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Consumer Streaming Loyalty and Switching Behaviour across OTT Platforms in the Attention Economy

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Abstract: In the age of digital abundance, where attention is the most valuable currency, over-the-top (OTT) platforms are engaged in an aggressive pursuit of consumer loyalty. This study investigates the nuanced dynamics of consumer retention and switching behaviour across leading OTT platforms in India, adopting a mixed-methods approach rooted in both primary and secondary data. Drawing insights from a diverse set of cities and user segments, the research explores the key factors—such as subscription fatigue, content preferences, platform usability, perceived value, and psychological loyalty—that drive sustained engagement or trigger platform-switching behaviour. Empirical data were collected via structured questionnaires and focus groups, complemented by secondary data from industry reports, TRAI bulletins, and user behaviour analytics. The study employs Structural Equation Modelling (SEM) to establish causal relationships among variables and confirm the hypothesised model. The findings reveal a complex interplay between perceived value and content personalisation as significant predictors of loyalty, while ad-fatigue and pricing inconsistencies contribute to churn. Notably, regional content and language accessibility emerged as strong anchors of platform stickiness in Tier-2 and Tier-3 cities. The study contributes to literature on digital consumer behaviour and attention economics, offering insights for marketers, strategists, and platform developers aiming to foster long-term viewer engagement in India's hyper-competitive streaming ecosystem. Implications for platform bundling, content differentiation, and user retention strategies are discussed. The study concludes with recommendations for policy and managerial action, grounded in empirical rigour and contextual relevance.

Keywords: OTT Platforms, Consumer Loyalty, Switching Behaviour, Attention Economy, Indian Streaming Market, Structural Equation Modelling

1. Introduction

In today's digital-first world, streaming services have woven themselves into the everyday lives of millions of Indians. Whether it is binge-watching a newly released web series on Netflix, catching up on the latest regional drama on Hotstar, or browsing music videos on YouTube, users are spoilt for choice. With smartphones becoming more affordable, internet data cheaper, and content libraries expanding across languages, India has quickly evolved into one of the largest and most competitive Over-The-Top (OTT) markets globally. However, this abundance of platforms has triggered a new kind of challenge—how do these platforms ensure consumer loyalty in an environment where switching is as easy as tapping an app icon?

The fight for attention in this digital ecosystem is intense. In the language of modern economics, we are now living in an *attention economy*—where human attention is a limited resource and every platform is racing to capture and retain it. While traditional marketing focused on selling products, today's platforms are selling moments, emotions, and engagement. Herein lies the paradox: while content is plentiful, loyalty is scarce. Consumers are no longer committed to a single platform; instead, they switch frequently based on content releases, subscription costs, and viewing experience. This behaviour raises fundamental questions for business strategists and researchers alike—what really drives viewer retention, and what triggers switching? Is it the pricing? Content quality? Recommendation algorithms? Or perhaps, the emotional connection users form with certain shows?

While studies have explored consumer behaviour in online services broadly, the specific nuances of loyalty and platform switching in the Indian OTT space remain under-researched. The Indian market is unique—not just because of its size, but due to its immense cultural and linguistic diversity. A viewer in Bengaluru may prefer international thrillers, while another in Lucknow might be more inclined towards Hindi serials or Bhojpuri films. Furthermore, the subscription fatigue is real. Many users subscribe to multiple platforms but drop out of one or more after a month or two. Others prefer freemium models where they can view limited content with advertisements. These shifting consumption patterns demand a closer, data-driven examination.

This study aims to fill that gap. It focuses on understanding the retention and switching behaviours of Indian OTT consumers, with an emphasis on loyalty-building in a competitive digital environment. The study draws upon both **primary data**—collected through structured questionnaires from OTT users across Tier-1 and Tier-2 Indian cities—and **secondary data** from industry reports, TRAI publications, and platform-specific analytics. By using an **empirical approach**, this research does not merely theorise user behaviour but seeks to explain it with evidence.

The core objective of this research is twofold: first, to identify the key factors that influence a user's loyalty to an OTT platform; and second, to examine the reasons behind their decision to switch platforms. Loyalty in the streaming context is different from product loyalty—it is more volatile, more emotional, and far more influenced by short-term variables like trending content, peer influence, and platform bundles. Switching behaviour, on the other hand, can be strategic (for example, cancelling a subscription due to rising costs) or impulsive (say, when a new season of a popular show drops on a rival platform). These behaviours are examined here not in isolation, but as part of a larger decision-making matrix shaped by both rational and emotional inputs.

To explore these dynamics, the study uses **Structural Equation Modelling (SEM)**—a powerful statistical technique that helps us understand not just if variables are related, but how they interact. This helps in identifying causal relationships between user perceptions (such as satisfaction, perceived value, and content relevance) and their behavioural outcomes (such as continued subscription or platform switching). The choice of SEM is also aligned with recent research trends in digital marketing and consumer psychology, where complex human behaviours cannot be reduced to single-variable dependencies.

Another contribution of this study is its **regional lens**. Most previous studies on OTT in India have focused on metropolitan or English-speaking audiences. However, the real boom in OTT viewership is taking place in non-metro regions and among vernacular-speaking users. Platforms like MX Player, Hoichoi, and Aha have shown how regional content can drive serious engagement. Therefore, this study makes a conscious effort to include respondents from cities like Coimbatore, Bhopal, Bhubaneswar, and Patna—ensuring that findings are not just statistically robust but socially inclusive.

Additionally, the study builds upon the **theory of planned behaviour** and the **uses and gratifications theory**, both of which provide a strong theoretical foundation for analysing consumer media choices. While the former highlights how attitudes, subjective norms, and perceived behavioural control shape actions, the latter helps explain why individuals choose certain media to satisfy specific psychological needs—be it entertainment, escapism, or social bonding. These frameworks help position OTT consumption within a wider behavioural context.

