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Contextual Segmentation of Media Consumption Behavior: A Deep Learning-Driven Cluster Analysis

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Contextual Segmentation of Media Consumption Behavior: A Deep Learning–Driven Cluster Analysis

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Abstract

This study examines contextual patterns in over-the-top (OTT) streaming consumption through deep learning-driven cluster analysis, advancing our understanding of contemporary media repertoires. Drawing on media repertoire theory, we analyze how users develop personalized combinations of media platforms and usage patterns across temporal, spatial, and technological contexts. Using longitudinal diary data from the Korea Media Panel (2021-2024), we apply Gated Recurrent Unit (GRU) autoencoders to compress 12-day behavioral sequences into latent representations, subsequently identifying distinct consumption clusters through k-means analysis. Our findings reveal three primary usage repertoires: Conventional Home Viewing (51%), characterized by traditional single-device evening consumption; Heavy Prime-Time (29%), featuring intensive multi-device usage during evening hours; and Daytime Flexible (20%), demonstrating distributed consumption throughout the day across mobile devices. Multinomial regression analysis confirms significant demographic and behavioral differences between clusters, with age, gender, income, and OTT usage frequency serving as key predictors of cluster membership. The study contributes methodologically by demonstrating how sequence-based deep learning can operationalize media repertoire theory without imposing restrictive analytical assumptions. Practically, our findings illuminate strategic opportunities for telecommunications operators and content providers in mature OTT markets. The identification of distinct contextual usage patterns—from concentrated prime-time multi-screening to distributed mobile consumption—suggests targeted service design strategies. Furthermore, the relationship between consumption repertoires and mobile carrier choice reveals how infrastructure providers must consider usage patterns beyond aggregate metrics. This research establishes a computational framework for analyzing technology-mediated behavioral patterns in high-connectivity environments.

1 Introduction

The proliferation of smartphones and high-speed broadband internet has dramatically reshaped how audiences consume video content, accelerating a shift away from traditional broadcast and cable television toward over-the-top (OTT) streaming services (Tefertiller, 2018; Cha, 2013). This "cord-cutting" trend was amplified by the COVID-19 pandemic, during which homebound consumers turned increasingly to OTT platforms for entertainment (Sung & Kim, 2023). Subscriber numbers for major OTT services surged under lockdown conditions; although growth has since plateaued in mature markets, competition in the OTT space remains intense (Kwak, Oh, & Lee, 2021). In South Korea's saturated OTT market, for example, a multitude of global (e.g., Netflix, Disney+) and domestic (e.g., Wavve, Tving) providers vie for users, making customer retention and differentiation more critical than ever (Massaro & Kim, 2022; Nam & Jung, 2021).

The technological infrastructure underlying this transformation fundamentally alters the theoretical landscape of media consumption. Unlike traditional broadcasting systems constrained by spectrum limitations and fixed scheduling, OTT services leverage advanced telecommunications infrastructure to enable ubiquitous access across multiple devices and contexts (Massaro & Kim, 2022). This technological shift necessitates a theoretical framework that can accommodate the complex interplay between technological affordances and user behavior patterns. In this highly penetrated context, OTT services are not a monolithic medium but encompass a range of content delivery models—from live-streaming broadcasts to on-demand libraries—accessible on virtually any internet-connected device. The flexibility for viewers to watch any content, anytime, anywhere, on any device fundamentally alters viewing habits compared to linear TV (Bondad-Brown, Rice, & Pearce, 2012; Dimmick, Feaster, & Hoplamazian, 2011).

To understand this complexity, we adopt the media repertoire approach as our primary theoretical framework (Taneja, Webster, Malthouse, & Ksiazek, 2012; Kim, S.J., 2016). Media repertoire theory posits that individuals develop personalized combinations of media platforms and usage patterns that collectively satisfy their information and entertainment needs across different contexts (Heeter, 1985; Kim, S.J., 2016). This approach moves beyond traditional displacement theories that assume simple substitution relationships between old and new media,

recognizing instead that contemporary audiences maintain complex, contextually-dependent relationships with multiple media platforms simultaneously.

The repertoire framework is particularly relevant for OTT consumption because it accounts for the multidimensional nature of viewing choices. Unlike traditional TV viewing, which was largely constrained to specific times and locations, OTT consumption occurs across varied temporal, spatial, and technological contexts that shape content selection and engagement patterns (Kim, S.J., 2016; Menon & Arora, 2022). Traditional analytical approaches to media consumption research, while valuable, face significant limitations when applied to the complex, high-dimensional behavioral data characteristic of multi-platform OTT usage. Deep learning approaches, specifically sequence-based autoencoders, offer significant advantages for this analytical challenge by automatically learning complex temporal dependencies and extracting meaningful latent representations from high-dimensional behavioral sequences without requiring manual feature engineering (Chung, Gulcehre, Cho, & Bengio, 2014).

This study leverages South Korea's exceptional telecommunications infrastructure to examine OTT consumption patterns under optimal technological conditions. South Korea's nationwide 5G coverage, ubiquitous public Wi-Fi networks, and high-speed fixed broadband infrastructure create an environment where technical barriers to streaming are minimized (Massaro & Kim, 2022). These conditions enable Korean consumers to fluidly switch between locations and devices without experiencing the connectivity constraints that might influence consumption patterns in less developed markets.

To address the identified gaps in understanding contextual OTT consumption, this study investigates OTT viewing behavior through a holistic, context-centric approach grounded in media repertoire theory. We leverage large-scale, longitudinal data from the Korea Media Panel to capture how viewing varies across situational dimensions: primarily time (when content is consumed), location (where viewing takes place), and device (what hardware is used). From this rich dataset, we extract key contextual variables and apply sequence-based machine learning and clustering techniques to identify patterns in OTT consumption.

2 Literature Review

2.1 Media Repertoires and Technology-Mediated Consumption

The transformation of media consumption through OTT services necessitates a theoretical framework that can accommodate the complex interplay between technological affordances and contextual usage patterns (Taneja, Webster, Malthouse, & Ksiazek, 2012). Media repertoire theory provides this foundation by conceptualizing how individuals develop personalized combinations of media platforms and usage contexts that collectively satisfy their information and entertainment needs (Heeter, 1985; Taneja et al., 2012; Yuan, 2011). Unlike traditional media consumption theories that assumed relatively static platform choices, the repertoire approach recognizes that contemporary audiences maintain dynamic, contextually dependent relationships with multiple media technologies simultaneously (Kim, S.J., 2016; Webster & Ksiazek, 2012).

The repertoire framework has gained particular relevance in the digital media era because it addresses the fundamental shift from scarcity-based to abundance-based media environments (Webster & Ksiazek, 2012). Where traditional broadcasting operated under spectrum limitations and fixed scheduling constraints, OTT services leverage advanced telecommunications infrastructure to enable ubiquitous access across multiple devices and contexts (Kim, S.J., 2016; Massaro & Kim, 2022). This technological transformation requires theoretical models that can account for how users navigate expanded choice sets while managing temporal, spatial, and technological constraints in their media consumption decisions (Taneja et al., 2012; Wang & Tchernev, 2012).

The advent of OTT streaming has been accompanied by significant shifts in overall media usage, often characterized through the lens of media substitution theory (Cha & Chan-Olmsted, 2012). A consistent finding across studies is that new media platforms tend to displace time spent with traditional media, although the degree of substitution or complementarity can vary by medium and user segment (Cha & Chan-Olmsted, 2012; Dimmick, Chen, & Li, 2004). Early research on media substitution noted that as internet use rose, consumers spent fewer hours on legacy channels like live TV or print newspapers (Ferguson & Perse, 2000; Kayany & Yelsma, 2000). Over the past decade, the diffusion of broadband and streaming services has accelerated this trend: increased OTT viewing is strongly linked to declines in conventional TV viewing, especially among cord-cutters (Cha, 2013; Lee & Lee, 2015; Tefertiller, 2018).

