mutually subscribed OTT service in respondent's network	POOQ	37	5.6%
	TVING	14	2.1%
	Oksusu	58	8.7%
	OllehTV Mobile	53	8.0%
	U+ Mobile TV	19	2.9%
	YouTube	350	52.8%
	Netflix	80	12.1%
	Watcha	1	0.1%
	Other	3	0.5%

Not Applicable	48	7.2%

We can identify the most popular alternatives within each category by the corresponding number of respondents who indicate a positive selection. These statistics are indicated in Figure 1, 2, 3, and 4. (Code names for the variables are listed in Table 1.) Since respondents are able to select more than one alternative from each category, the total number of positive selections exceeds the sample size. For the location category, nearly every respondent selected home as a place of viewing; indoor public spaces is another preferred location, followed by the transit (Figure 1). In parallel to the selection of the location alternatives, smartphones and televisions received the most selection in the device category (Figure 2). The higher selection of smartphones over the television suggest that consumers also use their smartphones to watch video content at home. The content distributor category shows a relatively even distribution of selection of alternatives, excluding OTT services (Figure 3). Public broadcasting channels are the most common avenue of content viewing, followed by content services focused on user generated content, cable TV, and alternative public broadcasting channels. In the genre category, entertainment is most popular, followed by press and Korean drama. Entertainment's popularity is expected because this includes South Korean variety shows, which can be described as light-hearted, unscripted programs designed for casual viewing enjoyed by all age groups; this includes game shows, reality, and competitive talent shows (Lee, 2021). Korean drama's popularity can also be explained by family-friendly tone, with little to no scenes of nudity or sex, which opens itself to a wider audience unlike foreign dramas (BBC, 2021).

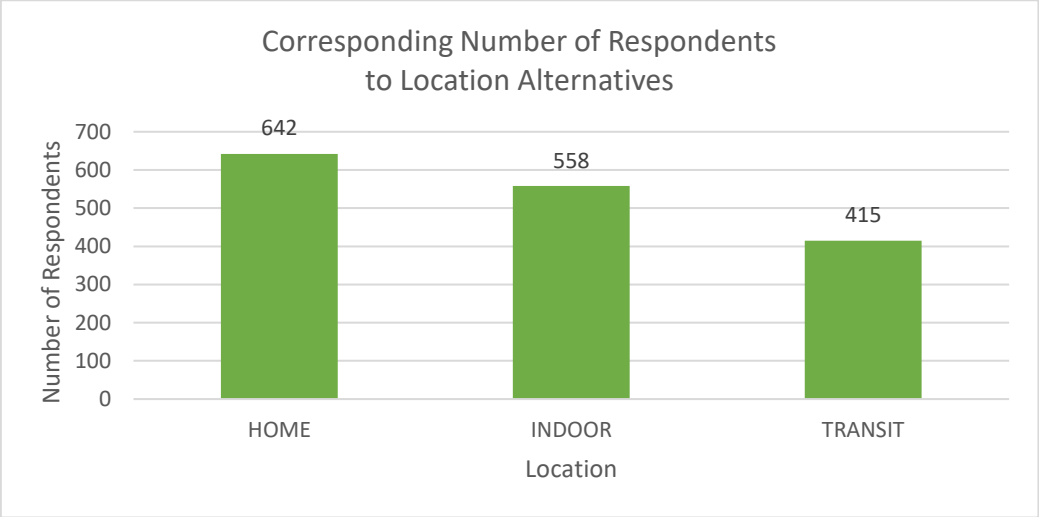

Figure 1. Corresponding number of respondents to location alternatives

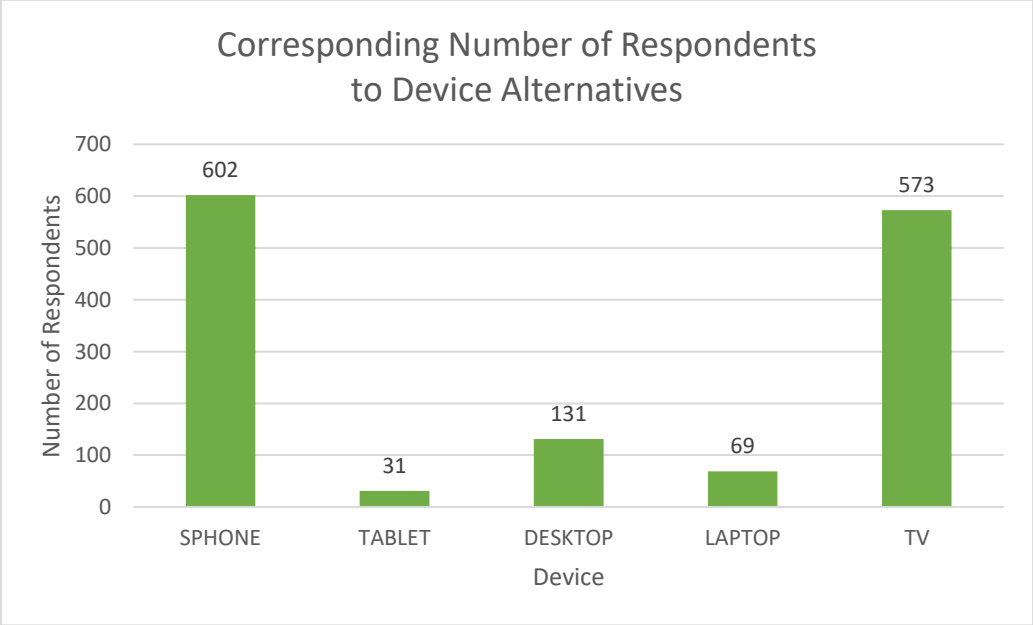

Figure 2. Corresponding number of respondents to device alternatives

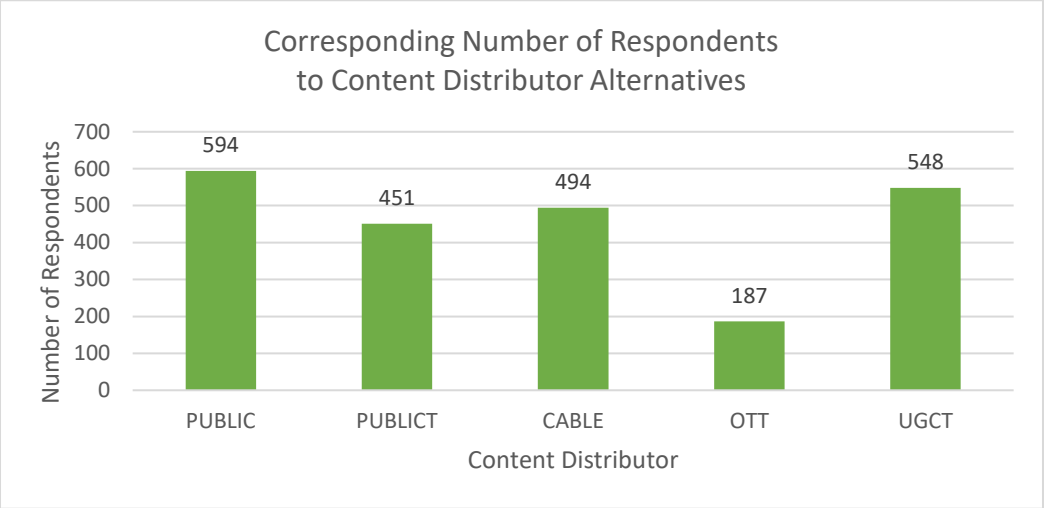

Figure 3. Corresponding number of respondents to content distributor alternatives