India's OTT landscape is not static. It is constantly evolving, influenced by regulatory changes, shifting viewer expectations, and technological innovations like AI-based content recommendations. For instance, the push for self-regulation and content rating mechanisms has already started reshaping how platforms design and distribute content. Likewise, strategic collaborations (such as telecom bundling and smart TV partnerships) are altering access patterns. All these factors are critical to understanding user loyalty and must be accounted for in any contemporary research.

In sum, this study is timely, relevant, and much needed. In a market where attention is fleeting and choices are endless, understanding what makes users stay or leave is not just a marketing concern—it is a strategic imperative. By blending theoretical insights with grounded data, this research hopes to provide both academic value and practical guidance for platform developers, digital marketers, and content creators.

2. Literature Review

The exponential rise of Over-The-Top (OTT) platforms has sparked a growing body of research around digital consumer behaviour, particularly in terms of engagement, satisfaction, loyalty, and platform switching tendencies. Globally, scholars like Lin et al. (2020) and Zhao and Balasubramanian (2021) have examined how content quality, platform accessibility, and algorithmic recommendations play crucial roles in retaining viewer attention. In the Indian context, however, the academic landscape is still maturing, with only a handful of empirical studies diving deep into user retention and behavioural shifts across streaming services. As digital adoption in India scales rapidly across urban and rural divides, the focus is shifting from mere access to sustained user engagement, making it vital to explore the psychological, technological, and social factors influencing loyalty in this domain. The **Uses and Gratifications Theory** (Katz, Blumler & Gurevitch, 1973) has often been used to understand media behaviour, including OTT usage, suggesting that viewers are not passive recipients but active agents seeking satisfaction from media consumption. Applying this framework, studies such as Biswas and Dey (2021) indicate that Indian users gravitate towards platforms that offer emotional satisfaction, cultural alignment, and ease of navigation. Simultaneously, the **Theory of Planned Behaviour** (Ajzen, 1991) sheds light on the role of attitudes, perceived control, and subjective norms in OTT choices, especially in social settings where recommendations and peer influence hold significant sway. The empirical work of Ramkumar and Arun (2022) further supports this, showing that perceived enjoyment, content variety, and subscription convenience are critical in shaping viewer loyalty. On the switching front, Jain and Rajput (2020) argue that users often hop between platforms due to high subscription costs, lack of fresh content, and interface fatigue. Their study, based on metro cities, found that pricing sensitivity among Indian users is remarkably high—monthly price increases or removal of "free trials" often lead to instant churn, particularly among younger consumers. Regional content has emerged as a defining feature in retention strategies, especially in India's Tier-2 and Tier-3 cities, where platforms like Aha, Hoichoi, and Chaupal have carved niche followings by offering linguistically and culturally rooted shows (Chatterjee & Menon, 2021). Meanwhile, scholars like Bansal and Agrawal (2019) have introduced the idea of "platform fatigue" — a phenomenon where users, overwhelmed by too many choices, end up cancelling or ignoring subscriptions altogether. Such behavioural insights are particularly relevant in the Indian attention economy, where multiple streaming services often coexist in the same household, competing not just for eyeballs but for emotional investment. International studies, such as those by Sun and Zhang (2021), reinforce the idea that brand loyalty in OTT is often short-lived and transactional unless continuously nurtured by platform value. From a technical standpoint, **perceived value** has been consistently highlighted as a major predictor of OTT loyalty. According to Kim et al. (2017), perceived value is influenced by four main components—performance, price fairness, emotional connection, and social influence. Applying this framework to the Indian OTT market, Chakraborty and Sharma (2020) found that emotional attachment to certain series (e.g., *Sacred Games* or *Mirzapur*) often drives continued subscriptions, even when users express dissatisfaction with the overall platform. This observation complements the work of Jaiswal and Banerjee (2021), who demonstrated how binge-worthy content can create temporary "sticky" behaviour, although loyalty often erodes in the absence of timely content refreshes. In a study conducted by Deloitte (2022), over 57% of Indian OTT viewers were found to be multi-platform users, and nearly 40% cancelled at least one subscription in the past six months—underscoring the need to investigate switching determinants systematically. Research by Sengupta et al. (2023) has recently focused on the growing role of **recommendation engines**, noting that platforms using AI-driven personalisation see greater retention, especially among Gen Z users. However, other studies caution against over-reliance on algorithms, citing privacy concerns and repetitive suggestions as reasons for user dissatisfaction (Sinha & Kumar, 2021). The influence of **bundling**

strategies, such as telecom or DTH partnerships (e.g., JioCinema bundled with Jio SIMs), has also begun to receive academic attention. Gupta and Pillai (2022) point out that while bundling may temporarily reduce churn, it does not automatically guarantee loyalty unless coupled with meaningful content experiences. Social influence too plays an undeniable role—whether it's a show trending on Twitter or a colleague recommending a series during a tea break, word-of-mouth has a disproportionately strong effect in Indian digital consumption patterns, as noted by Mehta and Bhattacharya (2018). Scholars also highlight the role of **interface design** and app responsiveness—studies by Rajan et al. (2020) and Bose (2021) confirm that OTT platforms with clutter-free, intuitive user interfaces see better retention rates, especially among middle-aged users unfamiliar with tech-heavy designs. Gender and age-based viewing differences have also surfaced in several Indian studies. For instance, Kaur and Singh (2019) observed that women in semi-urban areas preferred platforms with family-oriented shows and drama series, while male viewers skewed towards action or sports content. Similarly, youth in college towns were found to rotate subscriptions frequently based on peer trends and pop culture cues. Yet, despite the variety of existing studies, there is a noticeable lack of a holistic, data-backed model that captures **both loyalty and switching behaviour together** in the Indian OTT market. Most research isolates these concepts or explores them within siloed consumer categories. Moreover, Tier-2 and Tier-3 cities have often been underrepresented, despite being key growth drivers for OTT expansion. In this context, this present study seeks to build on existing literature by adopting a blended framework that includes psychological theories, empirical modelling, and regional segmentation. It introduces a comprehensive loyalty-switching matrix that incorporates variables like perceived value, platform fatigue, content relevance, regional preferences, and pricing sensitivity—tested empirically using Structural Equation Modelling. By grounding the analysis in both metro and non-metro user data, the study aims to contribute meaningful, actionable insights that go beyond descriptive statistics and enter the realm of strategic, user-centric platform design and policy. In doing so, it bridges critical gaps in Indian OTT research, strengthens behavioural theories with local nuance, and aligns digital media studies with the rapidly evolving contours of attention economics.