However, the repertoire perspective reveals that this displacement is not absolute but rather context-dependent (Kim, S.J., 2016; Wonneberger, Schoenbach, & van Meurs, 2012). In a recent econometric analysis of U.S. households, Malone et al. (2023) demonstrated meaningful substitution between OTT and linear television. Yet research examining the Korean media landscape has documented more nuanced patterns, with significant reductions in traditional TV viewing time as OTT adoption increases being primarily concentrated in specific viewing contexts rather than representing complete platform abandonment (Woo, Choi, Shin, & Lee, 2014; Kim, Kim, & Nam, 2016). This suggests that users develop repertoires that may include both traditional and new media platforms, with usage patterns varying by context rather than representing wholesale migration from one to another (Taneja et al., 2012).

Longitudinal data on younger audiences further confirm this complexity in displacement patterns (Twenge, Martin, & Spitzberg, 2019). Among U.S. teenagers, time spent on traditional television has plummeted as digital media use has surged, yet the repertoire approach suggests this represents not simple substitution but the development of new contextual usage patterns that may complement rather than completely replace traditional viewing in certain situations (Kim, S.J., 2016; Bury & Li, 2015). These results echo earlier work in media economics showing that when new content delivery options become available, audiences reallocate their attention in ways that reflect contextual optimization rather than simple platform switching (Gentzkow, 2007; Westlund & Färdigh, 2015).

The Korean context provides particularly valuable insights into this dynamic because the advanced telecommunications infrastructure minimizes technical constraints that might artificially limit repertoire development (Massaro & Kim, 2022). Woo et al. (2014) observed that in South Korea the introduction of home broadband initially decreased time spent on some traditional media, but that the arrival of smartphones actually increased some television viewing, suggesting a complex mix of substitution and complementarity enabled by technological capabilities. This finding illustrates how repertoire development depends not only on user preferences but also on the technological affordances that enable different combinations of media use across contexts (Kim, S.J., 2016; Wang & Tchernev, 2012).

The repertoire framework emphasizes that media choices are inherently contextual, with technological affordances playing a crucial role in shaping available options (Taneja et al., 2012; Kim, S.J., 2016). Prior studies have identified important device, location, content,

and demographic factors associated with OTT usage behaviors, but these have typically been examined in isolation rather than as integrated components of user repertoires (Bondad-Brown, Rice, & Pearce, 2012). In terms of devices, consumers are increasingly accessing OTT content on personal mobile gadgets in addition to or instead of television sets, creating new possibilities for contextual consumption patterns (McCreery & Krugman, 2015; Kim, Baek, & Kim, 2021).

Research on device preferences shows that heavy streaming users tend to utilize multiple devices flexibly, adapting their choice of screen based on viewing context and content type, whereas lighter users often stick with traditional TV sets as their primary viewing device (Bondad-Brown et al., 2012; Kim, Baek, & Kim, 2021). Cross-national research on mobile video use indicates that younger viewers especially have gravitated toward small-screen viewing, with many now watching television programs through mobile apps rather than via traditional TV sets—effectively blurring the line between "TV" and "mobile" media (Kim, S.J., 2016; Taneja et al., 2012; McCreery & Krugman, 2015).

The location dimension of media repertoires has been particularly transformed by mobile technologies and ubiquitous connectivity (Dimmick, Feaster, & Hoplamazian, 2011). Historically, most long-form video viewing took place in the home environment, often in the evening (Bondad-Brown et al., 2012). OTT services have untethered viewing from fixed places—users can now watch anywhere, turning previously unviable moments and venues into streaming opportunities (Dimmick et al., 2011; Kim, Lee, & Ahn, 2016). Research on mobile media usage demonstrates that these technologies occupy "interstitial" spaces and times in people's daily routines, enabling video consumption during commutes, breaks, and other previously idle moments (Dimmick, Feaster, & Hoplamazian, 2011; Kim, Lee, & Ahn, 2016; Menon & Arora, 2022).

The COVID-19 pandemic provided a natural experiment in how location constraints influence repertoire development (Sung & Kim, 2023). During lockdowns, when people spent more time at home, OTT and online video use surged, but the patterns reflected expansions of existing repertoires rather than wholesale behavioral change. One panel study in Korea found that increases in time spent at home were a major driver of the jump in OTT usage during the pandemic—when individuals stayed home all day, they filled more of that time with streaming while maintaining their existing contextual preferences for different types of content and devices (Sung & Kim, 2023).

2.2 Limitations of Traditional Analytical Approaches

While existing research has greatly advanced understanding of OTT adoption and the erosion of legacy media, most studies to date have treated media use as a relatively static choice or as a one-time shift from old to new platforms (Webster & Ksiazek, 2012; Kim, Lee, & Ahn, 2016). Traditional audience analyses often measure media consumption in aggregate or focus on a single primary platform, implicitly assuming that individuals make stable choices between media and use them uniformly across contexts (Kim, Lee, & Ahn, 2016; Webster & Ksiazek, 2012). This approach fundamentally misaligns with the repertoire framework, which emphasizes that media behavior is highly dynamic, multidimensional, and context-dependent (Kim, S.J., 2016; Taneja et al., 2012).

In everyday life, OTT consumption is not a one-off decision but rather a series of situational choices that vary from moment to moment within individual repertoires (Wang & Tchernev, 2012; Wonneberger et al., 2012). The same individual might stream short videos on a smartphone during a weekday lunch break, then settle in for a long-form series on a smart TV at home that night (Nam & Jung, 2021; Tefertiller & Sheehan, 2019). Traditional metrics that simply tally a person's OTT hours would label this individual a single-category "OTT user"—missing the interplay of when, where, and how in shaping their viewing patterns and failing to capture the repertoire logic underlying their media choices (Kim, S.J., 2016).

As LaRose (2010) observes, media consumption is embedded in daily routines and often governed by habit and contextual cues; analyzing it only in the aggregate can obscure important patterns that define user repertoires. Early uses-and-gratifications research emphasized that media choices are situationally motivated—people select media to fit the moment's needs and constraints (Papacharissi & Rubin, 2000; Stafford, Stafford, & Schkade, 2004)—yet much OTT research still aggregates usage as if it were context-free, fundamentally misunderstanding the repertoire-based nature of contemporary media consumption (Kim, S.J., 2016; Webster & Ksiazek, 2012).

The analytical challenges extend beyond conceptual issues to practical methodological limitations (Chung, Gulcehre, Cho, & Bengio, 2014). Recent studies provide clues that contextual dynamics matter, though few have analyzed all dimensions together using appropriate analytical techniques (Kim, S.J., 2016). Some works have examined individual contextual factors in isolation, such as increases in home time boosting streaming during

COVID-19 lockdowns (Sung & Kim, 2023) or device-specific preferences across user groups (Bondad-Brown et al., 2012; Kim, Baek, & Kim, 2021). However, traditional statistical methods struggle to integrate these factors to examine media use as a coordinated pattern of behaviors across multiple dimensions simultaneously (Taneja et al., 2012; Wang & Tchernev, 2012).

The consequence is a methodological gap in understanding the temporal rhythms and situational nuances of OTT consumption repertoires (Wonneberger et al., 2012). Standard regression approaches require researchers to pre-specify interaction terms and relationships between contextual variables, imposing assumptions about how time, location, and device factors combine to influence media choices (Kim, S.J., 2016). When usage patterns involve complex temporal dependencies and high-dimensional categorical variables, traditional methods often fail to capture the latent structures that characterize different repertoire types (Chung et al., 2014).

Without considering when and where people engage with OTT, and on which device, researchers risk drawing incomplete or even misleading conclusions about viewing behavior (Kim, S.J., 2016; Taneja et al., 2012). A decline in traditional TV viewing in the evening might not indicate an overall decline in television content consumption—viewers could be watching the same shows via OTT on other screens (Sung & Kim, 2023; Bury & Li, 2015). Such nuances only emerge when usage is analyzed as integrated repertoires rather than treated as undifferentiated totals (Taneja et al., 2012).