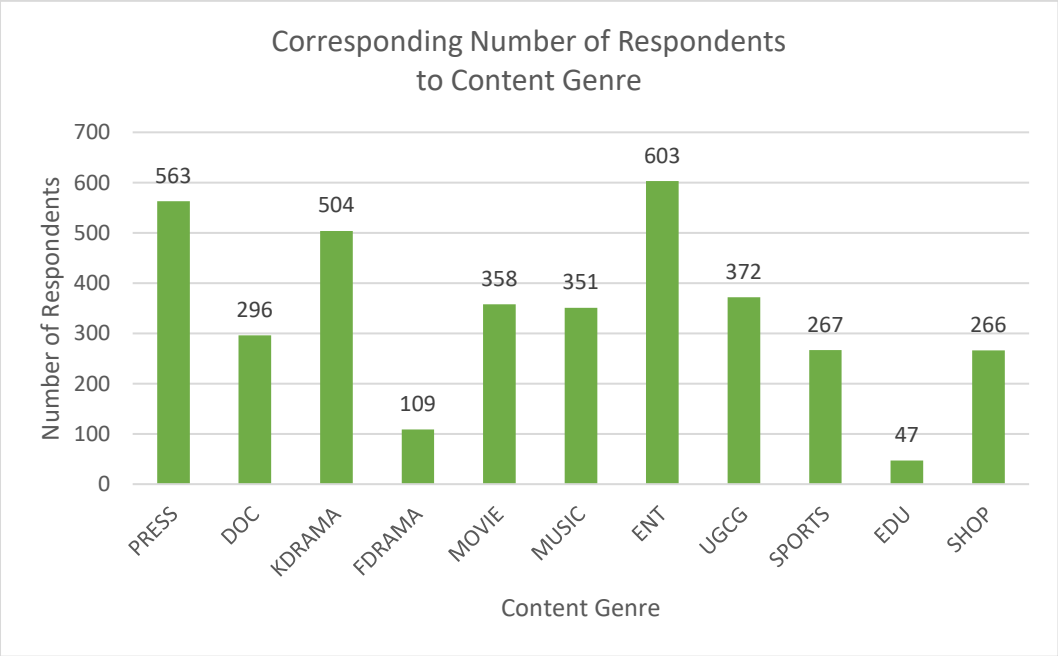

Figure 4. Corresponding number of respondents to genre alternatives

4.2 Estimation and Interpretation

4.2.1 The Effect of User Characteristics on Consumers' Choice

We can analyze the effect of user characteristics on the choice in the content viewing experience by estimating the independent variable's correlation β summarized in Table 5.

4.2.1.1 Alternative Specific Constant (ASC)

The alternative-specific constant captures the average effect on utility not explained by the listed independent variables (Train, 2003). The estimation results of ASC in relation to choices made for the content viewing experience reveal that consumers prefer viewing content on their smartphones; this was the only significant device in this category. In regards to genre of content, variety shows are most favored by consumers, followed by music related content and Korean dramas. Press and sports related content are least favored by consumers, followed by educational content and documentaries. The estimation results indicate only one significant location, the home, and no content distributor is found to be significant.

4.2.1.2 Age Variable

Younger consumers prefer to watch videos on transit, while no significant location is found for older consumers. Younger consumers favor watching on their smartphones, and their laptops and desktops; tablets come last on the list. They enjoy watching music related content the most, followed by educational content, entertainment, movies, and foreign dramas. Older audience have a significant relationship with television and their go-to channels are terrestrial network. Older consumers have a significant relationship

Table 5. Multivariate probit estimation result

		DEMOGRAPHIC		SUBCSCRIPTION		SUBSCRIPTION MOTIVATION					
	ASC	AGE	GENDER	OTT	MEDIA	P_CHAN	RES	N_CHAN	CABLE	VOD	BUNDL
HOME	1.566*	0.029	-1.248*	-0.126	-0.043	-0.998	-0.133	0.939	0.291	0.771	1.405
INDOOR	0.322	0	0.476*	0.733*	-0.143	-0.259	-0.183	0.067	-0.04	0.416*	0.236
TRANSIT	0.119	-0.02*	0.02	1.173*	-0.011	0.215	-0.146	0.153	-0.164	0.081	0.255
SPHONE	1.319*	-0.036*	0.534	2.14*	-0.524	-0.333	-0.111	0.304	-0.936*	0.224	0.542
TABLET	-0.364	-0.015*	0.106	0.256	-1.058*	0.559*	-0.126	0.205	-0.016	-0.031	-0.211
DESKTOP	-0.372	-0.02*	0.621*	0.173	0.534	-0.234	0.017	-0.006	-0.236	-0.263	0.031
LAPTOP	-0.081	-0.029*	0.043	0.002	0.2	0.042	-0.206	-0.174	0.006	0.007	0.088
TV	-0.312	0.043*	-0.588	-0.409	2.233*	0.152	0.116	0.033	0.471	0.148	0.419
PUBLIC	-0.073	0.034*	0.031	0.031	1.466*	-0.701*	-0.27	0.486	0.569	0.351	-0.079
PUBLICT	-0.091	0.005	0.002	-0.06	0.488	0.014	0.03	-0.349*	0.33*	0.206	-0.137
CABLE	-0.025	-0.004	0.09	-0.102	1.115*	-0.204	0.121	-0.043	0.572*	0.338*	0.038
OTT	-0.217	-0.022*	0.315*	0.405*	0.209	-0.305*	-0.288	-0.286	-0.019	0.284	-0.01
UGCT	0.615	-0.013	0.205	0.981*	-0.359	-0.289	0.19	0.459	-0.04	0.099	0.264
PRESS	-1.222*	0.041*	-0.08	-0.041	0.877	-0.235	-0.424	0.207	0.031	0.467	0.532*
DOC	-0.887*	0.011*	0.027	-0.025	0.249	-0.104	-0.048	0.045	0.127	0.148	-0.047
KDRAMA	0.736*	0.005	-0.546*	-0.059	0.008	-0.097	-0.13	0.144	0.177	0.17	0.099
FDRAMA	-0.463	-0.007*	0.099	-0.044	0.22	-0.092	0.005	-0.066	0.07	0.168	-0.141
MOVIE	-0.139	-0.01*	0.027	0.082	0.51	-0.02	-0.134	0.415*	-0.032	0.203	0.211
MUSIC	0.901*	-0.02*	-0.125	0.146	0.124	-0.139	-0.257	-0.145	0.309*	0.095	0.148
ENT	2.019*	-0.015*	-0.098	0.003	0.067	0.096	0.005	0.235	-0.093	-0.076	0.153
UGCG	-0.372	-0.006	0.148	0.673*	-0.665*	-0.041	-0.041	0.35*	0.009	-0.148	0.292
SPORTS	-1.19*	0.009	1.152*	0.045	0.063	-0.061	0.037	0.159	-0.099	0.148	-0.202
EDU	-0.965*	-0.019*	-0.112	0.193	0.225	0.004	-0.223	0.011	-0.174	-0.201	-0.062
SHOP	-0.371	-0.007	-0.413*	0.107	0.376	-0.046	0.006	0.299*	0.052	-0.018	0.289*

Highlighted results are significant at 1%.

with factual programming, such as press-related content and documentaries. Although our analysis indicates that young people do consume non-fictional genres, such as educational content, news tends to be more preferred by an older audience. Interestingly, similar observations were reported by Rubin and Rubin back in 1982. They found older adults were motivated to watch the news and nonfictional programs to keep up with the change happening in the world or within their communities. This satisfied their need for information in order to power mass communication within this demographic group. While younger consumers may not be *watching* the news, they may be keeping up with the news from a variety of on- and off-line sources (Valkenburg & Piotrowski, 2017). On the other hand, Meijer (2007) suggests there is a declining appetite for news among young people due to fundamental technological changes in culture and overwhelming amount of information and entertainment that are now available.

4.2.1.3 Gender Variable

Differences are also found between female and male audiences. Female viewers watch from home while male viewers report watching at indoor public locations, such as the office. This may be because there is a higher labor force participation amongst the male population in comparison to the female population in South Korea (World Bank, 2022). Our survey population also indicates a higher labor force participation from the male population (92%) than the female population (67.7%). As one could expect, sports, which also includes e-sports, is found to be significant among male viewers. They prefer to watch on desktop; the male viewers' environment could provide context to their pick of device and what program they choose to watch. For example, Eastman and Land (1997) contextualize public sports viewing by observing the cultural production the viewing space induces. However, Chung

(2015) has found televised sports viewing is not motivated by social engagement, but rather, Korean spectators play the video content on as a way to pass time. On the other hand, the male counterpart watch Korean dramas and home shopping programming. Korean TV home shopping is known for its competitive price offerings and entertainment quality (Chung, 2012).

