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Assessing User Behaviour Toward Annual Subscription Purchases: A Netflix Case Study

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ABSTRACT

Purpose: This study aims to develop and validate a model to understand the factors influencing users' decisions to subscribe annually to over-the-top (OTT) platforms like Netflix, which stream content via internet-connected devices ***Design/methodology/approach:*** A total of 526 respondents participated in the study. The population targeted consisted of active Netflix subscribers in India, as the research aimed to investigate behavioural patterns specific to users of this streaming platform. Employing a quantitative approach, the research collected data through structured questionnaires and used structural equation modelling with Smart PLS to test the theoretical model. ***Findings***: The findings reveal that perceived value, attitude, image, price, quality, and risk significantly impact subscription decisions. Particularly in price-sensitive markets like India, the effect of price on perceived value is expected. However, the study also uncovers that risk perceptions, including concerns about data security and refund policies, significantly affect perceived value. This research merges the Consumer Perception Factor Model with the Consumer Perceived Risk Model to create a novel framework tailored for Indian consumers' subscription behaviour towards Netflix. Validating this integrated model using Smart PLS enhances its relevance. By focusing on Netflix, the study re-evaluates the roles of attitude, image, price, and risk in shaping value perceptions and subscription intentions in the Indian context. ***Research limitations/implications***: The study sample is dominated by age group of 22- 35. This puts constraint on the generalization to a broader population. The questionnaire was not having a vernacular equivalent. This puts additional constraint on generalization. ***Practical implications***: This study serves as a guide for business practitioners facing decisions on prioritizing parameters. In emerging markets like India, focusing on price and risk factors is crucial. Marketers should optimize pricing strategies and ensure high-quality offerings to boost perceived value and drive subscriptions. While customer attitude significantly affects purchase intention, the negative impact of perceived image requires a nuanced brand management approach. Marketers can use this framework to craft strategies that balance positive perceptions and address perceived risks. For instance, highlighting product quality and offering risk-reduction measures, such as easy returns, can enhance consumer confidence and purchase intentions. ***Originality/value:*** This study makes a novel contribution to consumer behaviour research by integrating the Consumer Perception Factor Model with the Consumer Perceived Risk Model, addressing a key gap in the literature. Unlike prior studies that treat perception and risk separately, this unified framework reveals how perceived product attributes and risks dynamically interact to shape consumer attitudes and purchase intentions. The integration provides a more holistic understanding of decision-making, showing how positive perceptions can lower risk perceptions, and vice versa. This enriched perspective enables marketers to develop more precise strategies, aligning product positioning with consumer expectations in risk-sensitive purchasing contexts.

Keywords: Consumer Perception; Perceived Attitude; Perceived Risk; Perceived Value; Netflix Buying subscription.

INTRODUCTION

The audio-visual industry has undergone a revolution because of technological advancements on the Internet, which have altered how viewers may now access and enjoy new films and television series. The main reason for this shift is the introduction of streaming technology, a service that facilitates online multimedia content distribution. According to Dall 'Orto and Silva (2017), streaming is a dynamic technology that can be used for both receiving and transmitting content via the Internet, and its use in the entertainment industry is rapidly expanding. An increasing number of individuals are utilizing this technology on a daily basis to access a vast array of real-time content. (Lima 2015) claims that streaming enables consumers to purchase internet services and see films and TV series at their convenience.

Streaming media services such as Spotify, iTunes and Pandora etc. for music, and YouTube, Netflix, Amazon Prime Instant Video, HULU, and HBO etc. for video have witnessed large scale adoption in recent years. While previous research (e.g., Saccomori, 2015; Wayne, 2021; Yao, 2023) has largely focused on the strategic and operational dimensions of OTT platforms, limited attention has been given to understanding the consumer behaviour driving subscription decisions. To address this gap, the objective of this study is to investigate the behavioural factors influencing user willingness to purchase Netflix subscriptions in India, with particular emphasis on perceived value, pricing sensitivity, and content preferences. A variety of screen sizes, , including tablets, smartphones, laptops, desktop PCs, and televisions, can access streaming services. As streaming technology continues to grow globally, it is gradually replacing traditional media such as television, radio, and cinema (Yao, 2023). The long-term success of these platforms depends largely on their ability to attract and retain paying subscribers. This prompts a key question based on research objective : What influences a consumer's decision to subscribe, content appeal alone, or do factors such as pricing also matter, particularly in emerging markets like India? (RQ1).

With over 200 million subscribers in 190 countries, Netflix is the biggest subscription video-on-demand service worldwide. However, fame has become a little ethereal in the age of streaming television. (Wayne, 2021). Netflix is global - roughly 60% of Netflix's members are outside US and a significant minority do not consume content in English at all. Netflix is localized in 22 languages and that list is growing. Though English is the top language for users on Netflix Search, less than 59% of users use it for searching (Lamkhede and Das 2019).

As digital media gains greater acceptance across industries, the use of streaming services continues to rise. In this context, the objective of this study is to analyse end-user behaviour toward purchasing Netflix's annual subscription plan in India and to develop actionable suggestions for increasing subscription uptake in emerging markets. Specifically, the study seeks to address Research Question 2 (RQ2): What are the key factors influencing consumer behaviour toward Netflix subscriptions in emerging markets like India?

OTT Platforms: OTT platforms use the internet to distribute audio and video content instead of traditional cable or satellite methods. Their interoperability with a wide range of devices, extensive content collection, and on-demand access are what define them. Due to the continuous digitization process and the increasing usage of broadband internet technology, there is a huge increase in the availability of moving audio-visual material for clients to view (Budzinski et al., 2020). Due to the disruption of traditional media and broadcasting by OTT platforms, consumer watching patterns have changed and cord-cutting has increased. Research indicates that user happiness and subscription selections are influenced by personalised suggestions and a variety of content. The author of the study conducted a rigorous analysis and found that consuming any kind of information entails behaviour that eventually turns into a habit. Indians have traditionally had a taste for a wide variety of media. A modest number of channels on a typical household television limited the inventiveness of young India. OTT providers exploited and capitalised on this creativity (Nijhawan and Dahiya, 2023). Netflix is a provider of movie streaming services that allow consumers to rent films online for a predetermined monthly fee. OTT (Over-the-Top) technology is utilised by Netflix, the most widely used subscription-based Internet television network globally, to provide well designed on-demand streaming video services (Pereira, 2015). In the first two quarters of 2023, Netflix brought in $16.349 billion in revenue (Shewale ,2023). As of Q2 2023, Netflix had 238.39 million global subscribers and had launched 891 original projects, generating $31.61 billion in revenue and $4.49 billion in net profit (Shewale, 2023).