Recognizing these limitations, there is a clear need for more sophisticated analytical frameworks that can identify repertoire patterns from complex behavioral data (Kim, S.J., 2016; Yuan, 2011). Such frameworks must track how consumption unfolds across different times of day, in different locations, and on different devices, and interpret these choices as interrelated parts of overall media repertoires (Kim, S.J., 2016; Yuan, 2011; Taneja et al., 2012). Recent advances in machine learning, particularly deep learning approaches designed for sequence modeling, offer promising solutions (Chung, Gulcehre, Cho, & Bengio, 2014). Recurrent neural networks and autoencoders can automatically learn complex temporal dependencies and extract meaningful latent representations from high-dimensional behavioral sequences without requiring manual specification of interaction terms (Chung et al., 2014).

The notion of personal media repertoires has theoretical precedent dating back to early multi-channel TV studies (Heeter, 1985), and recent theoretical work has explicitly advocated a repertoire approach to the cross-platform media environment (Taneja et al., 2012; Kim, S.J., 2016). However, empirical applications have been limited by analytical constraints (Webster & Ksiazek, 2012). Machine learning approaches enable researchers to operationalize repertoire theory by identifying distinct usage profiles that emerge from data rather than being imposed through researcher assumptions (Chung et al., 2014). In the context of OTT, a repertoire perspective suggests we should expect distinct usage profiles—for instance, one profile might be "primetime at-home binge-watching on TV," while another is "on-the-go catch-up viewing in spare moments," each representing different contextual integration strategies (Wang & Tchernev, 2012; Wonneberger et al., 2012; Tefertiller & Sheehan, 2019).

2.3 Advanced Segmentation Approaches and Computational Methods

Given the importance of context and the limitations of traditional approaches, recent studies have begun to segment OTT audiences and usage patterns in more sophisticated ways (Shim, Lee, & Oh, 2022; Kwak, Oh, & Lee, 2021). Rather than treating OTT viewers as a uniform bloc, researchers are identifying distinct repertoires or clusters of media use that vary by situation, though most have relied on survey-based classifications rather than behavioral pattern recognition (Kim, S.J., 2016; Kim, S., Lee, C., Lee, J., & Kim, J., 2021; Taneja et al., 2012).

In the OTT domain, comparative research by Shin and Park (2021) found significant differences in user satisfaction and expectations between global OTT services and local Korean OTT services—evidence that audience segments respond differently depending on content scope and perceived quality. Such findings underscore that OTT behavior can diverge markedly across user groups and contexts, reinforcing the need for segmentation models that can capture repertoire differences rather than simple demographic or preference categories (Kwak et al., 2021; Kim & Lee, 2024).

Traditional clustering and latent class analysis techniques have been applied to identify usage-based audience segments, but these approaches face limitations when dealing with the temporal and contextual complexity of modern media repertoires (Shim et al., 2022). For instance, Shim, Lee, and Oh (2022) applied latent class regression to OTT viewership data and uncovered multiple user classes with distinct content preferences and viewing habits, while

cross-national analyses often segment OTT users by their motivations and value orientations (Kwak et al., 2021). However, these studies typically rely on survey responses or aggregate usage measures rather than analyzing the detailed temporal and contextual patterns that define media repertoires (Kim, S.J., 2016; Taneja et al., 2012).

The application of deep learning techniques to media consumption research represents a significant methodological advancement that enables more sophisticated repertoire identification (Chung et al., 2014). While traditional clustering approaches have relied on predefined features or survey responses, deep learning methods can automatically discover latent patterns in complex behavioral sequences (Chung et al., 2014). This capability is particularly valuable for repertoire analysis because it allows researchers to identify naturally occurring clusters of similar contextual usage patterns without imposing restrictive assumptions (Kim, S.J., 2016).

Recent developments in sequence modeling, particularly autoencoders based on recurrent neural networks, have shown promise for extracting meaningful representations from temporal behavioral data (Chung et al., 2014). These methods can handle the high-dimensional, temporally-dependent nature of media consumption logs while learning compact representations that capture the essential characteristics of different repertoire types (Chung et al., 2014). The autoencoder architecture is particularly well-suited to this application because it forces the model to learn the most informative aspects of behavioral sequences while discarding noise (Chung et al., 2014).

Clustering approaches in high-dimensional spaces require careful validation to ensure that identified patterns are meaningful and stable (Kim, S.J., 2016). Traditional clustering validation measures remain relevant, but recent research in machine learning has emphasized the importance of examining cluster stability across different subsamples and initialization conditions (Chung et al., 2014). For media repertoire analysis, external validation using known behavioral or demographic characteristics provides additional confidence that identified clusters represent meaningful behavioral differences rather than analytical artifacts (Shim et al., 2022; Kwak et al., 2021).

The identification of meaningful repertoire segments depends critically on the technological context in which media consumption occurs (Massaro & Kim, 2022). Research examining OTT usage patterns has consistently found that technological constraints shape the

feasibility of different contextual consumption strategies (Kim, Kim, & Nam, 2016; Kim, M.S., Kim, E., Hwang, Kim, & Kim, 2017). Some viewers prefer to access global OTT services through their existing pay-TV platforms (Lim & Kim, 2023), indicating how service context and delivery mechanisms can segment audiences beyond simple content preferences.

Consumer-value research has revealed distinct consumption profiles: Chakraborty et al. (2023) found that entertainment-driven versus convenience-driven users showed different patterns of trust and continued subscription intentions. These findings suggest that repertoire differences reflect not only contextual constraints but also underlying value orientations that guide how users integrate OTT services into their daily routines (Tsai, Tang, & Ou, 2024; Dwyer, Shim, Lee, & Hutchinson, 2018). Content preferences and viewing motivations further characterize OTT consumption behavior, with research on digital natives' media choices revealing that younger audiences increasingly favor content that can be consumed in brief sessions, particularly on mobile devices (Nam & Jung, 2021).

Studies examining binge-watching behavior show that certain content types, especially serialized dramas and exclusive original series, drive extended viewing sessions and subscription loyalty, with self-reported motivations including entertainment, escape, and social connection (Sung, Kang, & Lee, 2018; Panda & Pandey, 2017). At the same time, viewers still turn to OTT for traditional long-form content when context allows extended viewing—OTT users often marathon multiple episodes when they have free evening hours at home (Tefertiller & Sheehan, 2019; Pilotta & Schultz, 2005).

The technological infrastructure available to users fundamentally shapes the repertoire options available to them (Massaro & Kim, 2022). In markets with advanced telecommunications infrastructure like South Korea, technical barriers to contextual switching are minimized, enabling users to develop more sophisticated repertoires that fully exploit the flexibility offered by OTT services (Shin, Park, & Lee, 2016). Understanding repertoire patterns under optimal technological conditions provides valuable insights for predicting how usage patterns may evolve as infrastructure capabilities expand in other markets (Kim, M.S. et al., 2017).

However, prior segmentation efforts have generally been limited to survey-based classifications or single-dimension groupings without jointly considering the full context of use and the technological factors that enable different repertoire strategies (Kim, S.J., 2016;

Shim et al., 2022). Few works have algorithmically clustered behavioral sequences of OTT consumption that integrate time, place, and device dimensions while accounting for the infrastructure requirements that make different patterns feasible (Chung et al., 2014).

Our approach builds on this emerging direction by using deep learning techniques to identify repertoire-based user segments defined by context rather than by any single factor (Kim, S.J., 2016; Chung et al., 2014). This methodological contribution extends the literature on OTT audience segmentation with a novel approach that integrates multiple contextual variables simultaneously while accounting for the temporal dependencies that characterize media repertoires (Taneja et al., 2012; Wang & Tchernev, 2012). The resulting clusters of OTT usage provide a nuanced framework for understanding audience behavior that aligns with repertoire theory while leveraging computational methods capable of handling the complexity inherent in contemporary media consumption patterns (Chung et al., 2014; Kim, S.J., 2016). Such context-centric clusters carry practical implications for telecommunications strategies and media business policies while advancing theoretical understanding of how technological affordances interact with user preferences to shape media repertoires (Massaro & Kim, 2022; Menon & Arora, 2022).