4.2.1.4 Subscription Status Variable

OTT service subscribers' preferred locations of viewing is found to be indoor public space and/or on transit. Their preferred devices are desktop (at 5% significance level) and smartphone (at 1% significance level). This is consistent with Dwyer et al. (2018)'s finding, in which they accredit the rapid adoption of smart devices for the growth of OTT services in Korea. As expected, OTT-produced content and user-generated content are found to be significant amongst OTT service subscribers. Their favorite genres include user-generated style (i.e. vlogs and DIY videos), music-related content (i.e. concert recordings and music videos), and home shopping content.

Interestingly, pay TV subscribers prefer viewing on a different device from OTT service subscribers. Their preferred device is the television, while non-subscribers prefer to watch on the tablet. Pay TV users also favor different producers. They have a preference for traditional broadcasting programming and cable channels. Pay TV subscribers enjoy watching news, movies, and home-shopping content, whereas non-subscribers favor user generated content.

4.2.1.5 Subscription Motivation Variables

The purpose of analyzing the subscription motivation was to see if it had a significant effect on the way consumers choose content. However no apparent patterns are found.

Consumer preference varies by their motivation to sign up for subscription services. Those who are motivated to watch more general programming content or due to a bundled offering from their telecommunication provider favor movies, user-generated content, and home shopping content. Those who are motivated to watch VOD prefer watching movies and the news.

4.2.2 Simultaneous Choice in Media Content

4.2.2.1 Correlation Among Location and Device Alternatives

Table 6. Variance-covariance matrix of location and device alternatives

	SPHONE	TABLET	DESKT	LAPTOP	TV
HOME	0.08	0.14	-0.03	0.22	0.88*
INDOOR	0.61*	0.14	0.4*	0.28*	0.15
TRANSIT	0.7*	0.12	0.24*	0.15	0.04

Highlighted results are significant at 1%.

Results are somewhat expected since locations limit devices that can be used. Home and TV show a noticeable complementary relationship. All devices, except the tablet, show a complementary relationship with indoor public spaces. The smartphone, followed by desktop, laptop, the television are used to view content in indoor public spaces; the same devices chosen in indoor public spaces, excluding the laptop, also show a complementarity relationship with places of transit. Smartphones are heavily favored outside the home in indoor public spaces, as well as on transit, relative to other devices.

While it is possible that some employees are distracted by entertainment at work as observed in Karlsen & Ytre-Arne's study (2021), this is considered unlikely in the Korean office setting due to Korean office culture. Although some forms of micro-breaks have been

found to be helpful for employees in recovering from work, cognitive micro-break activities have mixed effects (Kim et al., 2016b). “Pleasurable” off-job activities, such as watching video clips, lead to recovery outcomes. However, depending on the degree of immersion, some employees may encounter difficulty context-switching into their work roles. In another study, Liu et al. (2021) observe mood enhancements and improved willingness to engage in tasks from their subjects after watching short-form videos. They report, watching short-form videos is most effective in relieving physiological stress among other micro-break activities.

Content consumption in the indoor public space can be interpreted in other ways. The indoor public space variable in our study also includes cafes, libraries, schools, “PC bangs” and any other indoor space that is outside the home. Thus, consumers could be streaming content at a location that is not the office. For instance, there has been growth in premium coffee consumption which has fueled the development of Korean café culture; consumers are motivated to spend their time at cafes to signal their wealth and prestige (Kim and Jang, 2017). Alternatively, college students may be multitasking or distracted in class or at the library; they also may be consuming content in between classes. In fact, South Korean Millennials and Generation Z consume 44.9% of their time watching video media (Yoon, 2020). Generation Z entails people born between 1997 and 2012 and Millennials are born between 1981 and 1996 (Dimock, 2019).

4.2.2.2 Correlation Among Location and Content Distributor Alternatives

Table 7. Variance-covariance matrix of location and content distributor alternatives

	PUBLIC	PUBLICT	CABLE	OTT	UGCT
HOME	0.72*	0.41*	0.39*	0.16	0.21
INDOOR	0.22*	0.05	0.06	0.33*	0.44*

TRANSIT	0.3*	0.06	0.11	0.14	0.47*

Highlighted results are significant at 1%.

General traditional programming, including cable TV, are complementary to the viewing experience at home. Interestingly, OTT produced content is insignificant in this case. This may be because consumers prefer watching on their TV in their homes. Both alternatives are found to be complementary with traditional broadcasting channels, as shown in Table 6 and Table 10 respectively. Although not shown in Table 7, OTT distributor content is also a significant choice but at the 5% significance level. Consumers tend to prefer user-generated content in indoor public settings and on their commute. We can interpret that people may prefer short videos in the distracted environment as they do not require consumer's attention for extended periods of time. The average YouTube video length in 2018 was 11.7 minutes, although the average length tends to vary by topic category (Statista, 2021). In another study by Pew Research Center, the average video length among the top 250,000 channels was found to be between 13 and 14 minutes (Alexander, 2019). As mentioned above, watching short-form videos has a positive effect on work-related wellbeing. On the other hand, the average network drama tends to fill 30- or 60-minute time slots, averaging 42 minutes (Volpe, 2017).

4.2.2.3 Correlation Among Location and Genre Alternatives

The result for this section can be found in Table 8. People enjoy watching news and Korean drama in the comfort of their home, followed by movies, entertainment shows, shopping, educational content, and sports. Documentaries, Korean dramas, and entertainment are only complementary to the home alternative. User-generated content received the least amount of attention within the home according to our results. However,

people are likely to be consuming user-generated content via social media platforms, such as TikTok and Instagram, instead of OTT or pay TV services. For instance, TikTok has slowly been expanding its video upload length from 15 seconds to 60 seconds, then three minutes, and now 10 minutes (Malik, 2022). TikTok's spokesperson explained, "We introduced longer videos, giving our community more time to create and be entertained on TikTok." This flexibility widens the scope of contents that can now be shared on the platform, such as cooking and beauty tutorials, and educational content. This puts pressure on user generated content distributors like YouTube as social media platforms like TikTok edge into the media and entertainment industry.

Movies, educational content, and shopping are still the top choice of genres in the indoor public space. Given user generated content distributor and indoor public spaces have a complementary significant relationship as indicated in Table 7, we can assume viewers are learning on the job through educational content on user generated content distributor services like YouTube. The significant result of educational content may be indicating that workers refer to tutorial videos to accomplish their given tasks at work. It may also signify college students watching tutorials on campus, in the library, or some other indoor public space. Sports, Korean dramas, and entertainment shows are not as favored in the indoor public space. Movies are found to be most significant in relation to the indoor public space. Movies may be played in the background, as white noise; in this case, it is likely that viewers select movies they have already watched or those with simply story lines that do not require consumer's full attention. This requirement to focus on content may be why users shy away from watching movies on commute. Instead, people's go-to genres are user-generated content, followed by news, music-, and sports-related content.

Table 8. Variance-covariance matrix of location and genre alternatives

	PRESS	DOC	KDRAM	FDRAM	MOVIE	MUSIC	ENT	UGCG	SPORTS	EDU	SHOP
HOME	0.69*	0.41*	0.63*	0.17	0.49*	0.32*	0.48*	0.17	0.33*	0.39	0.4*
INDOOR	0.28	-0.01	0.15	0.09	0.41*	0.27*	0.18	0.29*	0.14	0.38*	0.32*
TRANSIT	0.27*	-0.1	-0.02	-0.02	0.23*	0.25*	-0.11	0.35*	0.24*	0.08	0.19*

Highlighted results are significant at 1%.

Table 9. Variance-covariance matrix of device alternatives

	SPHONE	TABLET	DESKT	LAPTOP	TV
SPHONE	1	0	0.28*	0.05	-0.07
TABLET		1	0.1	0.2	0.12
DESKT			1	-0.3*	-0.05
LAPTOP				1	0.15
TV					1

Highlighted results are significant at 1%.