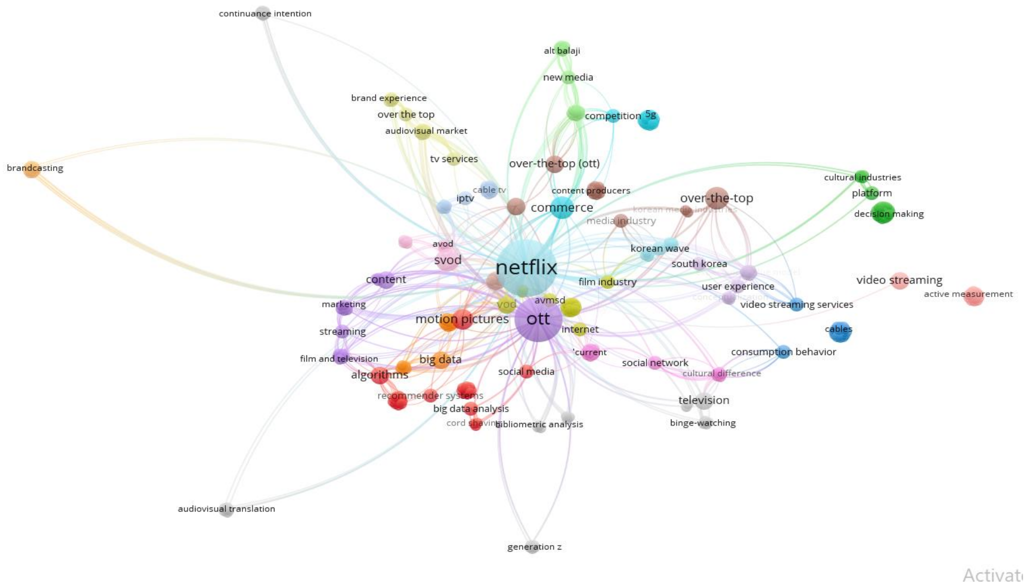
By focusing on consumer behaviour toward annual subscription decisions in the Indian market, this study contributes to the broader understanding of streaming media adoption in emerging economies and offers strategic insights to enhance Netflix's market penetration and consumer retention in these regions.

REVIEW OF LITERATURE FOR RESEARCH PAPER ON NETFLIX

Total 41 papers published on Netflix OTT platform between 2020-2023 using keywords - Customer preference, OTT Platform, Online Streaming, Factors, Customer Perception, Amazon, Netflix.

There is total 34 clusters of key words with a minimum strength of 3 networks observed totalling 334 words. The focus of the papers was Netflix and OTT platform exploring the various aspects of the same from different perspective. (figure I)

Fig.1: Network analysis based on the key words used in Title and abstract

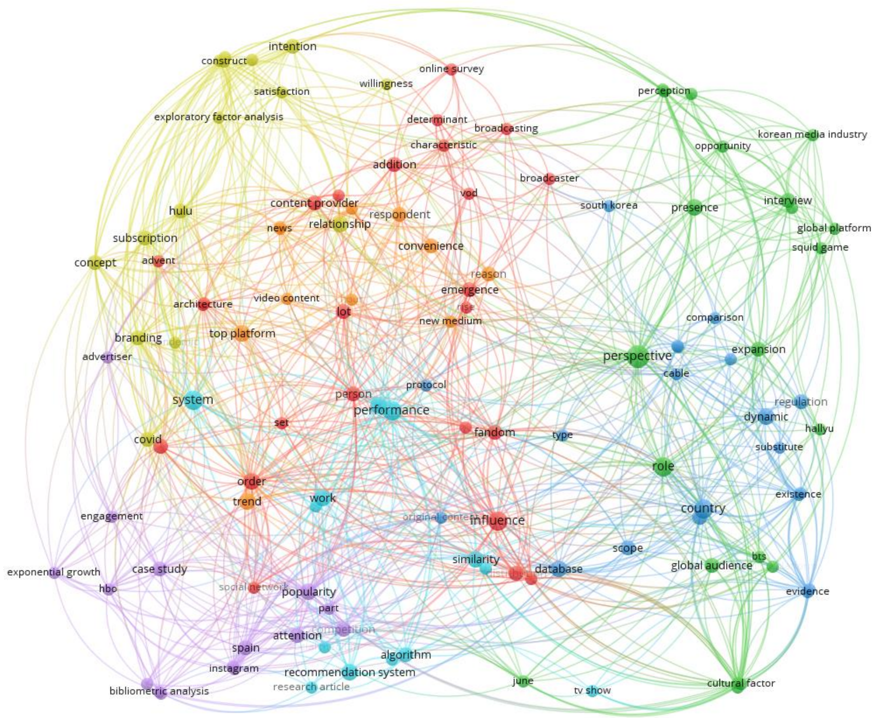


The next section relates to network analysis based on words.

Network analysis based on the words used in Title and abstract

The binary method of word count used to identify the network of key words in title and abstracts. There were 1330 items but with a threshold of minimum occurrence of 10 could get only 7 items in the papers published related to the Netflix and OTT platform. It showed 29 items with minimum occurrence of 5, whereas when it reduced to minimum of 2 occurrences then the items reached to 200 numbers. The same was observed 91 for minimum 3 occurrences. The network analysis of 200 items is as under with 5 major clusters focussing on **-** conveniences, production, popularity, global culture, country specific words in the abstract and titles of the papers. (figure II)

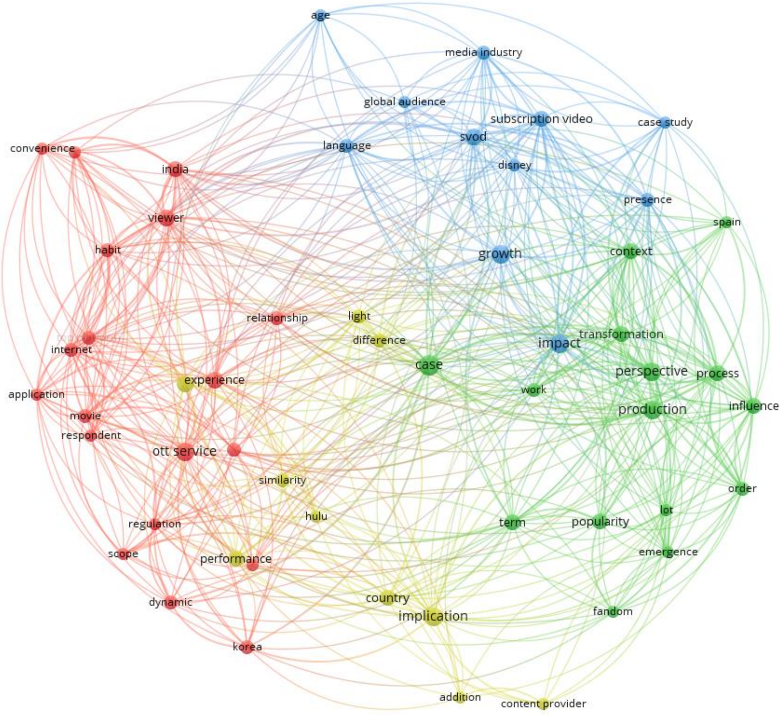
Figure II - Network analysis based on the words used in Title and abstract



The network analysis with 91 items is as under with the relevance score above 60% resulting in only 55 items**-**

In this, we can find out three main clusters with two minor clusters. The focus area for words used in abstracts was case analysis with OTT platform, application, influence, perspective, popularity, context, etc. with occurrences frequency above 5. Other words were used but the frequency was less than 5 times. (Figure. III)

Figure III: Network analysis based on the words with less frequency



To date, research on OTT platforms has been largely conducted by independent authors without a network of collaborators. As OTT platforms are relatively new, researchers are investigating consumer experiences and behaviours using available data. Keywords used in the search for relevant studies included Customer Preference, Subscription OTT Platform, Online Streaming, Factors, Customer Perception, Amazon, and Netflix. A notable research gap is the lack of studies from an Indian perspective on OTT platform subscriptions. This paper aims to address this gap by focusing on the Indian market.