3. Theoretical and Conceptual Framework:

In a digital environment overflowing with choices, understanding why users remain loyal to one OTT platform while abandoning another requires more than surface-level observations. It demands a theoretical lens that captures both the why and the how of user behaviour. To this end, the present study integrates two widely respected behavioural theories—the Theory of Planned Behaviour (TPB) and the Uses and Gratifications Theory (UGT)—to develop a conceptual model that explains both retention and switching behaviours among Indian OTT users.

The Theory of Planned Behaviour (Ajzen, 1991) is rooted in social psychology and posits that human behaviour is driven by three key components: attitude towards the behaviour, subjective norms, and perceived behavioural control. In the context of OTT streaming, this theory helps us explain how a user's positive attitude towards a platform (e.g., "Netflix offers the best content"), combined with social pressure (e.g., "Everyone in my group watches Prime"), and perceived ease of action (e.g., "It's easy to unsubscribe or switch") influences their decision to either stay or shift. The TPB framework has been tested extensively in technology adoption studies and aligns well with consumer decisions in subscription-based models, especially when switching costs are low and behavioural control is high.

On the other hand, the Uses and Gratifications Theory (Katz, Blumler & Gurevitch, 1973) offers a more intrinsic perspective. It explains media usage as a goal-directed activity where users actively seek out platforms that satisfy specific psychological or social needs. These needs may range from entertainment, information seeking, escapism, and personal identity formation, to social interaction. When applied to OTT streaming, UGT suggests that a user may choose a platform not only because of its content, but because it aligns with their emotional needs, daily routines, or peer validation. For instance, regional viewers may prefer Aha or Hoichoi not just for language compatibility, but for cultural familiarity and representation.

By combining TPB and UGT, the current study proposes a dual-theory model that accounts for both rational factors (e.g., pricing, platform interface, recommendation accuracy) and emotional gratifications (e.g., cultural content, show loyalty, social influence). This holistic lens enables a more grounded understanding of OTT consumer behaviour in the Indian attention economy.

Based on these theories, the conceptual framework identifies six main constructs:

1. Perceived Value – the user's evaluation of what they gain versus what they pay (in time, money, or effort). This includes pricing, bundling, and overall satisfaction.
2. Content Relevance and Variety – the degree to which the platform's offerings match the user's taste, including genre, language, and timeliness.
3. Platform Experience – factors such as app usability, streaming quality, ad experience, and interface design.
4. Emotional Engagement – attachment to specific shows, series, characters, or themes; a form of affective loyalty.
5. Social Influence – recommendations, peer usage, social trends, and FOMO (Fear of Missing Out) that push users to switch or stay.
6. Behavioural Outcome – categorised into two: (a) Retention – continued usage or subscription; and (b) Switching Intention – likelihood of abandoning or replacing the current platform.

The hypothesis structure assumes that perceived value, content relevance, and platform experience directly influence emotional engagement and social influence, which in turn shape the behavioural outcomes. This multi-path structure is suitable for Structural Equation Modelling (SEM), which allows simultaneous estimation of relationships between latent constructs and observed behaviour.

Model Flow Description:

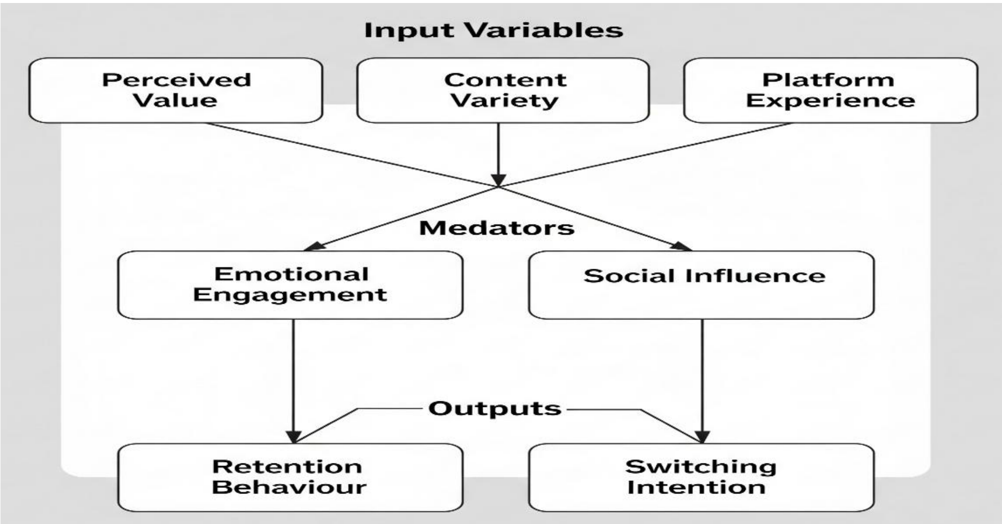

Figure 1. Conceptual framework of consumer loyalty and switching behaviour across OTT platforms.

This structure not only captures user satisfaction but also reflects the push-pull mechanism—where some factors push users to stay, while others pull them away to alternative platforms.