4.2.2.4 Correlation Among Device Alternatives

The result for this section can be found in Table 9. Viewers who use their smartphones to watch video content also use desktop to consume content. The negative covariance between laptop and desktop represents coincidental simultaneous choice. While Jeong et al. (2017) study's report TV and smartphone to be the most prevalent device choice when it comes to multi-tasking, our result does not signal a significant relationship between these two devices. This may be because our survey specifically asks device usage pertaining to consuming video content, and Jeong et al.'s study (2017) does not specify media activity related to device usage. Based on these two observations, we can interpret consumers are not simultaneously viewing video content on the television and their smartphone.

4.2.2.5 Correlation Among Device and Content Distributor Alternatives

Table 10. Variance-covariance matrix of device and content alternatives

	PUBLIC	PUBLICT	CABLE	OTT	UGCT
SPHONE	0.15	-0.1	-0.08	0.01	0.71*
TABLET	0.05	0.12	0.18	0.35*	0.03
DESKT	0.02	-0.05	0.04	0.36*	0.14
LAPTOP	0	0.24*	0.19	0.32*	0.09
TV	0.74*	0.44*	0.46*	0.17	0.12

Highlighted results are significant at 1%.

User generated content only shows a significant complementary relationship with smartphones. This is consistent with YouTube's statistics that YouTube users prefer mobile over desktop. In 2019, YouTube observed 70% of view time came from mobile devices (Mohsin, 2021).

Tablet, desktop, and laptop only have a significant complementary relationship with one producer, OTT services. On the TV, consumers prefer public programming the most,

followed by cable TV and alternative public programming; OTT content is significant but at the 5% significance level. This may suggest that OTT service users prefer watching OTT content on bigger screens. In fact, Netflix reported that while most Netflix subscribers sign up on phones or computers, 70% of viewing takes place on TVs (Kafka, 2018). We can interpret those consumers who use the TV to watch video content strongly prefer traditional broadcasting programming. Given users prefer user generated content distributers via smartphones, creators uploading content on these types of services should optimize their visual graphics for smaller screens.

4.2.2.6 Correlation Among Device and Genre Alternatives

Results for this section can be found in Table 11. Smartphone users favor user-generated content, followed by music and movies. On the other hand, smartphones and documentaries are coincidentally simultaneously chosen. Tablet users enjoy watching sports and movies on their device, followed by foreign dramas and user-generated content. Desktop users consume educational content the most, followed by shopping-, and music-related content; they also enjoy watching user-generated content and movies. More or less laptop users are indifferent to content related to shopping, education, as well as movies. Out of all devices, people prefer to consume shopping content on the TV the most. TV shows a complementary relationship to most of the genres. Consumers especially enjoy watching the news and Korean dramas on the TV, followed by entertainment, documentaries, movies, and educational content. Sports and music-related content are also consumed on the TV. We can conclude viewers are not selective of the genre they watch on the TV. Content providers generating or distributing user-generated or music-related content should prioritize mobile viewers.

Table 11. Variance-covariance matrix of device and genre alternatives

	PRESS	DOC	KDRAM	FDRAM	MOVIE	MUSIC	ENT	UGCG	SPORTS	EDU	SHOP
SPHONE	0.11	-0.24*	0.05	-0.01	0.2	0.33*	-0.05	0.48*	-0.01	0.05	0.08
TABLET	-0.05	-0.01	0.03	0.3*	0.36*	0.05	0.02	0.24	0.38*	0.19	0.05
DESKT	0.13	-0.06	-0.16	0.09	0.14	0.23*	0.01	0.16	0.12	0.29*	0.23*
LAPTOP	0.07	-0.04	0.09	0.08	0.22*	0.13	0	0.07	0.12	0.21	0.28*
TV	0.7*	0.49*	0.66*	0.13	0.44*	0.26*	0.54*	0.11	0.35*	0.4*	0.38*

Highlighted results are significant at 1%.

Table 12. Variance-covariance matrix of content distributor and genre alternatives

	PRESS	DOC	KDRAM	FDRAM	MOVIE	MUSIC	ENT	UGCG	SPORTS	EDU	SHOP
PUBLIC	0.71*	0.49*	0.63*	0.13	0.43*	0.16	0.6*	0.19*	0.34*	0.24	0.25*
PUBLICT	0.38*	0.36*	0.28*	0.16	0.22*	0.17*	0.37*	0.04	0.2*	0.16	0.16*
CABLE	0.34*	0.21*	0.29*	0.16	0.23*	0.15	0.38*	0.26*	0.29*	0.12	0.28*
OTT	0.15	0.15	0.12	0.43*	0.17*	0.14	0.06	0.14	0.24*	0.32*	0.18*
UGCT	0.04	-0.24*	0.01	-0.11	0.25*	0.47*	0.01	0.57*	-0.07	0.09	0.15

Highlighted results are significant at 1%.

Table 13. Variance-covariance matrix of genre alternatives

	PRESS	DOC	KDRAM	FDRAM	MOVIE	MUSIC	ENT	UGCG	SPORTS	EDU	SHOP
PRESS	1	0.49*	0.58*	0.12	0.37*	0.3*	0.41*	-0.01	0.4*	0.17	0.38*
DOC		1	0.39*	0.11	0.14*	-0.02	0.29*	-0.05	0.27*	0.15	0.05
KDRAM			1	0.21*	0.32*	0.15	0.58*	0.11	0.19*	0.11	0.2*
FDRAM				1	0.17	0.19*	0.13	0.06	0.26*	-0.04	-0.11
MOVIE					1	0.22*	0.39*	0.3*	0.24*	0.23	0.35*
MUSIC						1	0.02	0.21*	0.05	-0.04	0.28*
ENT							1	0.16	0.04	0.17	0.35*
UGCG								1	0.12	0.12	0.1
SPORTS									1	0.26*	0.09
EDU										1	0.31*
SHOP											1

Highlighted results are significant at 1%.

4.2.2.7 Correlation Among Content Distributor Alternatives

Table 14. Variance-covariance matrix of content distributor alternatives

	PUBLIC	PUBLICT	CABLE	OTT	UGCT
PUBLIC	1	0.53*	0.46*	0.09	0.1
PUBLICT		1	0.38*	0.12	-0.06
CABLE			1	0.44*	0.04
OTT				1	-0.11
UGCT					1

Highlighted results are significant at 1%.

Terrestrial programming is complementary to alternative terrestrial programming and cable TV. Cable TV also shows a complementary relationship to OTT, while user-content suppliers do not show any significant relationship with other types of producers. This makes cable TV content the most popular and complementary alternative to other distributor alternatives. This result varies with Li's (2017) study based in Taiwan where OTT is most competitive among digital cable and IPTV.

4.2.2.8 Correlation Among Content Distributor and Genre Alternatives

Results for this section can be found in Table 12. Public programming has the strongest complementary relationships, especially with news, Korean dramas, entertainment, documentaries, and movies. It has no significant relationship with foreign drama. Alternative public programming also show a similar complementary relationship with genres that are also complementary to public programming. Alternative public programming has no significant relationship with user-generated genre. Cable TV has a fairly even complementary relationship with all genres, except for education. OTT-produced content has a complementary relationship with sports, educational content, and

foreign drama; our result also indicates an insignificant relationship with entertainment shows. While Netflix has been securing Korean dramas, the Korean audience is still able to consume Korean drama via public broadcasting channels. Viewers of user-generated content favor content produced in user-generated content styles, such as vlogs or DIY tutorials, music-related content, movies, and shopping-related content.