Indian Television Media

Indian television industry was valued at approximately $12 billion in 2022. Projections suggest that it will continue to grow at a robust pace, with estimates suggesting the market could reach around $15 billion by 2025(Broad cast Audience Research Council of India (2024).Top of Form

Bottom of Form

Therefore, India is unquestionably a fascinating place to do study on the production, usage, and distribution of televisual goods (Srivastava,2022).

Consumer Buying Behaviour

Comprehending the audience, is essential for achieving success in the initial marketing process. In one study, Tanuwijaya et al., (2021) highlighted the use of machine learning to profile and predict potential customers for Netflix, enhancing marketing efforts. Another study by Alan et al. (2020) demonstrated that Netflix's popularity is noticeable in Brazil and Portugal, with varying customer demographics and viewing habits in both countries. One of the main factors influencing customer behaviour is human psychology. Although this factor is complex to measure, nevertheless its plays a very important and powerful role in consumer buying decisions. Wilda et al. (2022) discovered that visual merchandising, celebrity endorsers, advertising creativity, and e-service quality positively impact Netflix app purchases. Social factors like family, friends, reference groups also equally influence the buying decision other than human psychology. Annisa et al. ,(2021) show that engagement with Netflix is influenced by Instagram content, exclusivity, motivation, and willingness to subscribe among millennials, with Perceived Price having a negative impact. Around the world, OTT platforms have grown at a remarkable pace. The rise and appeal of these platform is exclusively due to the capacity to provide unique, high-quality material that greatly surpasses the calibre and variety of traditional television viewing experiences (Singh et al., 2021). Kavitha (2021) suggested that quality content and accessibility are key factors influencing users to subscribe to OTT platforms, with Netflix as the most preferred platform and comedy as the preferred genre. Finally, Samala et al. (2021) identified various reasons for subscribing and not subscribing to OTT services and reveal that content, convenience, features, price, and quality play essential roles in subscription decisions, influenced by demographic factors like age, occupation, and education.

Research on OTT platforms reveal several gaps. Tanuwijaya et al. (2021) highlighted the use of machine learning for customer profiling, but its effectiveness across different regions and cultures remains underexplored. Alan et al. (2020) noted regional differences in Netflix's popularity in Brazil and Portugal, with a lack of similar studies in emerging markets like India. Wilda et al. (2022) examined factors like visual merchandising and celebrity endorsements but more research is needed on how human psychology impacts subscription decisions. Social influences, Instagram content's role, and variations in content quality and accessibility across platforms also warrant further investigation.

Theoretical Foundation

This research draws upon and integrates two established theoretical models, the Consumer Perception Factor Model and the Consumer Perceived Risk Model, to develop a novel framework that explains consumer subscription behaviour in the context of digital streaming services, with a specific focus on Netflix in the Indian market. The Consumer Perception Factor Model examines how individuals cognitively and emotionally evaluates key product attributes. These include perceived value, which reflects a customer's overall assessment of utility based on what is received versus what is given (Zeithaml, 1988); perceived quality, which captures the user's judgement about the excellence or superiority of the service (Hafifi & Mohd, 2016); perceived price, referring to the consumer's assessment of pricing fairness and affordability (Asyraf, 2023); and perceived brand image and attitude, which denote the mental picture and emotional response associated with the brand (Ginanjar et al., 2019). Positive perceptions of these elements are known to foster favourable attitudes and stronger purchase or subscription intentions, an insight particularly pertinent to intangible, experience-driven services like Netflix.

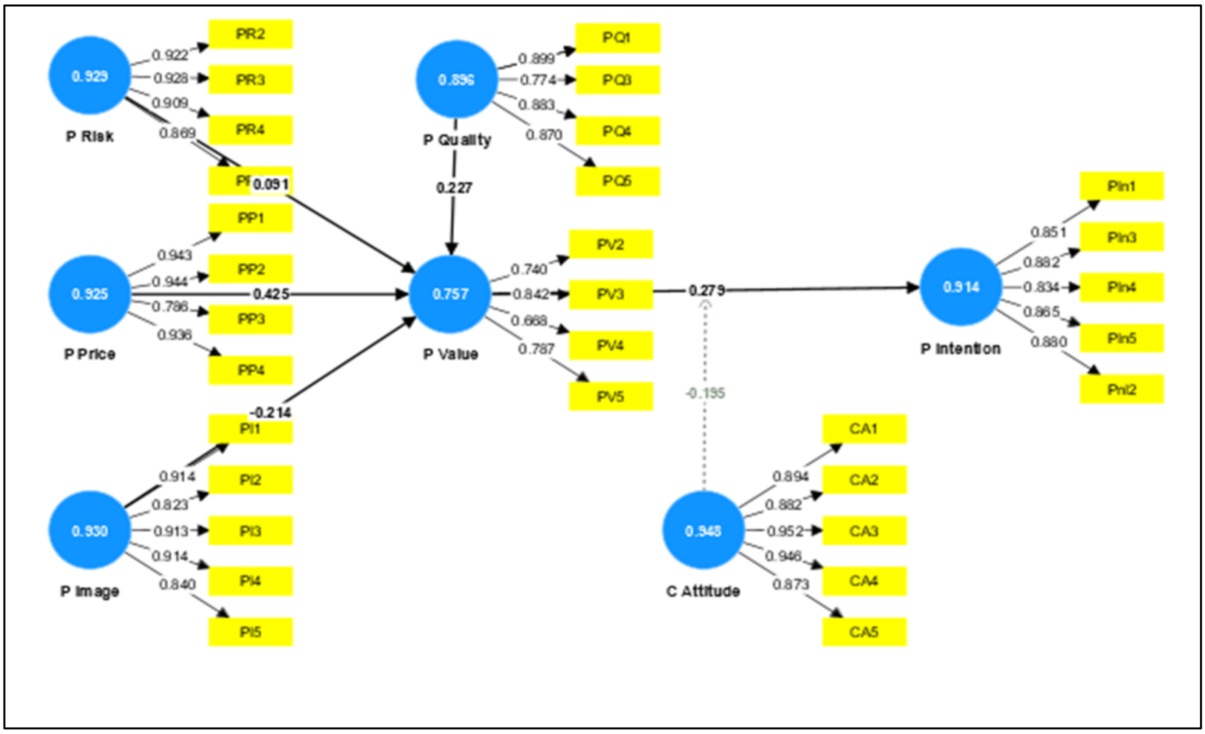
In contrast, the Consumer Perceived Risk Model addresses the various uncertainties and negative expectations associated with the consumption decision. It encompasses dimensions such as performance risk (whether the service will meet expectations), financial risk (concern over value for money), time risk (the opportunity cost of content consumption), and social risk (perceived judgement from peers) (Jacoby & Kaplan, 1972; Cunningham, 1967). These risks are especially influential in emerging markets like India, where cautious spending behaviour and value sensitivity are prevalent. Often, even when product perceptions are positive, high perceived risk can undermine purchase intentions. Thus, by merging both models, this research provides a more holistic and interactive framework. It not only highlights how favourable perceptions can reduce risk perceptions but also how elevated risks may dampen the impact of positive attributes, offering a deeper understanding of subscription behaviour in digital streaming contexts.