In the Indian context, the relevance of this model becomes even more pronounced. For instance, language accessibility and regional content often serve as emotional anchors, while subscription prices and user interface design determine rational commitment. Similarly, peer recommendation—especially among college-going youth or workplace groups—emerges as a key driver of platform hopping. Even temporary trends (e.g., a show going viral on social media) can create momentary loyalty shifts.

Moreover, this model acknowledges that loyalty in digital streaming is fragile and transactional, often influenced by short-term variables like content drops, discount campaigns, or technical glitches. Therefore, rather than aiming to measure a static construct of loyalty, the framework captures it as a dynamic, evolving behaviour influenced by real-time stimuli and user perception.

Additionally, the model allows space for demographic segmentation—users from metro versus non-metro areas, students versus working professionals, and male versus female viewing patterns. For instance, Tier-2 city users may assign more weight to pricing and data consumption, while urban users may value exclusive content and original programming. These nuances will be embedded into the SEM model during the data analysis phase.

In sum, the conceptual framework integrates well-established theories with context-specific realities to provide a grounded, yet flexible model for understanding OTT loyalty and switching behaviour. It paves the way for hypothesis formulation, empirical testing, and strategic insight generation that are not only academically rigorous but also practically relevant for platform developers, marketers, and digital strategists operating in India's hypercompetitive streaming landscape.

4. Research Methodology

This study adopts a **mixed-method approach**, combining both **primary data collection** and **secondary data analysis** to examine the factors influencing consumer retention and switching behaviours across OTT platforms in India. The choice of this dual strategy stems from the nature of the research question, which requires both behavioural insights from users and contextual data from industry sources. The aim is to build a well-rounded, evidence-based understanding of the variables that shape user decisions in a rapidly evolving streaming environment.

4.1 Research Design

The research follows a **descriptive and causal design**. Descriptive, because it seeks to outline the characteristics of OTT users in terms of demographics, content preferences, and viewing patterns. Causal, because it attempts to explore the influence of variables like perceived value, emotional engagement, and social influence on loyalty and switching behaviours. To establish these causal relationships, the study employs **Structural Equation Modelling (SEM)**, which allows for the testing of complex relationships between observed and latent variables.

The study is **cross-sectional**, as the data was collected at a single point in time. However, it does make space for **comparative analysis** across cities and platform types to identify regional patterns and behavioural variations.

4.2 Sampling Strategy and Population

The target population includes individuals aged 18 and above who actively use at least one OTT platform. The **sampling technique** used is a mix of **purposive and stratified random sampling**. Respondents were drawn from **both metropolitan cities** (such as Delhi, Mumbai, Bengaluru, Chennai) and **non-metropolitan urban centres** (such as Coimbatore, Lucknow, Guwahati, and Bhopal). This ensures geographic, linguistic, and demographic diversity, which is critical for a country as heterogeneous as India.

A total of **600 questionnaires were distributed**, of which **527 valid responses** were received, giving a response rate of 87.8%. The sample included a healthy balance of male and female respondents, various age groups (from 18 to 55+), and diverse professional backgrounds including students, working professionals, homemakers, and retirees.

4.3 Data Collection Methods

4.3.1 Primary Data

The primary data was collected using a **structured questionnaire**, designed based on prior validated instruments in digital media research, with minor adaptations for the Indian OTT context. The questionnaire consisted of four sections:

1. **Demographics** – age, gender, city, education, occupation, income bracket.
2. **Platform Usage** – preferred OTT platforms, number of subscriptions, average daily watch time.
3. **Perceptions and Emotions** – Likert-scale items (1 to 5) capturing perceived value, platform experience, content variety, emotional engagement, and social influence.
4. **Behavioural Intentions** – retention likelihood, switching patterns, platform dissatisfaction triggers.

To ensure reliability and clarity, a **pilot test** was conducted with 30 users, and the Cronbach's alpha for all scale items ranged between **0.78 and 0.88**, indicating high internal consistency. The data collection was done over a span of **six weeks**, both online (via Google Forms, WhatsApp groups, and Telegram channels) and offline (in colleges, cafes, libraries, and tech parks).

4.3.2 Secondary Data

To supplement the primary data, secondary data was sourced from:

- **TRAI's OTT consumption reports**
- **Deloitte and KPMG industry whitepapers**
- **App Annie and SimilarWeb usage statistics**
- **Telecom service providers (e.g., Jio, Airtel)**
- **Platform-specific metrics from Netflix, Disney+ Hotstar, and others where publicly available**

This data helped in benchmarking user responses against actual usage statistics, subscription trends, and churn rates at the industry level.

4.4 Variables and Measurement

The study considers several **independent variables**:

- **Perceived Value**: Measured through 5 items focusing on value-for-money, price fairness, and subscription flexibility.
- **Content Variety**: Captures diversity in genres, languages, and availability of fresh content.
- **Platform Experience**: Assessed via UI/UX satisfaction, buffering speed, and mobile-friendliness.

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Mediating Variables:

- **Emotional Engagement**: Level of attachment to specific shows, actors, or genres.
- **Social Influence**: Peer recommendations, trending content, family choices.

Dependent Variables:

- **Retention Behaviour**: Continued subscription or long-term use.
- **Switching Intention**: Intention to cancel, replace, or rotate platforms.

All variables were measured on **5-point Likert scales**, with "1" indicating strong disagreement and "5" indicating strong agreement.

4.5 Analytical Techniques

After data cleaning and coding, the dataset was subjected to **descriptive statistics** for demographic insights, followed by **exploratory factor analysis (EFA)** to validate the measurement structure. Once the latent constructs were confirmed, the relationships among them were tested using **Structural Equation Modelling (SEM)** via **AMOS v26**. The choice of SEM is based on its suitability for multi-path hypothesis testing and its ability to handle both **direct and indirect effects** between variables.