4.2.2.9 Correlation Among Genre Alternatives

Results for this section can be found in Table 13. Press and Korean drama have the strongest complementary relationship, but press also has fairly distributed complementary relationships with the rest of the genres, which includes documentaries, variety shows, sports, shopping, movies, and music-related content. Documentaries have a complementary relationship with Korean drama, variety shows, and sports, and weaker relationships with educational content and movies. Korean drama has a strong complementary relationship with entertainment. Its complementary relationship with movies is fairly strong as well. Weaker links are found in foreign dramas, shopping, and sports. Foreign dramas are complementary to sports content, movies, and music content. Movies are complementary to all genres. Its strongest complementary relationship is with variety shows. People who enjoy watching movies also enjoy watching home shopping content. Music content shares a complementary relationship with shopping and user generated content. Variety shows have the strongest complementary relationship with shopping content and the least with user-generated content. User-generated style content has the weakest complementary relationship with sports. Sports and educational-content are complementary. Educational content and shopping content are also complementary.

Chapter 5. Discussion and Conclusion

This research uses multivariate probit model to analyze how demographic variables, subscription status and subscription motivation affect consumer's choice in video content and the means they choose to consume content. We also study the variances of alternatives and covariances between all possible pairs of alternatives that represent the context of consumer's video content consumption and the alternatives that classify content. This analysis has allowed us to identify significant relationships between alternatives in consumer's simultaneous choice. Given the significance of content and the need for user-centered strategy, our goal was to understand the context of user's content consumption. We can see the relationship between the context, such as whether the consumer's location and choice of device affected their choice in content.

We are able to differentiate content consumed by viewer's age, gender, subscription status, and subscription motivation. Demographic variables are often used to explain variation in consumer behavior such as purchase intention (Akhter, 2003; Beldona et al, 2011; Yang et al., 2015). Our results demonstrate the significance of age, especially in consumer's choice in device and content genre. Younger consumers have an appreciation for a wider selection of devices and genres, unlike the older consumers who have a narrower selection of preferences. Gender also shows a significant effect but it does not share as many significant relationships with alternatives across categories as age variables does. While Netflix has relied on behavioral data to segment viewers by their taste, and ignoring demographic data, our results suggest there is an apparent pattern between demographic variables and consumers' choices in the media selection process. Given the

company's shift away from data-driven decisions, and towards traditional judgement-based decisions, we believe awareness of trends and discussions among demographic groups would assist executives in picking content and working with producers and studios to set content direction (Wayne, 2021). Identifying relevant demographic variables could help managers understand the motivations and influences that drive consumer decisions in the media selection process.

We do not see as much significance in consumer's subscription status for OTT services and pay TV. OTT service subscribers and pay TV subscribers have different preferences. Preferences also vary by consumers' motivation to subscribe to paid services. By analyzing the correlation between subscription motivation and the study's alternatives, we are able to suggest a few takeaways. For example, subscribers who reasoned subscribing for more channels show a significance in their selection to view movies, user generated content, and home-shopping content. Given their preference for these genres of content, content distributors should secure content of these genres to maintain retention and to attract new subscribers who have similar motivations. Another example, among subscribers who are motivated to subscribe cable TV content, music is the only significant genre. Given this preference for music content, cable channels should lean into producing music content and be cognizant of consumer's preference for user generated content distributors as the favored avenue for music content.

There is also a pattern in consumer's preference for content distributor based on location. While public terrestrial channels is preferred in all the types of settings, consumers have a relatively strong preference of user generated content distribution outside the home. Given television is the only significant device used in the home, we can assume consumers may

have difficulty accessing OTT and user-generated content on the television. Although smart TVs account for more than 50% of the TV market share, the fact that consumers do not watch OTT and user-generated content may be indicating viewer's difficulty in accessing content. This interpretation resonates with Yu et al.'s (2016) and Alam et al.'s (2019) findings. KISDI Media Diary statistics (2022a) from 2019 also reveal that 97.1% of viewers used a smartphone to watch OTT content. Additionally, KISDI Media Diary statistics (2022b) from 2021 show that smartphones took up between 80% and 90% of the market share as the preferred device to consume user-generated content. Our study also shows a strong preference for smartphones to access user generated content distributors. However, it varies from KISDI Media Diary statistics in that 26.9% of viewers used a smartphone to access OTT services, as illustrated in Figure 5.

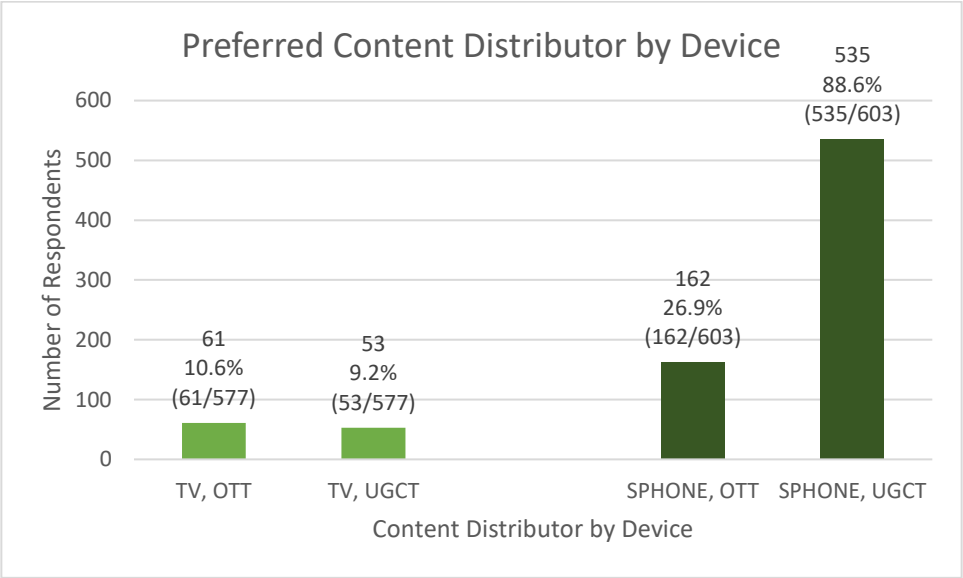

Figure 5. Preferred content distributor by device

Consumer's simultaneous choice in genre and content distributor reveal people view public broadcasting, alternative public broadcasting, and cable in a similar light. Foreign

OTT services should double down on producing and promoting foreign dramas and educational content for the Korean audience. These two genres show the strongest significant relationship with OTT services out of all the content distributor category: $\sigma_{OTT,FDRAM} = 0.43\ (\alpha = 0.01); \sigma_{CABLE,FRDRAM} = 0.16\ (\alpha = 0.05);\ \sigma_{PUBLICT,FDRAM} = 0.16\ (\alpha = 0.05);\ \sigma_{OTT,EDU} = 0.32\ (\alpha = 0.01); \sigma_{CABLE,FRDRAM} = 0.12\ (\alpha = 0.05);\ \sigma_{PUBLICT,FDRAM} = 0.16\ (\alpha = 0.05)$. In other words, consumers who consume foreign dramas and educational content most prefer viewing content from OTT services. Thus, OTT services should seize this opportunity to cater to their current customers. Since OTT services have a strong hold, other content distributors could aim to attract viewers who enjoy these genres of content, especially alternative public programming channels and cable TV should explore producing content in these genres.

This study demonstrates a method of analyzing consumer survey data to understand consumer media consumption behavior with a focus on the Korea audience. This study aims to demystify the media choices Korean consumers make but it does come with some limitations. Although our study demonstrates a method to understand the context of consumers' video content consumption behavior, it does not reveal the consumers' motivation in its entirety. Assumptions are made by interpreting fragmented results supplemented by existing literature and industry findings. However, our results to provide a starting point for managers to segment and further study specific audiences. The estimation results contribute to identifying who to research by identifying relevant demographic variables and what to research by analyzing the media selection that takes place in various environments and devices. This study could have benefited from qualitative user research to investigate the audience's motivation more in depth.