3 Methodology

3.1 Data

We utilized Korea Media Panel dataset, which consists of longitudinal time-use diary data and individual survey data. We used four years period (2021-2024), where each participant recorded their activities and context for three separate days in each year, yielding 12 diary days per participant. To ensure consistency, we filtered the data to include only participants who provided complete diary entries for all four years. This resulted in a subset of individuals with no missing days, each contributing a continuous sequence of 12 days. Each diary day was divided into 96 time slots of equal length (15-minute intervals covering 24 hours), so each participant's full record consists of 1,152 sequential time points (96 slots \times 12 days).

At each 15-minute interval, the diary captured eight categorical variables describing the participant's behavior and context: Sleep status, Location, two indicators of media use (Media1 and Media2), two activity descriptors (Activity1 and Activity2), and two indicators of social interaction or presence (Connection1 and Connection2). These variables jointly characterize what the participant was doing, where, with whom, and whether media were involved at each moment. We also have the individual panel survey dataset with demographic information and media consumption and spending variables.

Table 1. Basic statistics of individual-year dataset

Variable	Obs	Mean	S.D.	Min	Max	Variable	Obs	Perc.
Gender	31,304	1.55	0.50	1	2	Mobile Carrier		
Age	31,304	52.30	19.16	7	95	A	13,709	47%
Married	31,304	1.34	0.64	1	2	B	7,936	27%
Income	31,304	4.86	3.53	1	18	C	6,849	23%
Monthly phone bill	30,792	5.10	1.89	1	11	MVNO	718	2%
Monthly device instalment	30,792	1.56	0.99	1	11			
OTT use frequency	25,595	2.63	1.71	1	8	Cluster		
Total OTT viewing minutes	25,595	148.39	128.28	2	1230	0	16,092	51%
OTT usage min(weekday)	25,595	62.47	57.07	0	600	1	8,996	29%
OTT usage min(weekend)	25,595	85.93	79.16	0	659	2	6,216	20%

3.2 Clustering

3.2.1 Data Preprocessing

Before modeling, we transformed the raw diary entries into a suitable machine-learning format. Each of the eight categorical variables was converted into one-hot encoded vectors and concatenated to represent the state at each time slot, resulting in a 225-dimensional binary vector per time point. We appended temporal context features (month, day, weekday) to capture periodic patterns. The final preprocessed input for each participant was a sequence of 1,152 time steps.

3.2.2 GRU-Based Autoencoder

To learn compact representations of participants' time-use sequences, we implemented a recurrent autoencoder using Gated Recurrent Units (GRUs). The encoder processes each participant's 1,152-timestep sequence, compressing it into a 64-dimensional latent embedding that captures overall time-use patterns. The decoder reconstructs the original sequence from this latent representation, conditioned on temporal context features at each timestep. We trained the autoencoder using multi-category cross-entropy loss, optimized with AdamW.

3.2.3 Clustering

After training, we extracted each participant's 64-dimensional latent vector and applied k-means clustering to these embeddings. Prior to clustering, vectors were z-standardized to ensure equal contribution to Euclidean distance. We ran k-means with multiple random seeds and retained the solution minimizing within-cluster variance.

3.3 Regression Analysis

After acquiring the latent clusters using diary data, we perform multinomial regression analysis to check cluster membership using demographic variables and survey responses. This allows us to interpret the result of the latent behavioral clustering on the basis of actual individual-level variables. In addition, we perform a mobile carrier choice model to check the factors affecting mobile carrier choice.

4 Result

4.1 Clustering Results

The choice of three clusters was supported by cluster validity measures. The elbow method revealed a clear inflection at $K=3$ clusters, beyond which additional clusters yielded diminishing returns in explained variance. Similarly, silhouette analysis indicated that the three-cluster solution achieved a higher average silhouette coefficient than alternative solutions. A PCA scatter plot shows that the three clusters form well-separated groups in the reduced dimensional space, with minimal overlap.

A cluster analysis of OTT consumption behavior identified three distinct user clusters:

Figure 1 Elbow method and silhouette method result

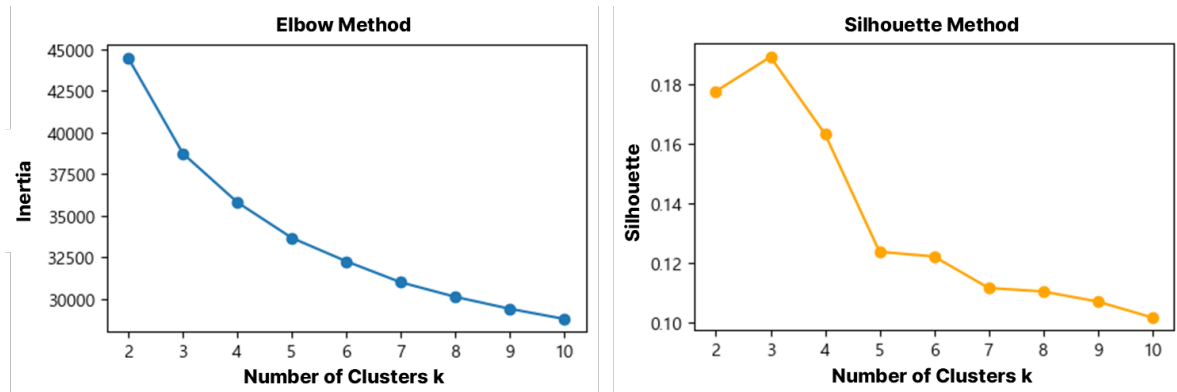
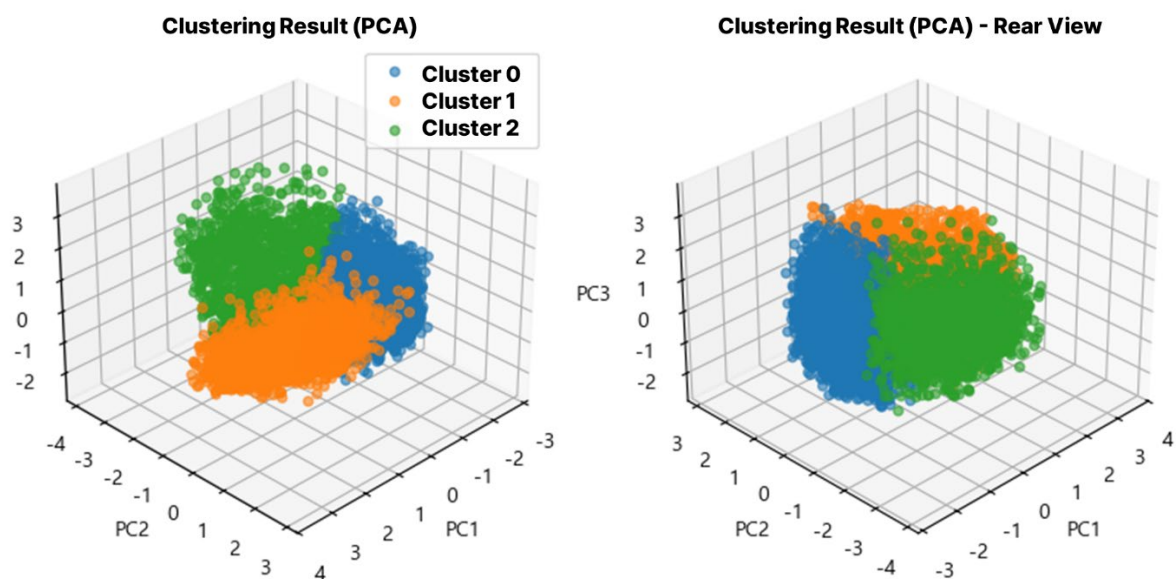


Figure 2 PCA Representation of clusters (3D)