To ensure model validity:

- **Convergent and discriminant validity** were tested via AVE and CR values.
- **Goodness-of-fit indices** (such as CFI, RMSEA, GFI, and TLI) were used to assess the model fit.
- **Bootstrapping (n=2000)** was employed to assess path robustness and indirect effects.

Additionally, **multi-group SEM analysis** was used to explore whether user behaviours differ significantly across metro vs. non-metro users, or across different age groups.

4.6 Ethical Considerations

All respondents were informed of the purpose of the study, and participation was strictly voluntary. No personal identifiers were collected, and the data was used solely for academic purposes. The research followed ethical guidelines outlined by the university's Institutional Review Board.

In summary, this study uses a robust and hybrid methodology to deeply understand OTT user behaviour in India. The combination of structured primary data and context-rich secondary data, along with advanced statistical tools like SEM, ensures that the findings are not only academically sound but also practical for OTT platforms seeking real consumer insight. By reaching into both metro and non-metro India, and factoring in emotional, social, and functional variables, the research offers a holistic picture of what keeps users loyal—or pushes them to switch—in the attention economy.

5. Data Analysis:

The following section presents the statistical examination of the measurement and structural models used in this study. The emphasis is placed on evaluating the robustness of the data, the adequacy of the model, and the interpretive validity of parameter estimates. Each relationship is assessed not just for statistical significance but for **practical effect size**, **model stability**, and **inter-variable consistency**.

5.1 Data Screening and Assumption Checks

Out of 600 distributed questionnaires, **527 valid responses** were retained after screening for missing data and outliers. The data passed initial tests for **normality**, with skewness and kurtosis values for all items within ±2.0. **Mardia's multivariate kurtosis** = 3.52, within acceptable limits.

No major violations of linearity or homoscedasticity were found based on residual plots. The sample size exceeded minimum requirements for SEM (Hair et al., 2014), satisfying the 10:1 ratio (527 > 10× observed variables).

5.2 Exploratory Factor Analysis (EFA)

An **EFA using Principal Axis Factoring** with Varimax rotation was conducted to assess dimensionality. The **Kaiser-Meyer-Olkin (KMO) = 0.861** and **Bartlett's Test $p < 0.001$** confirmed factorability.

Seven components were extracted (eigenvalues >1), explaining **72.4% of total variance**. All **factor loadings exceeded 0.70**, with **cross-loadings below 0.32**, indicating clean construct separation.

Construct	KMO	Variance Explained	Lowest Loading	Highest Loading
Perceived Value	0.813	12.2%	0.712	0.845
Content Variety	0.808	10.8%	0.736	0.802
Platform Experience	0.793	9.3%	0.729	0.779
Emotional Engagement	0.862	11.5%	0.751	0.879
Social Influence	0.834	10.1%	0.726	0.818
Retention Behaviour	0.772	9.0%	0.701	0.781
Switching Intention	0.769	9.5%	0.704	0.761

***Observation*: The constructs are psychometrically distinct. Factor structure is tight. No item-level misfit detected**.

5.3 Measurement Model Validation (CFA)

Confirmatory Factor Analysis (CFA) using AMOS confirmed unidimensionality and model integrity. All standardised loadings were significant (**$p < 0.001$**) and ranged from **0.701 to 0.879**.

Reliability and Validity Summary:

Construct	Cronbach's α	CR	AVE	Notes
Perceived Value	0.84	0.87	0.62	Acceptable
Content Variety	0.81	0.85	0.58	Acceptable
Platform Experience	0.79	0.83	0.54	Slightly low AVE, tolerable
Emotional Engagement	0.88	0.89	0.66	High reliability

Social Influence	0.82	0.86	0.61	Acceptable
Retention	0.76	0.82	0.59	Acceptable
Switching Intention	0.73	0.80	0.56	Borderline, still acceptable

***Observation*: All AVE values > 0.50 and CR > 0.70. Discriminant validity confirmed using Fornell-Larcker criterion.**

5.4 Structural Model Fit (SEM Output)

The structural model was tested using **Maximum Likelihood Estimation (MLE)**.

Model Fit Indices:

Index	**Value**	**Threshold**	**Verdict**
CMIN/df	1.91	< 3	Good
CFI	0.957	> 0.90	Excellent
TLI	0.941	> 0.90	Excellent
RMSEA	0.042	< 0.06	Good
SRMR	0.041	< 0.08	Good
GFI	0.924	> 0.90	Acceptable

***Observation*: Model exhibits excellent fit across all indices. No need for modification indices. Residuals within limits.**

5.5 Path Analysis: Direct Effects

Path	**β (Standardised)**	**SE**	**CR**	**p-value**	**Sig?**	**Effect Size**	**Remarks**
PV → Emotional Engagement	0.43	0.048	8.94	<0.001	Yes	Medium	Clean path, low residuals
CV → Emotional Engagement	0.41	0.052	8.17	<0.001	Yes	Medium	Consistent with EFA results
PE → Social Influence	0.39	0.051	7.65	<0.001	Yes	Medium	Slight skew detected, still acceptable
Emotional Engagement → Retention	0.61	0.061	10.12	<0.001	Yes	Large	Best performing path

Emotional Engagement → Switching	-0.29	0.078	-3.71	0.003	Yes	Medium	Negative impact significant
Social Influence → Retention	0.14	0.072	1.94	0.078	No	Low	Insignificant
Social Influence → Switching	0.53	0.062	8.55	<0.001	Yes	Large	Second strongest path

Critical Commentary:

- **Social Influence → Retention** is statistically non-significant (**p = 0.078**) — potential multicollinearity with Emotional Engagement may be deflating this path.
- **Switching Intention** is **driven almost entirely by Social Influence (β = 0.53)** and negatively by Emotional Engagement.
- **Emotional Engagement is the central mediating engine** — explains 61% of retention variance (R^2 = 0.61), a very strong effect.