Bibliography

Akhter, S. H. (2003). Digital Divide and purchase intention: Why demographic psychology matters. Journal of Economic Psychology, 24(3), 321–327. https://doi.org/10.1016/s0167-4870(02)00171-x

Alam, I., Khusro, S., & Khan, M. (2019). Usability barriers in Smart TV user interfaces: A review and recommendations. *2019 International Conference on Frontiers of Information Technology (FIT)*. https://doi.org/10.1109/fit47737.2019.00069

Alexander, J. (2019, July 26). *YouTube videos keep getting longer*. The Verge. Retrieved from https://www.theverge.com/2019/7/26/8888003/youtube-video-length-contrapoints-lindsay-ellis-shelby-church-ad-revenue

BBC. (2021, October 16). *Squid Game: The rise of korean drama addiction*. BBC News. Retrieved from https://www.bbc.com/news/entertainment-arts-58896247

Beldona, S., Racherla, P., & Mundhra, G. D. (2011). To buy or not to buy: Indian Consumers' choice of online versus offline channels for air travel purchase. Journal of Hospitality Marketing & Management, 20(8), 831–854. https://doi.org/10.1080/19368623.2011.577693

Chib, S., & Greenberg, E. (1998). Analysis of multivariate probit models. *Biometrika*, *85*(2), 347–361. https://doi.org/10.1093/biomet/85.2.347

Chung, J.-won. (2012, December 21). *Show hosts buttress of TV home shopping*. The Korea Herald. Retrieved from http://www.koreaherald.com/view.php?ud=20121221000544

Chung, Y. N. (2015). The Effects of Fans' Motives on Televised Sports Viewing in South Korea. *International Journal of Humanities and Social Science*, *5*(4).

Dimock, M. (2022, April 21). Defining generations: Where millennials end and generation Z begins. Pew Research Center. Retrieved June 8, 2022, from https://www.pewresearch.org/fact-tank/2019/01/17/where-millennials-end-and-generation-z-begins/

Donga. (2021, November 28). 넷플릭스에맥못추네...디즈니·애플 *TV+* 부진왜? *[Can't Keep Up with Netflix...Disney·AppleTV+ Why Sluggish]*. www.donga.com. Retrieved from https://www.donga.com/news/Culture/article/all/20211128/110489508/1

Doyle, G. (2010). From television to multi-platform. *Convergence: The International Journal of Research into New Media Technologies*, *16*(4), 431–449. https://doi.org/10.1177/1354856510375145

Doyle, G. (2016). Resistance of channels: Television distribution in the multiplatform era. *Telematics and Informatics*, *33*(2), 693–702. https://doi.org/10.1016/j.tele.2015.06.015

Dwyer, T., Shim, Y., Lee, H., & Hutchinson, J. (2018). Comparing Digital Media Industries in South Korea and Australia: The Case of Netflix Take-Up. *International Journal of Communication*, *12*.

Eastman, S. T., & Land, A. M. (1997). The best of both worlds: Sports fans find good seats at the bar. *Journal of Sport and Social Issues*, *21*(2), 156–178. https://doi.org/10.1177/019372397021002004

Edwards, Y. D., & Allenby, G. M. (2003). Multivariate analysis of multiple response data. Journal of Marketing Research, 40(3), 321–334. https://doi.org/10.1509/jmkr.40.3.321.19233

Germann, F., Lilien, G. L., & Rangaswamy, A. (2013). Performance implications of deploying marketing analytics. *International Journal of Research in Marketing*, *30*(2), 114–128. https://doi.org/10.1016/j.ijresmar.2012.10.001

Gleiberman, O. (2022, April 30). *Netflix lost subscribers, but it really lost something larger - call it mythology (column)*. Variety. Retrieved from https://variety.com/2022/film/columns/netflix-lost-subscribers-questions-1235255088/

Guerrero, E., Diego, P., & Pardo, A. (2012). Distributing Audiovisual Contents in the new digital scenario: Multiplatform strategies of the main Spanish TV networks. *Handbook of Social Media Management*, 349–373. https://doi.org/10.1007/978-3-642-28897-5_20

Hong, S. (2022, April 29). "이것도실패, 한국에서망신?" 디즈니 *40* 만명'주르륵' *["Another failure, in Korea?" Disney loses 400,000 Viwers]*. 헤럴드경제[Herald Corp]. Retrieved from https://biz.heraldcorp.com/view.php?ud=20220429000697

Isson, J.-P., & Harriott, J. (2012). *Win with Advanced Business Analytics: Creating Business Value from Your Data*. Wiley.

Jeong, S.-H., Yum, J.-Y., Choi, I., Choi, S., & Chung, M. (2017). Daypart differences in media multitasking: A diary study. *The Korean Journal of Advertising*, *28*(1), 127–149. https://doi.org/10.14377/kja.2017.1.15.6

Kafka, P. (2018, March 8). *You can watch netflix on any screen you want, but you're probably watching it on a TV*. Vox. Retrieved from https://www.vox.com/2018/3/7/17094610/netflix-70-percent-tv-viewing-statistics.

Karlsen, F., & Ytre-Arne, B. (2021). Intrusive Media and knowledge work: How knowledge workers negotiate digital media norms in the pursuit of focused work. *Information, Communication & Society*, 1–16. https://doi.org/10.1080/1369118x.2021.1933561

Kim, D., & Jang, S. (2017). Symbolic consumption in upscale cafés. *Journal of Hospitality & Tourism Research*, *41*(2), 154–179. https://doi.org/10.1177/1096348014525633

Kim, J., Kim, S., & Nam, C. (2016a). Competitive Dynamics in the Korean Video Platform Market: Traditional Pay TV platforms vs. Ott Platforms. *Telematics and Informatics*, *33*(2), 711–721. https://doi.org/10.1016/j.tele.2015.06.014

Kim, S., Park, Y. A., & Niu, Q. (2016b). Micro-break activities at work to recover from daily work demands. *Journal of Organizational Behavior*, *38*(1), 28–44. https://doi.org/10.1002/job.2109

Kim, M. S., Kim, E., Hwang, S. Y., Kim, J., & Kim, S. (2017). Willingness to pay for over-the-top services in China and Korea. Telecommunications Policy, 41(3), 197–207. https://doi.org/10.1016/j.telpol.2016.12.011

Kim, S., Lee, C., Lee, J., & Kim, J. (2021). Over-the-top bundled services in the Korean Broadcasting and Telecommunications Market: Consumer Preference Analysis using a mixed logit model. *Telematics and Informatics*, *61*, 101599. https://doi.org/10.1016/j.tele.2021.101599

KISDI. (2022a). *OTT 서비스 이용매체(복수응답) [OTT service media use (multiple answers)]*. KISDI. Retrieved from https://stat.kisdi.re.kr/statHtml/statHtml.do?orgId=405&tblId=DT_405001_I096&conn_path=I2

KISDI. (2022b). *미디어 이용 행위별(영화/동영상/UCC/음악/음원/사진)_매체 [Media Usage Behavior (Movie/Video/UCC/Music/Sound/Photo)_Media]*. KISDI. Retrieved from

https://stat.kisdi.re.kr/statHtml/statHtml.do?orgId=405&tblId=DT_405001_MD056&conn_path=I2

Koo, Y., Lim, S., Kim, K., & Cho, Y. (2014). Analysis of user characteristics regarding social network services in South Korea using the multivariate probit model. *Technological Forecasting and Social Change*, *88*, 232–240. https://doi.org/10.1016/j.techfore.2014.07.001

Kroes, E. P., & Sheldon, R. J. (1988). Stated Preference Methods: An Introduction. Journal of Transport Economics and Policy, 22(1), 11–25. http://www.jstor.org/stable/20052832

Lang, B., & Shaw, L. (2013, November 20). *Who has greenlight power in Hollywood? A studio-by-studio guide*. TheWrap. Retrieved from https://www.thewrap.com/hollywood-greenlighting-power/

Lee, D. (2021, December 2). What are Korean variety shows? A guide to finding your next good watch. VICE. Retrieved June 8, 2022, from https://www.vice.com/en/article/k7wwyy/korean-variety-show-watch-guide

Li, S. S. (2017). Television media old and new: A niche analysis of Ott, IPTV, and digital cable in Taiwan. Telematics and Informatics, 34(7), 1024–1037. https://doi.org/10.1016/j.tele.2017.04.012

Liu, Y., Gao, Q., & Ma, L. (2021). Taking micro-breaks at work: Effects of watching funny short-form videos on subjective experience, physiological stress, and task performance. Cross-Cultural Design. Applications in Arts, Learning, Well-Being, and Social Development, 183–200. https://doi.org/10.1007/978-3-030-77077-8_15

Malik, A. (2022, February 28). Tiktok expands Max video length to 10 minutes, up from 3 minutes. TechCrunch. Retrieved June 8, 2022, from https://techcrunch.com/2022/02/28/tiktok-expands-max-video-length-to-10-minutes-up-from-3-minutes/

McFadden, D. (1973) Conditional logit analysis of qualitative choice behavior. In: Zarembka, P. (Ed.), Frontiers in Econometrics. Academic Press, New York, 105-142.