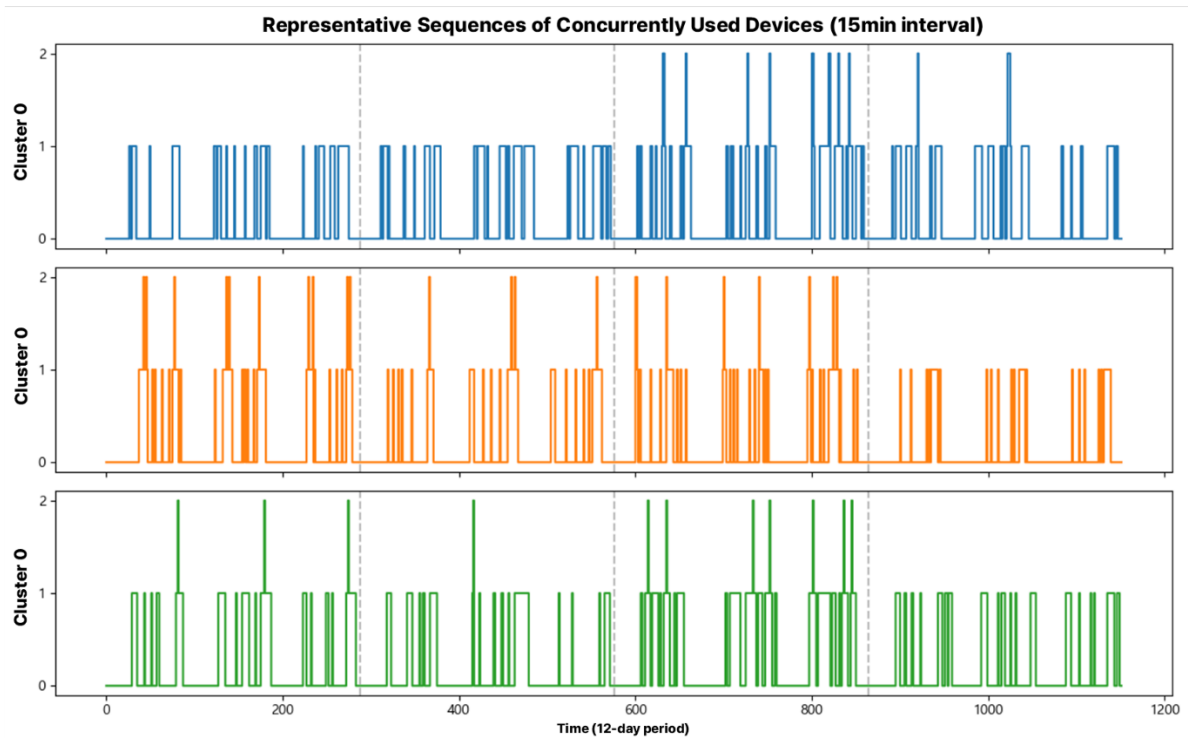


Cluster 0 – Conventional Home Viewing (Baseline): This cluster represents a more traditional viewing pattern centered in residential settings. Users in Cluster 0 predominantly consume content through a television or PC (and laptop), with connectivity mainly via a set-top box (e.g., cable/IPTV). Their viewing consists largely of scheduled broadcast programming and personal video content, with relatively limited use of OTT applications (see Figure 3).

Cluster 2 – Daytime Flexible: This cluster is characterized by flexible viewing times spread throughout the day and frequent on-the-go consumption. Users in Cluster 2 favor portable devices (smartphones, tablets) to watch content while in transit or outside the home, accessing a mix of terrestrial broadcasts, personal streaming (user-generated content), and on-demand videos via mobile networks or Wi-Fi (see Figure 1 for a typical usage context).

Cluster 1 – Heavy Prime-Time: This cluster is defined by heavy content consumption during peak prime-time hours, primarily in the home environment. Cluster 1 viewers often utilize multiple devices (TV, PC, tablet, smartphone) concurrently and engage with both traditional broadcast and OTT streaming content. They rely on various connection modes (e.g., set-top box, fixed broadband, mobile network, Wi-Fi) to support high-volume viewing in the evening (see Figure 2).

Figure 3 Concurrently used devices of representative user in each cluster



Representative sequences of concurrently used devices over a 12-day period (15-minute intervals) for a typical user in each cluster. Each panel plots the number of devices in use at the same time (0, 1, or 2) for one representative individual from Cluster 0 (blue), Cluster 1 (orange), and Cluster 2 (green). Cluster 0 – Balanced Mobile User: predominantly uses one device at a time, as indicated by the timeline staying at 1 concurrent device for most

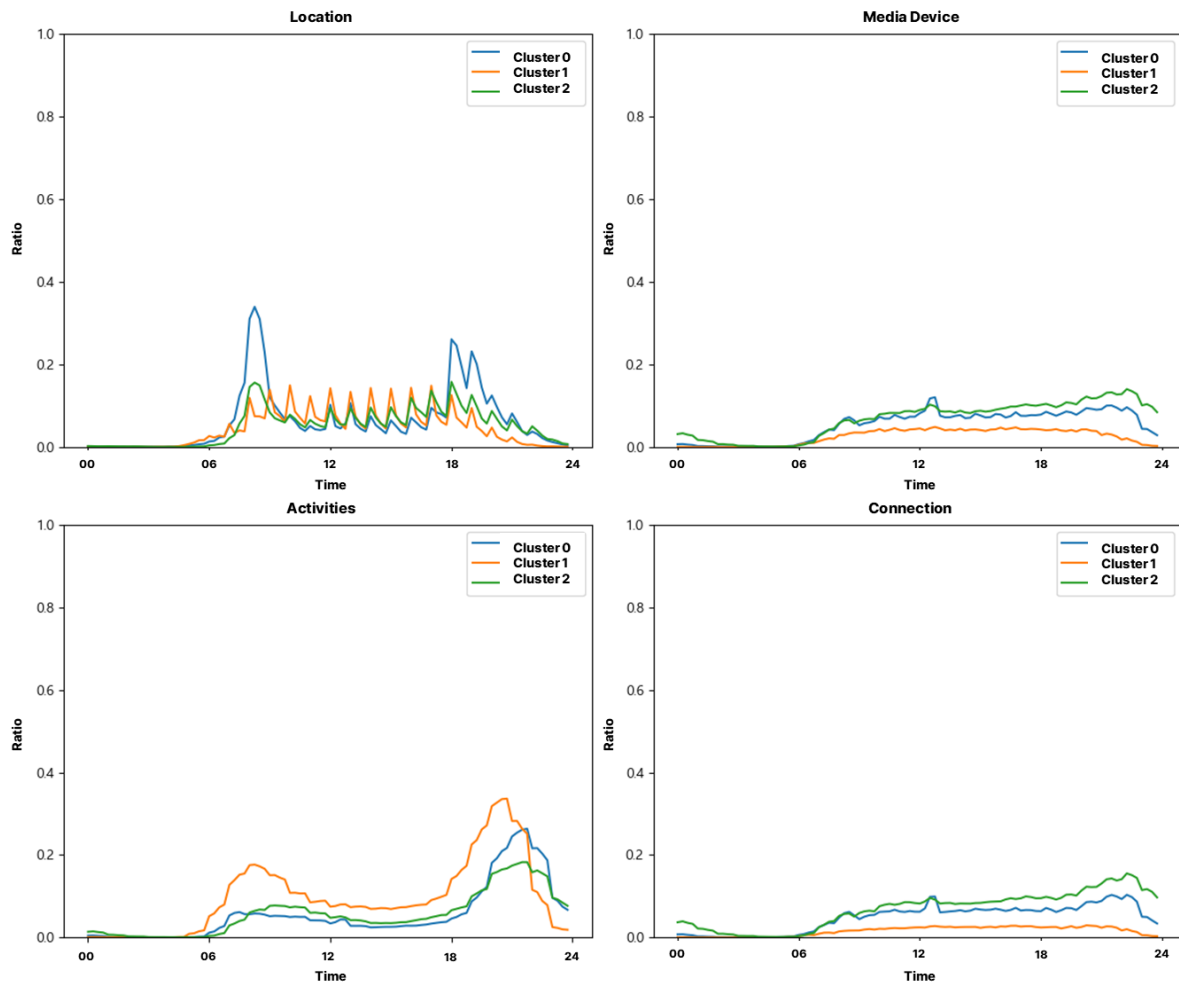
intervals and only rare, brief spikes to 2 devices. This suggests a single-tasking tendency with minimal multi-screen behavior. Cluster 1 – Heavy Prime-Time Streamer: exhibits the most frequent multi-device usage, with numerous intervals reaching 2 devices concurrently. These spikes are especially sustained during the evenings of each day (around prime-time hours), indicating that users in this cluster often use a second device (e.g. streaming on a tablet while browsing on a phone) in tandem during their peak viewing periods. Cluster 2 – Daytime Flexible Streamer: shows an intermediate pattern. This user also uses two devices at times, but such instances are less regular and shorter than in Cluster 1. The Cluster 2 timeline has a few two-device spikes scattered mostly in daytime hours, consistent with a more sporadic or situational multitasking behavior (for example, briefly juggling work and entertainment during the day). Overall, Cluster 1 stands out for its sustained concurrent device use, whereas Clusters 0 and 2 lean toward one-device-at-a-time with only occasional overlaps. These multi-device usage differences underscore the behavioral distinctions between clusters: heavy prime-time users not only consume more content, but often do so on multiple devices simultaneously, whereas balanced users stick to single-device viewing and flexible daytime users fall in between.