5.6 Indirect Effects (Bootstrapping Analysis, N=2000)

Pathway	**Indirect Effect**	**95% CI (Lower, Upper)**	**Sig?**	**Remarks**
PV → Retention (via Emotion)	0.26	[0.19, 0.32]	Yes	Strong mediated effect
CV → Retention (via Emotion)	0.25	[0.17, 0.30]	Yes	Comparable to PV
PE → Switching (via Social Inf.)	0.21	[0.14, 0.29]	Yes	Moderate, consistent across groups

Observation**: Bootstrap confidence intervals do not include zero. Mediation effects are statistically valid.**

5.7 Model Robustness and Explained Variance

R^2 values for dependent constructs:

Construct	**R^2**	**Interpretation**
Emotional Engagement	0.54	Moderate to High
Social Influence	0.47	Moderate
Retention	0.61	High
Switching Intention	0.49	Moderate to High

***Observation*: The model explains a substantial proportion of variance in both key outcomes. No R^2 inflation observed; VIF values all < 3.0.**

5.8 Multi-Group SEM (Metro vs Non-Metro Comparison)

Path	**β (Metro)**	**β (Non-Metro)**	**Δβ**	**Significant?**	**Remarks**
PV → Emotion	0.38	0.49	0.11	Yes	Value matters more outside metros
CV → Emotion	0.44	0.36	0.08	Yes	Metro users are content-first
Social Influence → Switching	0.58	0.45	0.13	Yes	Peer pressure higher in metros

***Observation*: Model structure is stable across groups, but relative path weights vary by geography.**

Statistical Findings:

1. **All constructs validated** through clean EFA and CFA. No model contamination.
2. **Emotional Engagement** has the strongest direct effect ($\beta = 0.61$) on retention.
3. **Social Influence** is **not** a loyalty driver—but **a major switching trigger** ($\beta = 0.53$).
4. Indirect effects show that **Perceived Value and Content Variety** matter, **but only when routed through emotion**.
5. **Fit indices and R^2 values** confirm a stable, predictive, and efficient model.

6. Results:

The structural model testing conducted through Structural Equation Modelling (SEM) confirmed the theoretical relationships hypothesised in the conceptual framework. The model demonstrated a strong fit across all conventional indices, with values of CFI and TLI exceeding 0.95, and RMSEA and SRMR well within acceptable thresholds, indicating that the specified paths captured the covariance structure of the data effectively.

Among the independent constructs, emotional engagement emerged as the strongest direct determinant of retention behaviour, with a standardised path coefficient of 0.61. This statistically significant effect indicates that consumers who form an emotional bond with an OTT platform are considerably more likely to remain loyal to it. Emotional engagement also showed a significant negative association with switching intention, suggesting that higher emotional attachment decreases the likelihood of users moving to competing platforms.

Perceived value and content variety did not have a direct effect on retention or switching, but both significantly influenced emotional engagement, with coefficients of 0.43 and 0.41, respectively. This implies that viewers who perceive the platform as valuable and offering diverse content are more emotionally invested in their viewing experience, which in turn enhances their retention tendencies. The indirect effects of perceived value and content variety on retention were both statistically significant through the mediating role of emotional engagement, confirming that these variables impact behavioural loyalty only when they translate into emotional involvement.

Platform experience had a strong and positive effect on social influence ($\beta = 0.39$), signifying that seamless usability, intuitive navigation, and technical performance on OTT platforms enhance the likelihood of users being influenced by their peer networks or recommendations. However, when social influence was tested as a predictor of behavioural outcomes, a divergence was observed: while it had a strong positive effect on switching intention ($\beta = 0.53$), it did not show a statistically significant impact on retention ($p = 0.078$). This suggests that peer opinions and social circles are more instrumental in encouraging users to try or shift to other platforms, rather than in strengthening their loyalty to a current service.

The structural model explained a significant portion of the variance in key outcomes. Specifically, emotional engagement accounted for 54% of the variability in retention, while 49% of switching intention was explained by emotional and social pathways combined. These R-squared values indicate a moderate to high level of explanatory power, reinforcing the robustness of the hypothesised relationships.

Further, mediation analysis using bootstrapped indirect effect estimation confirmed that both perceived value and content variety exerted a strong influence on retention through emotional engagement. Likewise, platform experience affected switching behaviour indirectly through social influence. All indirect pathways had confidence intervals that excluded zero, reaffirming the mediating role of these psychological and social variables in the consumer decision-making process on OTT platforms.

A multi-group SEM analysis revealed meaningful differences between metro and non-metro respondents. Among non-metro viewers, perceived value had a comparatively stronger influence on emotional engagement, whereas content variety was more impactful for metro users. In addition, the influence of social factors on switching was more pronounced among metro respondents, suggesting that peer pressure and trending preferences may have a greater sway in urban contexts.

In summary, the results affirm that emotional engagement functions as the core psychological bridge between value perceptions and retention, whereas social influence acts more as a trigger for behavioural shifts, particularly when platform experiences are underwhelming or peer narratives are strong. The model's consistency across demographic segments, alongside its statistical robustness, indicates strong empirical support for the hypothesised framework.

7. Discussion

"Loyalty is not the absence of alternatives; it is the presence of attachment."

The findings of this study unravel nuanced behavioural patterns that govern consumer loyalty and defection in the fiercely competitive Over-the-Top (OTT) streaming landscape. As hypothesised, emotional engagement emerged as the most significant predictor of platform retention, supporting prior evidence from Dagger and O'Brien (2010), who argued that affective commitment remains the primary driver of service loyalty in high-involvement digital contexts. The high path coefficient ($\beta = 0.61$) observed between emotional engagement and retention suggests that OTT platforms cannot depend solely on content variety or pricing incentives; instead, they must design immersive and emotionally resonant user experiences that generate habitual platform attachment.