Meijer, I. C. (2007). The paradox of popularity. *Journalism Studies*, *8*(1), 96–116. https://doi.org/10.1080/14616700601056874

Mohsin, M. (2022, June 1). 10 YouTube statistics that you need to know in 2021. Oberlo. Retrieved from https://www.oberlo.com/blog/youtube-statistics#:~:text=YouTube%20Users%20Prefer%20Mobile%20over%20Desktop,-Mobile%20is%20first&text=More%20than%2070%20percent%20of,devices%20(YouTube%2C%202019).

Nam, Y. (2014). An empirical analysis of media consuming behavior with temporal and spatial dimensions (dissertation).

Park, Y., (2008) 가치사슬을 고려한 디지털콘텐츠 이용실태 분석 [Analysis of Digital Content Utilization Considering Value Chain]. KISDI Issue Report 08-13. Korea Information Society Development Institute.

Park, S., & Lee, D. (2017). An empirical study on Consumer Online Shopping Channel Choice Behavior in Omni-Channel Environment. *Telematics and Informatics*, *34*(8), 1398–1407. https://doi.org/10.1016/j.tele.2017.06.003

Ransbotham, S. (2016, January 25). Avoiding analytical myopia. MIT Sloan Management Review. Retrieved June 8, 2022, from https://sloanreview.mit.edu/article/avoiding-analytical-myopia/

Roscoe, J. (2004). Multi-platform event television: Reconceptualizing our relationship with television. The Communication Review, 7(4), 363–369. https://doi.org/10.1080/10714420490886961

Rossi, P. E., Allenby, G. M., & McCulloch, R. (2005). Bayesian statistics and Marketing. Wiley.

Rubin, A. M., & Rubin, R. B. (1982). Older persons' TV viewing patterns and motivations. *Communication Research*, *9*(2), 287–313. https://doi.org/10.1177/009365082009002005

Russell, G. J., Ratneshwar, S., Shocker, A. D., Bell, D., Bodapati, A., Degeratu, A., Hildebrandt, L., Kim, N., Ramaswami, S., & Shankar, V. H. (1999). Multiple-Category Decision-Making: Review and Synthesis. *Marketing Letters*, *10*(3), 319–332. http://www.jstor.org/stable/40216542

Shamma, H., & Hassan, S. (2013). Customer-Driven benchmarking. Benchmarking: An International Journal, 20(3), 377–395. https://doi.org/10.1108/14635771311318144

Shin J., Kim C., & Lee M. (2014). Aanknalysis of Consumer's Purchasing Behavior on ICT Devices and Convergence Services in Korea. 정보화정책, 21(4), 81-97.

Shin, J., Park, Y., & Lee, D. (2016). Strategic management of over-the-top services: Focusing on Korean consumer adoption behavior. *Technological Forecasting and Social Change*, *112*, 329–337. https://doi.org/10.1016/j.techfore.2016.08.004

Shon, M., Lee, D., & Kim, J. H. (2021). Are global over-the-top platforms the destroyers of ecosystems or the catalysts of innovation? Telematics and Informatics, 60, 101581. https://doi.org/10.1016/j.tele.2021.101581

Sperling, N. (2022, April 19). Netflix loses subscribers for first time in 10 years. The New York Times. Retrieved June 8, 2022, from https://www.nytimes.com/2022/04/19/business/netflix-earnings-q1.html

Statista. (2021, August 23). YouTube average video length by Category 2018. Statista. Retrieved from https://www.statista.com/statistics/1026923/youtube-video-category-average-length/#:~:text=This%20statistic%20presents%20the%20average,of%206.8%20minutes%20per%20video. Taneja and Viswanathan (2014) https://ijoc.org/index.php/ijoc/article/view/2841/1193

Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge University Press.

Valkenburg, P. M., & Piotrowski, J. T. (2017). *Plugged In*. Yale University Press.

Volpe, A. (2017). *The one thing that isn't evolving with Netflix & Hulu's takeover of TV*. Thrillist. Retrieved from https://www.thrillist.com/entertainment/nation/netflix-episode-length-streaming-services-traditional-tv

Wardman, M. (1988). A Comparison of Revealed Preference and Stated Preference Models of Travel Behaviour. Journal of Transport Economics and Policy, 22(1), 71–91. http://www.jstor.org/stable/20052836

Wayne, M. L. (2021). Netflix audience data, streaming industry discourse, and the emerging realities of ‘popular’ television. Media, Culture & Society, 44(2), 193–209. https://doi.org/10.1177/01634437211022723

Woo, J. R., Ahn, J., Lee, J., & Koo, Y. (2015). Media channels and consumer purchasing decisions. Industrial Management & Data Systems, 115(8), 1510–1528. https://doi.org/10.1108/imds-02-2015-0036

World Bank. (2022). *Ratio of female to male labor force participation rate (%) (modeled ILO estimate) – korea, rep.* Data. Retrieved April 18, 2022, from https://data.worldbank.org/indicator/SL.TLF.CACT.FM.ZS?end=2019&locations=KR&start=2000

World Health Organization. (n.d.). *Smoke-free indoor public places and workplaces not elsewhere specified (national legislation)*. World Health Organization. Retrieved April 18, 2022, from https://www.who.int/data/gho/indicator-metadata-registry/imr-details/1240

Yang, L., Ha, L., Wang, F., & Abuljadail, M. (2015). Who pays for online content? A media dependency perspective comparing young and older people. International Journal on Media Management, 17(4), 277–294. https://doi.org/10.1080/14241277.2015.1107567

Yoon, J. S. (2020, August 5). South Korea: Media consumption for younger generations by medium 2019. Statista. Retrieved June 8, 2022, from https://www.statista.com/statistics/1139287/south-korea-media-consumption-for-younger-generations-by-medium/

Yu, E., Hong, A., & Hwang, J. (2016). A socio-technical analysis of factors affecting the adoption of Smart TV in Korea. Computers in Human Behavior, 61, 89–102. https://doi.org/10.1016/j.chb.2016.02.099

Appendix 1: Covariance-Variance Matrix of Location Alternatives

	HOME	INDOOR	TRANSIT
HOME	1	0.25	0.17
INDOOR		1	0.48*
TRANSIT			1

Highlighted results are significant at 1%.

Appendix 2: Survey

Page 2, Section A, Question 2-2

문 2-2. (문2-1.에서 시청시간을 10분 이상 응답한 응답자)
응답한 일주일 평균 미디어 시청시간을 ①기기별로 ②-1. 장소별, ②-2. 콘텐츠 종류별과 ②-3. 장르별 등 각 유형별 비중의 합이 100이 되도록 응답해 주십시오.
※ 해당 유형의 시청 시간이 없는 경우 0%로 응답해 주시면 됩니다.