To further illustrate each cluster's behavior, we examined usage patterns across mobility (out-of-home) vs. residential (at-home) contexts. Figure 4 and Figure 5 plot the temporal profiles of key usage metrics for each cluster over an average day, separated by context. Each figure contains four subplots showing (a) Location – the proportion of users in the cluster who are at home at a given hour (a proxy for being in a residential setting vs. out-of-home), (b) Media Device Usage – an index of content consumption intensity (e.g. streaming or media use) by hour, (c) Activity/Engagement – a measure of overall device engagement (such as active app use or multitasking level), and (d) Connection Type – the predominant network connection in use (with higher values indicating greater reliance on Wi-Fi over cellular data at that hour). By comparing these patterns, we can see how the clusters differ in their daily device habits when they are out-and-about versus when they are at home.

In mobile/out-of-home contexts, clear differences emerge in when and how users engage with content. The Location subplot in Figure 4 shows that Balanced Mobile Users (Cluster 0, blue) leave home relatively early in the day – the blue line drops sharply in the morning, indicating most of this cluster is out-of-home during standard daytime hours. Daytime Flexible Streamers (Cluster 2, green) also depart home in the morning, but their curve

transitions slightly later or more gradually, suggesting some members of this cluster have flexible routines (e.g. leaving home a bit later or returning earlier). Heavy Prime-Time Streamers (Cluster 1, orange) are the least mobile during the day – their home-presence line remains higher through the morning and midday, implying that a good portion of Cluster 1 either stays at home longer (perhaps retirees or home-based workers) or is not actively using devices while out. Correspondingly, the Media Device usage subplot reveals that Cluster 0 and Cluster 2 engage in modest content consumption during midday (the blue and green lines show small bumps around noon, possibly lunch-break video watching), whereas Cluster 1’s media use is virtually flat near zero in the daytime (orange line stays low) since those users reserve most of their viewing for the evening. The Activity/Engagement plot mirrors this: Cluster 1 shows very low engagement levels while out-of-home (consistent with being occupied with non-media activities or work), whereas Clusters 0 and 2 have slightly higher daytime device engagement. Finally, the Connection Type subplot highlights network usage differences. During daytime hours, Balanced Mobile (blue) and Daytime Flexible users (green) rely more on cellular data (their Wi-Fi usage proportion is lower), indicating they are indeed on the move and using mobile networks. Heavy Prime-Time users, in contrast, have a higher Wi-Fi usage even during the day (orange line stays comparatively high), which suggests many are either connected to home/office Wi-Fi or simply not using much mobile data until they get home. In sum, Figure 4 indicates that Balanced Mobile Users are the most “on-the-go” during the day (leaving home early, moderate device use via cellular networks), Daytime Flexible Streamers also use devices on the move but with a slightly different timing, and Heavy Prime-Time Streamers are relatively inactive in consuming content while away from home.

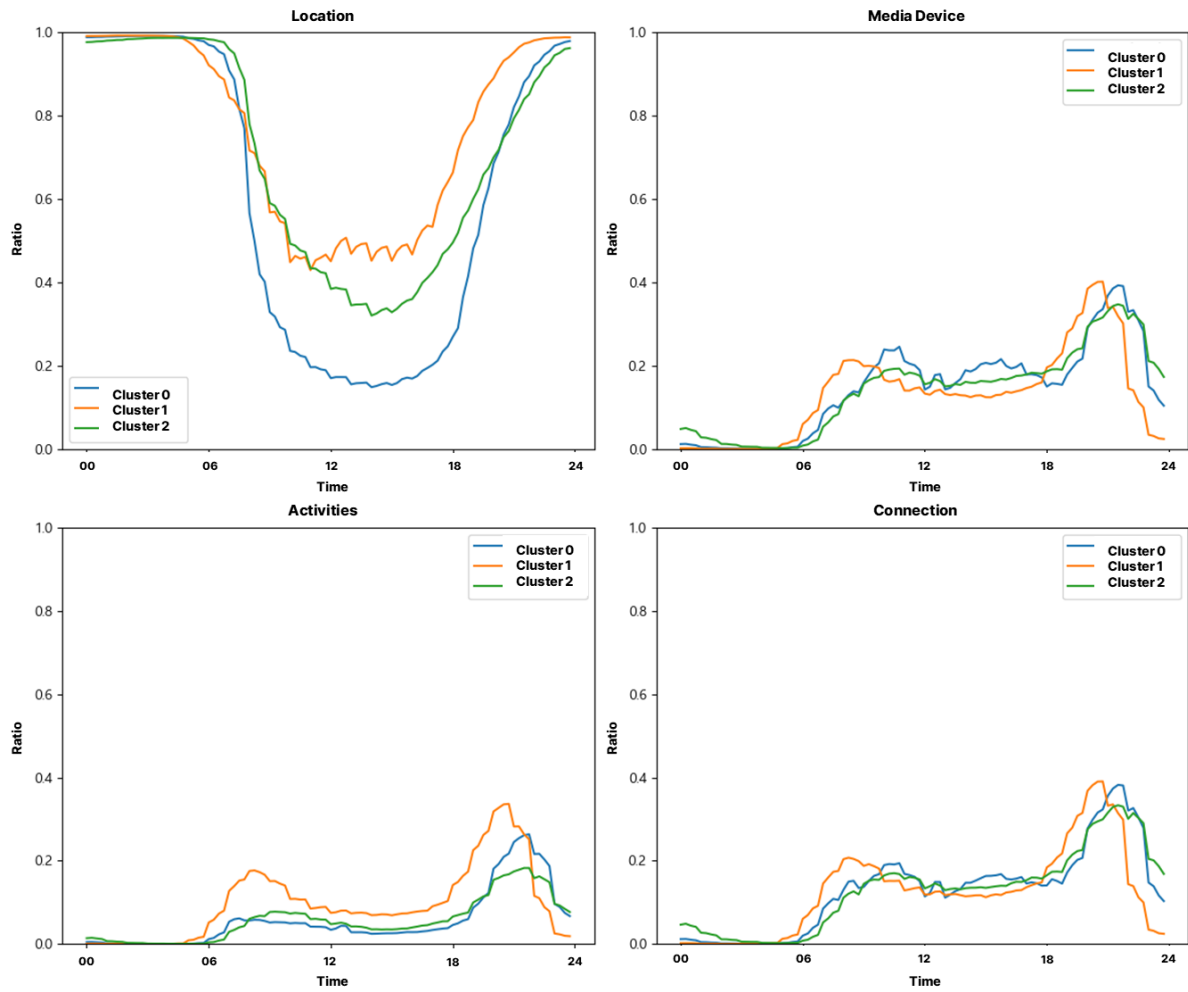
Figure 4 Cluster differences in daily device usage patterns during mobility contexts