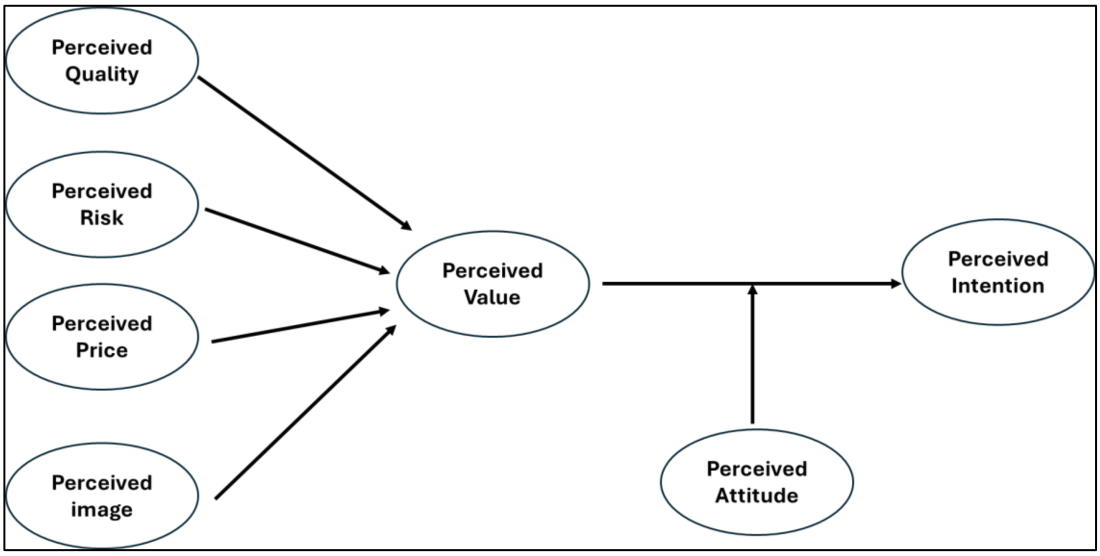
Developing A Theoretical Frame Work And Hypotheses

A framework for analysing the complex elements influencing customers' perceptions and assessments of goods, services, or brands is the Consumer Perception Factor Model, which is applied in marketing and consumer behaviour research. Product attributes, brand image, pricing, quality, cultural influences, advertising, reviews, personal experiences, emotional reactions, environmental factors, and competitive positioning are just a few of the elements it takes into account. These factors all work together to shape consumers' perceptions and affect their decision-making processes.

Conceptual Framework: The proposed conceptual framework has been developed from the Consumer Perception's Factors Model originated by Jaafar et al. (2012) and the conceptual model adapted from Sweeney et al. (1999) by integration both the model as given in Fig-IV

Figure V: Structural Equation Model with P value





The model developed by Jaafar et al. (2012) categorised factors into three major categories naming Intrinsic, Extrinsic and Consumers' Attitude. The conceptual model proposed by Sweeney et al. (1999) demonstrates the relationship between all the factors and perceived product value and assumed that it will eventually influence purchase intension to buy the product.

- **Perceived Attitude:** Individuals' subjective judgements of items are impacted by their previous behaviours, emotional responses, intentions for future actions, and cognitive assessments. Attitudes are the foundation for assessing certain items based on prior experiences, which in turn impact people's thoughts, emotions, and behaviours both now and in the future. (Ginanjar et al. 2019)
- **Perceived Image:** Perceived image refers to how customers see and understand a brand in light of their affinities and past experiences. Key elements that impact perceived image view include Brand Identity (physical qualities), Brand Personality (character and values), Brand Behaviour (communication and interactions), Brand Association (consistent associations), and Brand Competence (ability to satisfy requirements and wants) as per study of Ginanjar et al., (2019)
- **Perceived Price:** Although using a perceived value pricing strategy might be a little arbitrary, it can help a lot with product marketing as it aligns product pricing with what potential customers believe the product is worth. (Hafifi, Mohd 2016; Asyraf 2023).

- **Perceived Quality:** The term "perceived quality" refers to a customer's assessment of a product or service's overall quality or superiority over alternatives in relation to its intended purpose(Hafifi,2016;Srivastava,2022).
- **Perceived Risk:** The degree of doubt a customer has about whether the transaction they are making will be worthwhile (Nasiketha 2023).
- **Perceived Value:** The perceived value that a consumer places on a good or service(Srivastava,2022).

Developing Hypotheses

Attitude has long been considered a primary predictor of behavioural intention, as evidenced in models such as the Theory of Planned Behaviour (Ajzen, 1991) and the Theory of Reasoned Action (Fishbein & Ajzen, 1975). In the OTT context, a favourable attitude towards streaming platforms increases the likelihood of subscribing, as consumers rely on affective and cognitive evaluations (Chakraborty et al., 2023). Attitude integrates prior experiences, expectations, and satisfaction, making it a key driver in intention formation. Thus, we hypothesize:

H1: Subscription Purchase Intention is Influenced by Customer Attitude

Brand or platform image significantly contributes to the perceived value consumers associate with a service. A strong image creates expectations of reliability, entertainment quality, and technological competence, leading to enhanced value perception (Keller, 2003). In OTT markets, perceived image not only affects trust but also reduces ambiguity and perceived risk (Nasiketha, 2023). As image is an abstract representation of brand identity and consumer beliefs, its impact on perceived value is well-supported:

H2: Perceived Image Will Affect Perceived Value

The concept of value-for-money is especially critical in emerging markets such as India, where consumers are highly price-sensitive (Srivastava, 2023). According to Zeithaml (1988), perceived value arises from a trade-off between what is received and what is given (cost). While price may negatively influence perceived value (Annisa et al., 2021), consumers still consider price along with benefits when making a subscription decision. This dual role of price—as a cost and a value indicator, necessitates this hypothesis:

H3: Subscription Purchase Intention is Influenced by Perceived Value and Price

Perceived quality, defined as the consumer's judgment about a service's excellence (Parasuraman et al., 1988), is a crucial component of perceived value. In OTT services, quality can reflect video resolution, content exclusivity, and streaming speed. Higher perceived value often correlates with higher perceived quality, which then drives the intention to subscribe (Chakraborty et al., 2023; Zeithaml, 1988). Therefore, we propose:

H4: Perceived Quality, Influenced by Perceived Value, Affects Subscription Purchase Intention

Perceived risk refers to the uncertainty regarding outcomes of a service and the potential negative consequences of a decision (Bauer, 1960). In digital platforms, this includes data privacy, service reliability, and content relevance. Risk perception can diminish perceived value and deter purchase decisions (Nasiketha, 2023). Theoretical and empirical studies confirm that perceived risk inversely impacts perceived value and thereby behavioural intentions:

H5: Perceived Risk Will Affect Perceived Value and Thus Affect Purchase Intentions

The central role of perceived value in consumer decision-making is well established across sectors, including digital streaming. Zeithaml (1988) conceptualized perceived value as the overall consumer assessment of utility based on what is received versus what is given. In OTT services, value arises from diverse factors like content quality, interface, pricing, and convenience, which together shape subscription intentions (Chakraborty et al., 2023). Hence:

H6: Perceived Value Influences Subscription Purchase Intention

METHODOLOGY:

Research Design: The study adopted a quantitative research methodology, utilizing both primary and secondary data-gathering techniques. Data was primarily collected through structured questionnaires administered to Netflix users, enabling the mapping of their behaviour toward the platform. The collected responses were then analysed using structural equation modelling (SEM), a robust statistical technique that assesses complex relationships between multiple variables. For this analysis, the research employed Smart PLS (Partial Least Squares), a widely-used software tool recognized for its ability to handle sophisticated models incorporating both reflective and formative constructs. The primary objective of applying SEM was to rigorously test the theoretical model and assess the strength and direction of the relationships among key factors influencing users' decisions to subscribe to Netflix. The study was conducted in India during October-November 2023, providing insights into Netflix user behaviour in this specific context.

Sample Design:

A total of 526 respondents participated in the study. The population targeted consisted of active Netflix subscribers in India, as the research aimed to investigate behavioural patterns specific to users of this streaming platform. The sample frame comprised individuals who were verified Netflix users and accessible through online survey platforms and targeted digital outreach.

To ensure adequate representation and relevance, the study employed a random sampling method to promote diversity and reduce selection bias. This approach aligned with the study’s objective to explore usage behaviour, preferences, and perceptions among Netflix users, enabling meaningful insights from a clearly defined and active user base. The sample comprised 54 percent male and 46 percent female participants, reflecting a relatively balanced gender distribution.

In terms of age, the sample was dominated by respondents aged 22–35, with 68 percent falling within the 22–28 group and an additional 7 percent in the 29–35 category. This emphasis on young adults is justified, as this demographic constitutes the most active and engaged segment of Netflix's subscriber base in India. Their high digital literacy, content consumption frequency, and openness to streaming innovations make them particularly relevant for examining behavioural trends and platform preferences. Additionally, 21 percent of the sample came from the 15–21 age group, capturing insights from the emerging Gen Z cohort.

Although the sample is concentrated within the 22–35 age group, this does not constrain the generalisability of the findings. Rather, it enhances the study’s validity by focusing on the demographic segment most representative of current and future market behaviours on digital streaming platforms. The inclusion of younger users and the use of random sampling further support the robustness and applicability of the findings across similar consumer contexts.

Regarding employment status, 59 percent of participants were employed, suggesting that a majority of the respondents were financially independent and likely to have more discretionary income for streaming services like Netflix. A significant portion of the sample, 37 percent, were students, highlighting the study's relevance to individuals who may be more price-sensitive and likely to seek out affordable entertainment options.

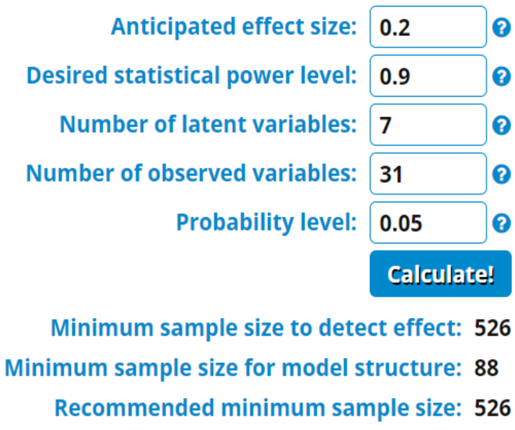
To ensure the statistical rigor of the analysis, the study employed specific power analysis parameters: an effect size of 0.3, a statistical power of 0.9, and a probability level (alpha) of 0.05. Additionally, the model being tested included 2 latent variables and 12 observable variables. According to these criteria, the minimum required sample size was calculated to be 200 respondents. Since the study involved 526 respondents, the sample size was well above the minimum required, ensuring the reliability and generalizability of the results. This aligns with the guidelines provided by Hair et al. (2010), which confirm that the sample size is sufficient for the proposed statistical analyses. Table -1 gives the sample profile of Netflix users

Table1: Sample Profile(N=526)

Variable	Values	Count	Percentage
Gender	Male	238	45%
	Female	288	55%
Income	Less than Rs0.3milion(85Rs=1$)	3	0%
	Rs. 0.3-0.8 lakh(85Rs=1$)	339	65%
	More than Rs. 0.8 lakh(85Rs=1$)	184	35%
Occupation	Employee	190	36%
	Business	133	25%
	Student	117	22%
	Housewife/no job	86	16%
Age(Years)	22-26	226	43%
	29-35	157	30%
	36-39	110	21%
	more than 40	33	6%

A systematic questionnaire has been used to gather data from 526 respondents. (At 0.3 effect size, 0.9 statistical power, 2 latent variables, 12 observable variables, and 0.05 probability level, the minimum necessary sample size is 200). The current study has employed non-probability purposive sampling. The study made use of both primary and secondary data-gathering methodologies. SMART PLS is the analysis tool, while the structural equation model is the approach employed in this work. The mentioned tool is used in this research work due to distribution issues in data as lack of normality. Calculation for Sample size by Daniel Soper tool as under:

a



Questionnaire design:

A systematic questionnaire was used to gather data from 489 respondents. Perceived value was measured based on the study by Zeithaml (1988), perceived attitude was measured according to Ginanjar et al. (2019), perceived image was assessed following Ginanjar et al. (2019), perceived price was evaluated based on Asyraf (2023), perceived quality was measured according to Hafifi (2016), and perceived risk was evaluated based on Nasiketha et al 2023). Reliability tests revealed that Cronbach's alpha, based on standardized items, was 0.833, with a Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy of 0.836.