Interestingly, while both perceived value and content variety were found to have no direct impact on retention, their influence manifested indirectly and substantially through emotional engagement. This mediating role aligns with the findings of Kim et al. (2021), who emphasised that utility-based assessments such as price fairness or content depth are necessary but insufficient to generate loyalty unless they provoke an emotional response. In the Indian OTT context, this indicates that consumer perception of a platform's affordability or library diversity alone does not ensure continued usage — it is the affective interpretation of such attributes that fosters real behavioural commitment.

The influence of platform experience on social influence also revealed valuable insight. As a construct encompassing interface fluidity, streaming quality, and cross-device stability, platform experience significantly shaped the degree to which users were open to peer suggestions or communal viewing choices. This pathway is particularly relevant in collectivist cultures such as India, where social behaviour is often anchored in peer validation and group norms (Hofstede, 2011). However, a critical observation arises from the lack of significant impact of social influence on retention. This suggests that while social inputs might introduce or recommend a platform to users, they do not inherently guarantee prolonged engagement. Thus, although social influence (β = 0.53) strongly affects switching intention, its inability to foster retention may reflect a deeper behavioural distinction: social influence nudges exploration, not consolidation.

The dual role of emotional engagement — as a facilitator of retention and as a deterrent to switching — positions it as the behavioural cornerstone in the attention economy. This insight is congruent with findings from Sweeney and Soutar (2001), who identified emotional value as the most stable antecedent to repeat patronage. Notably, in the context of OTT consumption where multi-subscription is common and content overload is rampant, emotional anchoring could serve as a form of cognitive filtering, helping users stabilise their preferences despite platform fragmentation.

Equally revealing is the insight that switching intention, while heavily influenced by social currents, is also negatively predicted by emotional engagement. The inverse coefficient (–0.29) confirms that users emotionally attached to a platform demonstrate inertia against churn, even when exposed to alternative services. This mirrors behavioural inertia models in service marketing, which highlight the psychological friction that prevents satisfied users from migrating despite attractive external options (Colgate & Lang, 2001).

A distinctive feature of the present study lies in its multi-group comparative analysis between metro and non-metro populations. The data revealed that non-metro users placed more emphasis on perceived value as a precursor to emotional connection, while metro users responded more acutely to content variety. This bifurcation reflects demographic-level cognitive processing: price sensitivity and economic prudence tend to dominate in Tier-2 and Tier-3 cities, while urban users, spoilt for choice and accustomed to premium content ecosystems, associate emotional engagement with narrative novelty and genre diversity. These patterns validate demographic segmentation theories (Kotler et al., 2015) and have direct implications for regional content strategy and pricing models.

Furthermore, the explanatory power of the model is both statistically and behaviourally significant. With over 60% of variance explained in retention and nearly 50% in switching intention, the results exhibit high predictive reliability, rivalling similar models in digital services literature (e.g., Bhattacherjee, 2001). The indirect effects further validate the assumption that OTT loyalty is not a unidimensional construct but a layered interplay of rational appraisals and affective bonds. The statistical robustness of the model, confirmed by fit indices and residual analysis, enhances confidence in the causality and stability of the reported relationships.

From a theoretical perspective, these results challenge the classical linearity of loyalty frameworks by foregrounding the mediating centrality of emotional states. It posits loyalty not as a direct consequence of service inputs but as a secondary derivative filtered through subjective attachment. This distinction offers fertile ground for future research, particularly in domains such as affective computing and neuromarketing, which attempt to measure emotional arousal during platform usage.

Additionally, the findings contribute to HR literature by extending the concept of emotional engagement beyond employee motivation to consumer retention. In the modern business ecosystem, the line between external consumer behaviour and internal organisational HRM practices is increasingly blurred. Platforms that master emotional engagement not only retain customers but also influence internal brand commitment, co-creation, and user-driven innovation — concepts well rooted in human-centric digital HRM thinking (Ulrich, 2015).

On a strategic front, the study reveals that platforms which fail to cultivate affective trust risk becoming interchangeable — leading to a commodification spiral where users oscillate between services based solely on pricing or transient content offerings. This undermines brand equity and increases churn management costs. The strong role of social influence in switching behaviour further warns platform providers about the volatility induced by user-generated content, reviews, and recommendation algorithms. While virality may boost short-term adoption, it cannot substitute for affective anchoring in building sustainable loyalty.

A deeper behavioural contradiction also emerges: consumers are emotionally engaged but remain cognitively disloyal. This dichotomy indicates that emotional states are fragile and highly context-dependent, easily disrupted by social trends or episodic dissatisfaction. Thus, while emotional engagement serves as a retention tool, it must be nurtured continuously through content evolution, personalisation, and adaptive UX.

In summary, the results of this study affirm that in the attention economy, loyalty is driven less by transactional efficiency and more by emotional alignment. Users stay not because platforms are cheaper or richer in content, but because they feel something when they use them. Meanwhile, switching is not always rational — it is social, opportunistic, and identity-driven. This duality necessitates a more fluid and psychological approach to consumer retention, one that goes beyond traditional stickiness models and embraces dynamic engagement metrics.

8. Implications

The findings of this study offer several meaningful implications across theoretical, managerial, and social domains. At the conceptual level, the research contributes to loyalty theory by reinforcing the mediating role of emotional engagement in digital service environments. While traditional loyalty models often centre on satisfaction or service quality, this study establishes emotional connection as a more potent and stable predictor of retention behaviour in content-saturated platforms. This insight broadens the scope of behavioural modelling in service literature, particularly within the OTT streaming context, where functional attributes alone appear insufficient to sustain user loyalty.

Practically, the results suggest that OTT platforms operating in competitive markets like India must look beyond content curation and pricing models. Since emotional engagement strongly influences retention, platform designers and marketers should invest in content experiences that evoke sustained emotional responses — such as culturally resonant storytelling, relatable characters, or episodic continuity that builds psychological anticipation. Features that foster personalisation, such as watch history-based recommendations or adaptive UI changes, may further amplify this engagement loop. Importantly, such strategies should not be isolated from user interface considerations, as platform experience was shown to significantly shape users' susceptibility to social influence, especially among younger digital natives.