① 기기별 시청시간 비중		②-1. 장소별 시청시간 비중		②-2. 콘텐츠 종류별 시청시간 비중		②-3. 장르별 시청시간 비중			
1. 스마트폰	%	① 집안(실내)	%	① 지상파채널 콘텐츠	%	① 보도 (뉴스, 시사)	%	⑦ 오락/연예/예능	%
		② 직장/학교 등(실내)	%	② 지상파계열 콘텐츠 (예: KBSN, MBC+, SBS Golf)	%	② 다큐멘터리	%	⑧ UCC 영상	%
		③ 공공장소(실내)	%	③ 케이블채널 콘텐츠	%	③ 드라마 (국내드라마)	%	⑨ 스포츠(e-sports 포함)	%
		④ 이동 중(실외)	%	④ OTT서비스 오리지널 콘텐츠 (예: 넷플릭스, 디즈니 등)	%	④ 드라마 (해외드라마)	%	⑩ 학습/교육	%
		⑤ 그 외 장소	%	⑤ 이용자 제작 콘텐츠 (예: Youtube 등)	%	⑤ 영화	%	⑪ 쇼핑	%
						⑥ 음악/공연 (뮤직비디오 등)	%	⑫ 기타	%
		총	100 %	총	100 %			총	100 %
2. 태블릿 PC	%	① 집안(실내)	%	① 지상파채널 콘텐츠	%	① 보도 (뉴스, 시사)	%	⑦ 오락/연예/예능	%
		② 직장/학교 등(실내)	%	② 지상파계열 콘텐츠 (예: KBSN, MBC+, SBS Golf)	%	② 다큐멘터리	%	⑧ UCC 영상	%
		③ 공공장소(실내)	%	③ 케이블채널 콘텐츠	%	③ 드라마 (국내드라마)	%	⑨ 스포츠(e-sports 포함)	%
		④ 이동 중(실외)	%	④ OTT서비스 오리지널 콘텐츠 (예: 넷플릭스, 디즈니 등)	%	④ 드라마 (해외드라마)	%	⑩ 학습/교육	%
		⑤ 그 외 장소	%	⑤ 이용자 제작 콘텐츠 (예: Youtube 등)	%	⑤ 영화	%	⑪ 쇼핑	%
						⑥ 음악/공연 (뮤직비디오 등)	%	⑫ 기타	%
		총	100 %	총	100 %			총	100 %

① 기기별 시청시간 비중		②-1. 장소별 시청시간 비중		②-2. 콘텐츠 종류별 시청시간 비중		②-3. 장르별 시청시간 비중			
3. 데스크탑 PC	%	① 집안(실내)	%	① 지상파채널 콘텐츠	%	① 보도 (뉴스, 시사)	%	⑦ 오락/연예/예능	%
		② 직장/학교 등(실내)	%	② 지상파계열 콘텐츠 (예: KBSN, MBC+, SBS Golf)	%	② 다큐멘터리	%	⑧ UCC 영상	%
		③ 공공장소(실내)	%	③ 케이블채널 콘텐츠	%	③ 드라마 (국내드라마)	%	⑨ 스포츠(e-sports 포함)	%
		④ 이동 중(실외)	%	④ OTT서비스 오리지널 콘텐츠 (예: 넷플릭스, 디즈니 등)	%	④ 드라마 (해외드라마)	%	⑩ 학습/교육	%
		⑤ 그 외 장소	%	⑤ 이용자 제작 콘텐츠 (예: Youtube 등)	%	⑤ 영화	%	⑪ 쇼핑	%
		총	100 %	총	100 %	⑥ 음악/공연 (뮤직비디오 등)	%	⑫ 기타	%
						총	100 %		
4. 노트북 PC	%	① 집안(실내)	%	① 지상파채널 콘텐츠	%	① 보도 (뉴스, 시사)	%	⑦ 오락/연예/예능	%
		② 직장/학교 등(실내)	%	② 지상파계열 콘텐츠 (예: KBSN, MBC+, SBS Golf)	%	② 다큐멘터리	%	⑧ UCC 영상	%
		③ 공공장소(실내)	%	③ 케이블채널 콘텐츠	%	③ 드라마 (국내드라마)	%	⑨ 스포츠(e-sports 포함)	%
		④ 이동 중(실외)	%	④ OTT서비스 오리지널 콘텐츠 (예: 넷플릭스, 디즈니 등)	%	④ 드라마 (해외드라마)	%	⑩ 학습/교육	%
		⑤ 그 외 장소	%	⑤ 이용자 제작 콘텐츠 (예: Youtube 등)	%	⑤ 영화	%	⑪ 쇼핑	%
		총	100 %	총	100 %	⑥ 음악/공연 (뮤직비디오 등)	%	⑫ 기타	%
						총	100 %		
5. TV	%	① 집안(실내)	%	① 지상파채널 콘텐츠	%	① 보도 (뉴스, 시사)	%	⑦ 오락/연예/예능	%
		② 직장/학교 등(실내)	%	② 지상파계열 콘텐츠 (예: KBSN, MBC+, SBS Golf)	%	② 다큐멘터리	%	⑧ UCC 영상	%
		③ 공공장소(실내)	%	③ 케이블채널 콘텐츠	%	③ 드라마 (국내드라마)	%	⑨ 스포츠(e-sports 포함)	%
		④ 이동 중(실외)	%	④ OTT서비스 오리지널 콘텐츠 (예: 넷플릭스, 디즈니 등)	%	④ 드라마 (해외드라마)	%	⑩ 학습/교육	%
		⑤ 그 외 장소	%	⑤ 이용자 제작 콘텐츠 (예: Youtube 등)	%	⑤ 영화	%	⑪ 쇼핑	%
		총	100 %	총	100 %	⑥ 음악/공연 (뮤직비디오 등)	%	⑫ 기타	%
						총	100 %		
총	100 %								

Page 4, Section B, Question 1

문1. (전체 응답자)
현재 귀댁에서는 케이블TV, IPTV, 위성방송/OTS 등 유료방송서비스를 이용하고 계십니까?

1. 예(이용함)
2. 아니오(이용하지 않음) ⟶ **다음 페이지 C. OTT 서비스 선호도 질문으로 이동하십시오.**

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문3. (문1.에서 1. 이용에 응답한 응답자)
다음은 귀댁에서 현재 유료방송서비스를 가입하게 된 계기(이유)를 묻는 질문으로, 귀댁과 가장 가까운 번호에 ○표해 주십시오.

	전혀 영향이 없었다	영향이 없는 편이었다	보통 이었다	영향이 많은 편이었다	매우 영향이 있었다
	1	2	3	4	5
1. 지상파 방송 채널을 수신하기 위해서	1	2	3	4	5
2. 지상파 방송 시청은 가능하나, 보다 선명한 화질로 보기 위해서	1	2	3	4	5
3. 종편 채널을 시청하기 위해서 (TV조선, JTBC, 채널A 등)	1	2	3	4	5
4. 종편 외 다양한 유료방송 채널을 시청하기 위해서 (TVN, OCN 등)	1	2	3	4	5
5. VOD (다시보기)를 시청하기 위해서	1	2	3	4	5
6. 현재 통신회사의 결합상품으로 인한 추가 할인 때문에	1	2	3	4	5

Page 5, Section C, Question 1

문1. (전체 응답자) 현재 귀하께서는 유료 또는 무료 OTT 서비스를 이용하고 계십니까?

1. 예 (이용함)
2. 아니오 (이용하지 않는다) ⟶ **다음 페이지 문3-1.로 이동하십시오.**

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문1-2. (문1.에서 1. 이용에 응답한 응답자) 현재 귀하께서는 OTT 서비스를 무료로 이용하십니까? 유료로 이용하십니까?

1. 무료 이용
2. 유료 이용 ⟶ **문2.으로 이동하십시오.**
3. 무료와 유료 둘 다 이용

Abstract (Korean)

미디어 콘텐츠 배급자와 제작자는 미디어 콘텐츠에 관한 소비자의 선택과 성향을 이해하여 소비자의 관심사에 맞는 콘텐츠를 기획, 제작, 배포한다. 본 논문에서는 다변량 프로빗 모형을 이용하여 미디어 콘텐츠 선택에 관한 인구 통계학적 특성, 구독 서비스 동기 및 구독 상태가 소비자의 의사 결정에 미치는 영향을 분석한다. 실증적 연구를 통해 위치, 장치, 콘텐츠 배포자, 콘텐츠 장르 대한 소비 행태를 검토할 수 있다. 이 연구에서는 소비자 선호도의 특성 기반으로 미디어 콘텐츠 선택과 배포 대한 전략을 제안한다.

주요어 : 미디어 콘텐츠, 동시선택, 다중선택, 다변량 프로빗 모형
학 번 : 2020-23704