The questionnaire was administered in English without a vernacular equivalent. This decision was based on the assumption that Netflix users in India are generally well-educated and digitally literate, with sufficient proficiency in English to comprehend and respond accurately to the questions. Since the study's objective was to analyse consumer behaviour, preferences, and perceptions among Netflix users, who typically fall within urban, educated, and tech-savvy segments, vernacular translations were deemed unnecessary.

Although the absence of vernacular versions could limit generalizability to non-English-speaking populations, the selected sample adequately represents the primary user base of Netflix in India. Therefore, this does not significantly constrain the findings' applicability. Regarding the reliability and validity of the measures, Table 2 provides further insights: the average variance extracted (AVE) is above 0.7, and the discriminant validity meets the accepted standards, ensuring robust construct measurement.

Table 2 – Construct Reliability and Validity

Construct reliability and validity - Overview

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
C Attitude	0.948	0.961	0.960	0.828
P Image	0.930	0.970	0.946	0.777
P Intention	0.914	0.916	0.936	0.744
P Price	0.925	0.942	0.947	0.819
P Quality	0.896	0.910	0.923	0.705
P Risk	0.929	0.954	0.949	0.823
P Value	0.757	0.764	0.846	0.581

The initial analysis indicates strong construct reliability and convergent validity. All constructs exhibit Cronbach's alpha and composite reliability (ρA and ρC) values greater than 0.70, and Average Variance Extracted (AVE) values above the commonly accepted threshold of 0.50. These results confirm that each construct reliably measures its intended concept.

Furthermore, all constructs demonstrate strong positive inter-correlations (above 0.75), indicating substantial associations among the key dimensions in the study, likely related to consumer perception and decision-making.

To assess discriminant validity, the Fornell-Larcker Criterion was applied. The square root of the AVE for each construct was found to be higher than its correlations with other constructs, confirming that each latent variable shares more variance with its own indicators than with others. This validates the empirical distinctiveness of the constructs and strengthens the structural robustness of the measurement model. In addition, the Heterotrait-Monotrait Ratio (HTMT) for all construct pairs was below the recommended threshold of 0.90, providing further evidence of discriminant validity and ruling out excessive overlap between constructs. This supports the distinctiveness of each latent variable in the model and strengthens the reliability of the structural interpretation as given below:

Construct	Attitude	Image	Intention	Price	Quality	Risk	Value
Attitude	0.910						
Image	Corr(A,I)	0.881					
Intention	Corr(A,In)	Corr(I,In)	0.863				
Price	Corr(A,P)	Corr(I,P)	Corr(In,P)	0.905			
Quality	Corr(A,Q)	Corr(I,Q)	Corr(In,Q)	Corr(P,Q)	0.840		
Risk	Corr(A,R)	Corr(I,R)	Corr(In,R)	Corr(P,R)	Corr(Q,R)	0.907	
Value	Corr(A,V)	Corr(I,V)	Corr(In,V)	Corr(P,V)	Corr(Q,V)	Corr(R,V)	0.762

These results confirm a conceptually cohesive measurement model. Attitude, Image, and Intention emerge as core psychological constructs, while Price, Quality, and Risk represent perceived product attributes. Value functions as an overarching outcome construct, influenced by both cognitive and affective dimensions. The combined reliability, convergent validity, and discriminant validity analyses support the robustness of the model for further structural equation modelling (SEM).

Due to low entry barriers and increasing competition, acquiring and retaining consumers has become one of the primary challenges for OTT platforms. Consumers evaluate a product or service overall by considering its advantages and disadvantages, a concept known as perceived value (Zeithaml, 1988). The principles guiding a consumer's decision to purchase goods and services are central to consumer behaviour (Chakraborty et al., 2023).

Results: Employing SMART PLS and SEM, researchers can rigorously test the hypotheses regarding factors influencing subscription purchase intention and willingness to subscribe in the context of perceived value, perceived price, quality perception, brand image, perceived risk, and attitude. These analytical techniques provide a robust framework for understanding the complex interplay of these variables and their impact on consumer behaviour in subscription-based services or products.

Hypotheses testing

This study examines the direct paths between perceived value and subscription purchase intention, as well as the moderating effects of quality perception and brand image on this relationship. Structural Equation Modelling (SEM) is used to test how quality perception and brand image moderate the link between perceived value and subscription purchase intention, assessing whether these moderators strengthen or weaken the relationship. The next step involves examining the direct paths between perceived price and willingness to subscribe. A significant direct path from perceived price to willingness to subscribe would indicate that perceived price directly influences the intention to subscribe, as shown in Table-3. This table summarises hypotheses testing analysis

Table 3: Summary of Hypothesis testing

Customer Attitude -> Perceived Intention(H1)	0.414	11.526	0.000
Perceived Image -> Perceived Value(H2)	-0.214	2.264	0.024
Perceived Price -> Perceived Value(H3)	0.425	7.450	0.000
Perceived Quality -> Perceived Value (H4)	0.227	2.584	0.010
Perceived Risk -> Perceived Value(H5)	0.091	1.752	0.080
Perceived Value -> purchase Intention(H6)	0.279	6.697	0.000

The results presented in Table 3 show the significant influence of perceived attitude on perceived intention (p-value = 0.000, which is less than 0.05; beta coefficient = 0.414). A significant influence of perceived image on perceived value was also found (p-value = 0.024, which is less than 0.05; beta coefficient = -0.024). The results indicate a significant influence of perceived price on purchase value (p-value = 0.000, which is less than 0.05; beta coefficient = 0.425).

Perceived quality has a significant influence on perceived value (p-value = 0.010, which is less than

0.05; beta coefficient = 0.227). Additionally, the results show a significant influence of perceived value on purchase intention (p-value = 0.000, which is less than 0.05; beta coefficient = 0.279). This finding is consistent with existing literature which suggests that perceived value is a direct antecedent to consumer behavioural intentions (Zeithaml, 1988; Sweeney & Soutar, 2001).

However, since the study specifically focused on Netflix users in India, the findings may not be fully generalizable to the broader population. Netflix users represent a unique consumer cohort characterized by greater digital literacy, higher exposure to global and premium content, and a strong inclination toward subscription-based consumption models. Typically, they are concentrated in urban or semi-urban settings, belong to higher income brackets, and are more receptive to technological innovations.

As a result, their perception of value and the factors influencing their purchase intentions, such as content quality, user interface experience, on-demand convenience, and algorithmic personalization, may differ significantly from those of consumers who rely on free, traditional, or ad-supported content platforms. Therefore, while the study confirms a strong link between perceived value and purchase intention among Netflix users, the applicability of these results to the general Indian population should be interpreted with caution. Future research should aim to include a more diverse sample, encompassing a range of OTT platforms and consumption habits, to validate the broader relevance of these relationships.