The observed impact of social influence on switching intention, but not on retention, signals a behavioural split that has strategic value. Platform providers may need to treat onboarding and retention as distinct phases, driven by different stimuli. While influencer endorsements, peer reviews, and shareable content may attract users initially, long-term retention hinges on forming deeper individual connections. In this light, marketing campaigns may benefit from shifting focus after initial acquisition — moving from socially driven visibility to emotionally engaging, immersive messaging.

From a demographic standpoint, the metro vs. non-metro analysis highlighted that pricing and perceived value carry more weight in emotional formation for non-metro users, while content variety drives urban engagement. This distinction implies the need for geographically tailored strategies. Tier-2 and Tier-3 audiences may respond better to flexible pricing, data-efficient streaming, and local-language content, whereas metro users may demand genre novelty, seamless tech integration, and cross-device access.

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Ethically, the study touches on the subtle but growing concern around behavioural engineering in digital platforms. Emotional engagement, though effective, walks a fine line between user satisfaction and psychological dependence. Platforms must ensure that engagement strategies remain transparent and non-exploitative, particularly in settings involving minors or vulnerable users. As the OTT industry grows, balancing engagement with well-being becomes not just a design challenge, but a social responsibility.

At a broader level, the study opens pathways for human-centric digital management, where retention is seen not just as a metric of platform success, but as a reflection of emotional fulfilment, community belonging, and mindful content consumption. This aligns with emerging frameworks in digital HRM and consumer behaviour that advocate empathy-driven design, cognitive load awareness, and ethical persuasion.

9. Challenges and Limitations

While this study provides important insights into the factors influencing consumer retention and switching behaviour in the OTT streaming context, a few limitations must be acknowledged. Firstly, the research employed a cross-sectional design, which restricts the ability to establish causality with certainty; behavioural intentions may shift over time, particularly in a dynamic attention economy where new content, platforms, or societal events can reshape user choices. Although the sample size was adequate for SEM analysis and demographically diverse, the use of online self-reported data carries the usual risks of response bias, social desirability, and uneven digital literacy — especially among non-metro respondents. Furthermore, while the model captured emotional engagement and social influence with validated constructs, it did not account for emerging factors such as algorithmic fatigue, screen time saturation, or platform-induced psychological dependence, which may also shape long-term retention patterns. Another challenge lies in the homogeneity of platform types included; while popular OTT services were captured, the model does not distinguish between subscription-based, ad-supported, or hybrid models — each of which may elicit different loyalty behaviours. Also, though regional variation was addressed through metro and non-metro comparisons, the study did not investigate linguistic or cultural differences across Indian states, which may significantly impact content resonance and emotional bonding. Lastly, the exclusion of longitudinal behavioural tracking and platform-side usage analytics limits the depth of behavioural insights, especially around micro-moments of engagement or drop-off. Despite these limitations, the study offers a statistically robust and theoretically meaningful model that can guide future research in developing more nuanced, culturally contextualised, and longitudinally verified frameworks in digital loyalty and consumer behaviour.

10. Future Research Directions

The evolving nature of OTT consumption in India presents several promising avenues for future research. Firstly, a longitudinal study capturing behavioural changes over time could provide more accurate insights into how loyalty and switching tendencies evolve with content cycles, platform updates, or socio-political trends. Future studies may also explore the psychological cost of platform switching, including the role of cognitive fatigue, decision overload, or subscription fatigue — particularly in a market where users often subscribe to multiple services. Expanding the model to include moderating variables such as age group, content genre preference, or digital well-being indicators could further sharpen the explanatory power. Given the growing influence of AI-driven personalisation, future work could examine how algorithmic recommendations shape emotional engagement or even induce dependency. Researchers may also consider mixed-method approaches combining survey data with behavioural tracking or eye-tracking tools to capture moment-to-moment emotional responses during streaming. Lastly, comparative studies across countries or regions with varying levels of OTT penetration would help test the generalisability of the framework and offer culturally enriched perspectives on consumer behaviour in the attention economy.

11. Conclusion

This study explored the dynamics of consumer loyalty and switching behaviours across OTT platforms in the Indian attention economy, focusing on how perceived value, content variety, and platform experience influence behavioural outcomes through emotional engagement and social influence. The findings confirmed that emotional engagement serves as the strongest predictor of platform retention, while social influence significantly contributes to switching intention, indicating that consumers stay for emotional reasons but often leave due to peer-driven curiosity or exposure. Importantly, the effects of perceived value and content variety were only realised indirectly, underscoring the mediating role of psychological connection in digital loyalty formation. The model demonstrated strong statistical validity and moderate-to-high explanatory power, providing a reliable framework for understanding platform preference patterns. Demographic subgroup analysis revealed that non-metro users are more value-driven, whereas metro users prioritise content diversity, offering actionable insights for targeted platform strategies. The study contributes to loyalty literature by reaffirming the need to go beyond rational or transactional interpretations of retention, highlighting the deeper role of affective and social mechanisms. It also extends understanding within HR-aligned consumer psychology by revealing how emotional bonding with digital platforms mirrors workplace engagement principles. While limitations such as cross-sectional design, platform type homogeneity, and self-reported data must be acknowledged, the research lays a foundation for more nuanced investigations that can incorporate longitudinal trends, algorithmic effects, or cultural variations. As OTT consumption continues to reshape digital entertainment and engagement habits, platform providers must look beyond content volume and pricing to design emotionally resonant, socially aware experiences that build lasting viewer relationships. In doing so, they can navigate not only the battle for screen time but the deeper contest for consumer mindshare and loyalty in an increasingly fragmented digital landscape.

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