In the home context, expected overall patterns emerge alongside notable between-cluster differences. The Location plot in Figure 5 confirms that by late evening nearly all users are in their residence (all cluster lines approach 1.0 after 21:00). However, differences appear in home presence during the daytime: Heavy Prime-Time Streamers (Cluster 1, orange) are the least likely to be at home in any given midday hour (their line dips lowest, since most are out until evening), whereas Daytime Flexible (Cluster 2, green) and especially some Balanced users (Cluster 0, blue) have a higher probability of being at home during daytime (e.g. blue line is somewhat elevated, suggesting a subset like homemakers or remote workers in Cluster 0). The Media Device usage subplot in Figure 5 underscores how each cluster utilizes their at-home time for content. Once at home in the evening, Cluster 1 (orange) exhibits a dramatic spike in media consumption during prime time – far surpassing the others – reflecting their heavy streaming/broadcast viewing habits after work. Cluster 0 (blue) shows a more moderate increase in the evening, while Cluster 2 (green) begins to ramp up slightly earlier in the late afternoon (indicating more staggered viewing times, possibly due to flexible schedules). The

Activity/Engagement subplot reflects these intensities: Cluster 1's engagement level at home skyrockets after 19:00, reaching the highest peak as they often juggle multiple content sources or devices at night. Cluster 2 also increases engagement in the evening, but not to the extreme level of Cluster 1, and Cluster 0 shows the smallest rise (consistent with a more relaxed, traditional viewing pattern). Finally, the Connection Type subplot highlights all clusters' reliance on Wi-Fi when at home. In the evening and late night hours, virtually everyone is on Wi-Fi (all lines approach the upper bound, as home broadband takes over streaming duties). One subtle difference is that Cluster 2 (green) and Cluster 0 (blue) start using Wi-Fi earlier (their curves climb in late afternoon/early evening), whereas Cluster 1 (orange) – many of whom might only go online after returning home later – catches up slightly later. By midnight, all groups converge to nearly full Wi-Fi usage. Overall, the residential context (Figure 5) reveals that Heavy Prime-Time Streamers dominate evening media use (both in amount and concurrency of devices), whereas Balanced users partake in more modest nightly viewing, and Daytime Flexible users distribute some of their usage to earlier parts of the day. Together, Figures 4 and 5 illustrate distinctly different daily rhythms across the clusters: Cluster 0 maintains a balanced routine with moderate, mostly single-device viewing centered in the evening; Cluster 1 concentrates their media activity into an intense, multi-device prime-time binge; and Cluster 2 spreads their consumption more flexibly across daytime and evening, with intermediate levels of intensity.

Figure 5 Cluster differences in daily device usage patterns during residential contexts



4.2 Regression Analysis for Cluster Membership

Table 2 presents the multinomial logistic regression results predicting cluster membership with Cluster 0 serving as the reference category. In the following analysis, Cluster 1 refers to the Heavy Prime-Time cluster and Cluster 2 to the Daytime Flexible cluster. Among demographic factors, gender and age emerged as significant predictors of cluster membership. Being male is associated with significantly lower odds of belonging to Cluster 1 or Cluster 2 relative to Cluster 0 ($\beta = -0.259$ (0.059)*** and $\beta = -0.499$ (0.051), respectively). Age demonstrates opposite effects on the two clusters, showing a positive association with membership in Cluster 1 (0.082 (0.002)) while exhibiting a negative association with Cluster 2 (-0.048 (0.002)*), compared to Cluster 0. Regarding marital status, a significant effect appears for Cluster 2, with married individuals less likely to be in Cluster 2 than in Cluster 0

($\beta = -0.145$ (0.054)), whereas the marriage effect for Cluster 1 does not reach statistical significance.

Examining socio-economic and billing factors reveals that higher income and greater mobile service expenses are linked to the baseline cluster. Household income exhibits significant negative coefficients for both Cluster 1 and Cluster 2 (-0.550 (0.011)*** and -0.511 (0.009)), indicating that members of the non-reference clusters have lower income on average than Cluster 0. Similarly, a higher monthly phone bill is associated with lower odds of being in Cluster 1 (-0.087 (0.016)) or Cluster 2 (-0.113 (0.014)) relative to Cluster 0. A higher monthly device installment for smartphone payments significantly decreases the likelihood of Cluster 1 membership (-0.092 (0.028)), although it shows no significant effect on Cluster 2 (0.006 (0.021), n.s.).

The analysis of OTT usage behavior demonstrates that indicators of OTT viewing behavior distinguish the clusters. More frequent OTT use serves as a strong predictor of the Heavy Prime-Time cluster, with each increase in OTT usage frequency raising the odds of being in Cluster 1 ($\beta = 0.095$ (0.014)), but conversely lowering the odds of being in Cluster 2 ($\beta = -0.085$ (0.014)) relative to the reference cluster. In contrast, total OTT viewing minutes shows no significant impact on Cluster 1 membership, but demonstrates a positive association with Cluster 2 membership ($\beta = 0.0014$ (0.0002)***), implying that Cluster 2 members accumulate more viewing time than those in Cluster 0.

Regarding mobile carrier subscription, the user's mobile carrier shows limited influence on cluster membership. There are no significant differences between Carrier B and Carrier A, nor for MVNO users, in predicting cluster membership. The only notable effect appears for Carrier C, where using Carrier C versus Carrier A significantly decreases the odds of belonging to Cluster 1 ($\beta = -0.316$ (0.058)***), while Carrier C does not significantly differ from Carrier A for Cluster 2. Members of the Heavy Prime-Time cluster are thus less likely to subscribe to Carrier C than those in the baseline cluster, whereas carrier choice does not emerge as a significant differentiator for the Daytime Flexible cluster.

Table 2. Results of multinomial logistic regression predicting cluster membership

Variable	Cluster 1 (vs 0) (Heavy Prime-Time)	Cluster 2 (vs 0) (Daytime Flexible)
Gender (male = 1)	−0.259 (0.059)***	−0.499 (0.051)***
Age (years)	0.082 (0.002)***	−0.048 (0.002)***
Married (= 1)	−0.016 (0.049)	−0.145 (0.054)**
Household income	−0.550 (0.011)***	−0.511 (0.009)***
Monthly phone bill	−0.087 (0.016)***	−0.113 (0.014)***
Monthly device instalment	−0.092 (0.028)***	0.006 (0.021)
OTT use frequency	0.095 (0.014)***	−0.085 (0.014)***
Total OTT viewing minutes	0.0002 (0.0002)	0.0014 (0.0002)***
Mobile-carrier (ref. = Carrier A)		
Carrier B	0.059 (0.053)	−0.068 (0.053)
Carrier C	−0.316 (0.058)***	−0.059 (0.054)
MVNO	0.079 (0.170)	0.142 (0.140)
Constant	−2.553 (0.234)***	5.047 (0.153)***

Notes: Robust standard errors in parentheses.

***p < 0.001, **p < 0.01, *p < 0.05.

4.3 Mobile Carrier Choice Model

Table 3 reports the results of the multinomial logit model examining mobile carrier choice with Carrier A serving as the reference outcome, analyzing factors influencing the likelihood of selecting Carrier B, Carrier C, or an MVNO. Demographic factors reveal significant variations in carrier preferences. Male users exhibit higher odds of subscribing to Carrier C ($\beta = 0.086$ (0.036)) and MVNOs ($\beta = 0.249$ (0.097)) compared to Carrier A, while gender shows no significant association with Carrier B adoption. Age emerges as a predictor for MVNO selection, with older users demonstrating reduced likelihood of choosing MVNOs over Carrier A ($\beta = -0.014$ (0.004)), though age effects remain non-significant for Carrier B or Carrier C preferences. Marital status significantly impacts Carrier C and MVNO adoption, as married individuals show increased propensity for Carrier C ($\beta = 0.087$ (0.035)*) and decreased likelihood of MVNO selection ($\beta = -0.348$ (0.125)**) relative to Carrier A, while marital status does not influence Carrier B choice.