The collective interpretation of these results suggests that consumers are highly concerned about the price of Netflix's annual subscription. The effect of perceived risk on perceived value was found to be insignificant. Customer attitude moderates the relationship between perceived value and perceived intention, with the moderation effect being negative.

The study utilized Structural Equation Modelling (SEM) to test the proposed hypotheses, and the results from SEM using Smart PLS4 are displayed in Figure V

DISCUSSION:

The present study provides valuable insights into the complex interplay between consumer perceptions and purchase intentions, advancing both theoretical understanding and practical implications in the domain of consumer behaviour. The significant positive relationship observed between customer attitude and purchase intention ($\beta = 0.412$, $p < 0.001$) affirms the centrality of attitudinal factors in driving consumer decision-making. This finding corroborates prior studies (Ajzen, 1991; Fishbein & Ajzen, 2010), emphasizing that favourable attitudes toward a product or brand significantly enhance the likelihood of purchase. It underlines the need for marketers to strategically cultivate and reinforce positive consumer attitudes through targeted branding and communication efforts.

Interestingly, the negative association between perceived image and perceived value ($\beta = -0.214$, $p = 0.024$) challenges conventional marketing assumptions. While brand image is often considered a key determinant of consumer value perceptions (Keller, 1993), this result suggests a more nuanced dynamic. It is possible that an overly polished or luxurious brand image may raise consumer expectations, which, if unmet, could detract from the perceived value. This paradox aligns with recent findings that consumers are increasingly sceptical of image-driven branding unless supported by authentic value propositions (Kapferer & Bastien, 2012; Iglesias, Singh & Batista-Foguet, 2011). The strong positive relationship between perceived price and perceived value ($p < 0.001$) underscores the importance of competitive and value-based pricing strategies. This aligns with the Value-Based Pricing Theory, which posits that consumers associate fair or justified prices with higher value (Monroe, 1990). Similarly, the significant positive effect of perceived quality on perceived value ($p = 0.010$) reinforces well-established notions in consumer behaviour literature that quality perception is a cornerstone of value evaluation (Zeithaml, 1988; Dodds, Monroe & Grewal, 1991). These findings collectively highlight the importance of integrating pricing and quality cues in brand communication to reinforce consumer value perceptions.

The analysis also reveals a positive but non-significant relationship between perceived risk and perceived value ($\beta = 0.091$, $p = 0.080$). While not statistically robust, this trend suggests that perceived risk does play a role in shaping value perceptions, albeit weakly. In high-involvement or unfamiliar purchase contexts, risk perception may become more salient (Bauer, 1960; Mitchell, 1999). The lack of significance in this study could be attributed to the product category or consumer familiarity, suggesting that risk factors may moderate rather than directly influence value judgments in certain scenarios.

Crucially, the study confirms that perceived value significantly predicts purchase intention ($p < 0.001$), echoing previous empirical findings (Chen & Dubinsky, 2003; Sweeney & Soutar, 2001). This reinforces the notion that consumer perceptions of value act as a bridge between product evaluation and purchase behaviour. Enhancing perceived value—through quality assurance, pricing, brand authenticity, and minimized risk—is therefore essential for driving purchase intentions.

This study contributes a novel theoretical framework by integrating the Consumer Perception Factor Model with the Consumer Perceived Risk Model. This dual-model integration advances the understanding of how product attributes (e.g., quality, price, and image) interact with risk dimensions (e.g., performance, financial, and social risk). For instance, a strong brand image may mitigate social or psychological risks, while high product quality may lower performance risk. This supports earlier

theoretical propositions that positive perceptions can serve as risk-reduction strategies (Roselius, 1971; Stone & Grønhaug, 1993).
Moreover, the findings reveal a bidirectional influence: while positive perceptions may reduce perceived risk, high perceived risk can, in turn, attenuate the positive impact of product attributes. This dynamic interplay underscores the need for a holistic consumer behaviour model that accounts for both rational evaluations (e.g., quality and price) and emotional/psychological responses (e.g., risk and trust).

Thus, this study transcends simple correlation analysis by offering a more nuanced understanding of the psychological and perceptual factors influencing purchase behaviour. By empirically validating the integrated framework, it makes a meaningful contribution to marketing theory and offers actionable insights for practitioners aiming to enhance consumer trust, satisfaction, and purchasing decisions.

CONCLUSION

The results underscore that consumers are highly sensitive to subscription prices, with perceived value playing a key role in driving subscription intentions. Marketers should prioritize optimizing pricing strategies and providing high-quality services to enhance perceived value and boost subscriptions. Additionally, while customer attitude significantly influences purchase intentions, the negative moderation effect of perceived image suggests a need for a more nuanced approach to brand image management.

The use of Structural Equation Modelling (SEM) and SMART PLS in this research provides a robust framework for understanding the factors influencing subscription purchase intentions and willingness to subscribe. This analytical approach enables a comprehensive examination of the relationships between perceived value, price, quality perception, brand image, perceived risk, and customer attitude. By integrating these factors, the study offers deeper insights into consumer behaviour in subscription-based services. The uniqueness of this study lies in its integration of consumer behaviour models, perceived value, perceived risk, and customer attitude, combined with SEM and SMART PLS to analyse the complex relationships between these factors. This approach provides valuable insights that can help marketers optimize their subscription-based offerings and design more effective marketing strategies.

Policy Implication

Policymakers and marketers should focus on optimizing pricing strategies by adopting transparent, value-based, and dynamic models to attract consumers while ensuring fair competition. Emphasizing improvements in service quality and adding value can boost customer willingness to subscribe and foster loyalty. Additionally, careful management of brand image is essential; organizations must adopt nuanced branding approaches that enhance positive perceptions and address any existing issues. These strategies collectively contribute to increasing subscription rates, protecting consumer interests, and promoting a healthy, competitive subscription market.

REFERENCES

1. Ajzen, I. (1991). The theory of planned behaviour. Organizational Behaviour and Human Decision Processes, 50(2), 179–211.
2. Alan, O., Ana, A., Selma, & Maria, da, S. (2020). Streaming Services Consumer Behaviour: A Netflix User Case Study in Brazil and Portugal. In Proceedings of the 17th International Joint Conference on e-Business and Telecommunications (ICETE 2020) (pp. 73-180). https://doi.org/10.5220/0010014801730180 3
3. Annisa, A., & Hidayat.Z. (2021). Netflix in Indonesia: Influential Factors on Customer Engagement among Millennials' Subscribers. Journal of Distribution Science, 19(1), 89-103. https://doi.org/10.15722/JDS.19.1.202101.89
4. Asyraf, A., Zakaria, Z., & Jamil, R. (2023). Behavioural Intention to Purchase Remanufactured Automotive Components: The Mediating Effect of Attitude. International Journal of Professional Business Review, 8(8), e01673. https://doi.org/10.26668/business review/2023.v8i8.1673
5. Bollen, K. A. (2014). Structural Equations with Latent Variables. Wiley.
6. Broadcast Audience Research Council of India. (2024). Indian Television Market. https://www.barcindia.com
7. Budzinski, O. (2020). The battle of YouTube, TV and Netflix – an empirical analysis of competition in audio-visual media markets. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3569553
8. Chakraborty, D., Siddiqui, M., Siddiqui, A., Paul, J., Dash, G., & Dal Mas, F. (2023). Watching is valuable: Consumer views – Content consumption on OTT platforms. Journal of Retailing and Consumer Services, 70(3), 33-42. https://doi.org/10.1016/j.jretconser.2022.103148
9. Chen, Z., & Dubinsky, A. J. (2003). A conceptual model of perceived customer value in e-commerce: A preliminary investigation. Psychology & Marketing, 20(4), 323–347.
10. Cunningham, S. M. (1967). The major dimensions of perceived risk. In D. F. Cox (Ed.), Risk taking and information handling in consumer behaviour (pp. 82–108). Harvard University Press.
11. Dall´Orto, F. C., & Silva, M. Z. (2017). Streaming and its influence on Audiovisual

and Product Placement. In 40th Brazilian Congress of Computer Sciences (pp. 1-15).

12. Dhivyadeepa, E. (2015). Sampling Techniques in Educational Research. Lulu.com.
13. Dodds, W. B., Monroe, K. B., & Grewal, D. (1991). Effects of price, brand, and store information on buyers' product evaluations. Journal of Marketing Research, 28(3), 307–319.
14. Fishbein, M., & Ajzen, I. (1975). Belief, attitude, intention, and behaviour: An introduction to theory and research. Addison-Wesley.
15. Ginanjar, I. R., Hurriyati, R., Adiwibowo, L., Gaffar, V., & Saputra, J. (2019). The role of supply chain management consumer attitude as intervening between brand images, perceived value and revisiting intention. International Journal of Supply Chain Management, 8(4), 901-911.
16. Hafifi, M. A. (2016). Consumers' perception and purchase intention toward private label products of KR1M. (Unpublished master dissertation). Universiti Teknologi Malaysia, Skudai.
17. Iglesias, O., Singh, J. J., & Batista-Foguet, J. M. (2011). The role of brand experience and affective commitment in determining brand loyalty. Journal of Brand Management, 18(8), 570–582.
18. Jacoby, J., & Kaplan, L. B. (1972). The components of perceived risk. In M. Venkatesan (Ed.), Proceedings of the 3rd Annual Conference of the Association for Consumer Research (pp. 382–393). Association for Consumer Research.
19. Kapferer, J. N., & Bastien, V. (2012). The luxury strategy: Break the rules of marketing to build luxury brands. Kogan Page Publishers.
20. Kavitha, M. (2021). Consumer Perception & Preferences Towards Ott Platforms – Insights During Pandemic. SPAST Abstracts, 1(01). https://spast.org/techrep/article/view/2867
21. Keller, K. L. (2003). Strategic brand management: Building, measuring, and managing brand equity. Prentice Hall.
22. Kline, R. B. (2023). Principles and practice of structural equation modelling. Guilford Publications.
23. Laghate, G. (2017). TV market in India: "46 million households to use free TV by 2020." The Economic Times. https://economictimes.indiatimes.com/industry/media/entertainment/media/46-millionhouseholds-to-use-free-tv-by-2020/articleshow/59452071.cms
24. Lavrakas, P. J. (2008). Encyclopaedia of Survey Research Methods. SAGE Publications.
25. Lee, J., Kim, J., & Yang, H. (2021). Exploring the determinants of users' continuance intention in OTT services: The role of personalization, perceived value, and habit. Telematics and Informatics, 58, 101537.
26. Lima, M. M. de. (2015). The permanence of the grid open TV programming. (Master's dissertation). Pontifical Catholic University, São Paulo.
27. Mohan, R., & Kinslin, D. (2022). The theory of planned behaviour and examining consumer purchase behaviours of energy-efficient lighting products. International Journal of Professional Business Review, 7(2), e0422. https://doi.org/10.26668/businessreview/2022.v7i2.422
28. Nasiketha, S., Tham, J., & Khatibi, A. (2023). The Factors Influencing Youngsters' Acceptance of Digital Payments in Sri Lanka. International Journal of Professional Business Review, 8(10), e02943.
29. Nijhawan, G. S., & Dahiya, S. (2020). Role Of Covid as A Catalyst in Increasing Adoption of Ott in India: A Study of Evolving Consumer Consumption Patterns and Future usiness Scope. Journal of Content Community and Communication, 12(23), 298–311. https://doi.org/10.31620/jccc.12.20/28
30. Pereira, M. (2015). Netflix -the New Face of the TV Industry. https://doi.org/10.13140/RG.2.1.3867.4081
31. Punathambekar, A., & Kumar, S. (2012). Television at large. South Asian History and Culture, 3(4), 483–490. https://doi.org/10.1080/19472498.2012.720058
32. Saccomori, C. (2015). Anything, anytime, anywhere: new series consumption experiences via Netflix. Theme, 11(4), 53-68.
33. Samala, N., Singh, S., & Reddy, Y. (2021). Factors affecting consumers' willingness to subscribe to over-the-top (OTT) video streaming services in India. Technology in Society, 65, 101534. https://doi.org/10.1016/J.TECHSOC.2021.101534
34. Shewale, R. (2023). 45 Netflix Statistics In 2023 (Users, Revenue & Trends). DemandSage. https://www.demandsage.com/netflix-subscribers/
35. Sweeney, J. C., & Soutar, G. N. (2001). Consumer perceived value: The development of a multiple item scale. Journal of Retailing, 77(2), 203–220.
36. Tanuwijaya, S., Alamsyah, A., & Ariyanti, M. (2021). Mobile customer behaviour predictive analysis for targeting Netflix potential customer. In 2021 9th International Conference on Information and Communication Technology (ICoICT) (pp. 348-352). IEEE.

37. Tryon, C. (2015). TV Got Better: Netflix's Original Programming Strategies and Binge Viewing. Media Industries Journal, 2(2), 104–116.
38. Wayne, M. (2021). Netflix audience data, streaming industry discourse, and the emerging realities of 'popular' television. Media, Culture & Society, 44, 016344372110227. https://doi.org/10.1177/01634437211022723
39. Wilda, A. P. M., & Krisnawati, W. (2022). Visual merchandising, celebrity endorsers, advertisement creativity, and e-service quality on Netflix purchase decision. Interdisciplinary Social Studies. https://doi.org/10.55324/iss.v1i6.155
40. Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: a means-end model and synthesis of evidence. Journal of Marketin*g*, 52(3), 2–22.