Economic status and service cost factors demonstrate clear differentiation patterns. Higher household income marginally reduces Carrier C preference ($\beta = -0.013$ (0.005)) while substantially increasing MVNO adoption likelihood ($\beta = 0.173$ (0.014)) compared to Carrier

A. Monthly phone bill magnitude strongly correlates with carrier loyalty, as elevated bills decrease odds of choosing Carrier B ($\beta = -0.038$ (0.010)) and MVNOs ($\beta = -1.161$ (0.037)) while slightly enhancing Carrier C selection probability ($\beta = 0.030$ (0.010)). Device installment payments exhibit divergent effects, positively associating with Carrier B adoption ($\beta = 0.039$ (0.015)) but negatively impacting MVNO selection ($\beta = -0.510$ (0.089)*), with no significant influence on Carrier C preference.

OTT usage behavior shows complex relationships with carrier choice. Increased OTT frequency negatively predicts all alternative carriers, reducing odds of selecting Carrier B ($\beta = -0.036$ (0.009)), Carrier C ($\beta = -0.039$ (0.010)), or MVNOs ($\beta = -0.152$ (0.031)) relative to Carrier A. Conversely, total OTT viewing minutes display contrasting effects, marginally decreasing Carrier B preference ($\beta = -0.00033$ (0.00014)) while increasing MVNO adoption likelihood ($\beta = 0.00147$ (0.00029)*), with no significant impact on Carrier C selection. These patterns suggest frequent OTT users tend to remain with the incumbent Carrier A, whereas extended viewing durations correlate with alternative provider preferences. (All coefficients include robust standard errors in parentheses, with *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.)

Table 3. Multinomial logit results for mobile carrier choice

Variable	Carrier B (vs A)	Carrier C (vs A)	MVNO (vs A)
Gender (male = 1)	0.039 (0.034)	0.086 (0.036)*	0.249 (0.097)**
Age (years)	0.002 (0.001)	-0.000 (0.001)	-0.014 (0.004)***
Married (= 1)	-0.018 (0.034)	0.087 (0.035)*	-0.348 (0.125)**
Household income	0.001 (0.005)	-0.013 (0.005)*	0.173 (0.014)***
Monthly phone bill	-0.038 (0.010)***	0.030 (0.010)**	-1.161 (0.037)***
Monthly device instalment	0.039 (0.015)**	-0.017 (0.016)	-0.510 (0.089)***
OTT use frequency	-0.036 (0.009)***	-0.039 (0.010)***	-0.152 (0.031)***
Total OTT viewing minutes	-0.00033 (0.00014)*	0.00020 (0.00014)	0.00147 (0.00029)***
Constant	-0.389 (0.102)***	-0.974 (0.107)***	2.642 (0.268)***

Notes: Robust standard errors in parentheses.

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

5 Conclusion

This study advances our understanding of contemporary media consumption by applying deep learning techniques to identify contextual patterns in OTT usage behavior. Through the analysis of longitudinal diary data from the Korea Media Panel (2021-2024), we demonstrate how GRU-based autoencoders can effectively capture the multidimensional nature of media repertoires in an era of ubiquitous connectivity. Our findings reveal three distinct consumption clusters—Conventional Home Viewing, Heavy Prime-Time, and Daytime Flexible—each characterized by unique patterns of temporal, spatial, and technological integration that extend beyond traditional demographic segmentation.

The theoretical contribution of this research lies in operationalizing media repertoire theory (Taneja et al., 2012; Kim, S.J., 2016) through computational methods that can handle the complexity of contemporary media behaviors. While previous studies have recognized the importance of context in media consumption (Wonneberger et al., 2012; Wang & Tchernev, 2012), our approach demonstrates how machine learning can identify naturally occurring repertoires from behavioral sequences without imposing restrictive analytical assumptions. The identified clusters validate the repertoire framework's emphasis on contextual optimization, showing that users develop distinct strategies for integrating OTT services based on the interplay of temporal availability, spatial mobility, and device accessibility rather than simple platform preferences.

Our findings carry significant implications for telecommunications operators and content providers operating in mature OTT markets. The Heavy Prime-Time cluster's intensive multi-device usage during evening hours suggests opportunities for bundled services and synchronized content experiences, while the Daytime Flexible cluster's distributed consumption patterns indicate demand for seamless cross-device functionality and mobile-optimized content formats. The persistence of a Conventional Home Viewing cluster, despite South Korea's advanced infrastructure, underscores that technological capabilities alone do not determine usage patterns—user preferences and contextual constraints remain paramount in shaping media repertoires (Massaro & Kim, 2022).

The relationship between cluster membership and mobile carrier choice reveals strategic considerations for telecommunications providers. The finding that Heavy Prime-Time users are less likely to subscribe to Carrier C, combined with the negative association

between OTT frequency and alternative carrier adoption, suggests that incumbent carriers may retain advantage among the most engaged streaming audiences. Conversely, the positive relationship between total viewing minutes and MVNO adoption indicates price-sensitive segments that accumulate substantial usage through efficient consumption strategies. These patterns highlight how infrastructure providers must consider usage repertoires, not merely aggregate consumption metrics, when designing service offerings.

From a methodological perspective, this study demonstrates the value of sequence-based deep learning for media research. The GRU autoencoder's ability to compress 12 days of diary data into meaningful latent representations while preserving temporal dependencies offers a scalable approach for analyzing complex behavioral patterns. This computational framework can be extended to other domains where contextual factors shape technology adoption and usage, from smart home devices to mobile health applications.

Several limitations warrant consideration in interpreting these findings. First, while the Korea Media Panel provides rich behavioral data, the three-day-per-year sampling may not fully capture seasonal variations or evolving usage patterns within individuals. Future research could benefit from continuous tracking methodologies that capture more granular temporal dynamics. Second, our analysis focuses on South Korea's unique technological context, where near-universal high-speed connectivity may enable repertoires not feasible in markets with infrastructure constraints. Comparative studies across markets with varying technological capabilities would illuminate how infrastructure shapes the boundaries of possible media repertoires (Kim, M.S. et al., 2017).

The exclusive focus on behavioral patterns, while methodologically valuable, omits motivational and experiential dimensions that influence media choices. Future research could integrate our clustering approach with survey measures of user satisfaction, content preferences, and perceived value to develop more comprehensive repertoire profiles (Chakraborty et al., 2023; Shin & Park, 2021). Additionally, examining how major events or content releases temporarily alter established repertoires would provide insights into the stability and flexibility of identified patterns.

Looking forward, several research directions emerge from this work. The application of more advanced neural architectures, such as transformer-based models, could capture longer-range dependencies and more complex contextual interactions in media consumption

sequences. Integrating content-level data—what users watch, not just when and where—would enable analysis of how repertoires relate to genre preferences and viewing motivations (Nam & Jung, 2021). Longitudinal analysis tracking how individual repertoires evolve over time, particularly as new services enter the market or infrastructure capabilities expand, would illuminate the dynamics of repertoire formation and transformation.

As global telecommunications infrastructure continues to advance and OTT services proliferate, understanding contextual consumption patterns becomes increasingly critical. This study provides a methodological framework and empirical foundation for analyzing media repertoires in high-connectivity environments. The identified patterns—from concentrated prime-time multi-screening to distributed mobile consumption—represent strategic opportunities for service providers while advancing theoretical understanding of technology-mediated behavior. Future applications of this approach across markets and media types will further illuminate how individuals navigate abundance in the digital media landscape, ultimately informing both academic theory and industry practice in an era of ubiquitous connectivity and content choice.

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