# A STUDY ON THE FACTORS AFFECTING THE ADOPTION OF AI BASED CHURN PREDICTION MODELS IN OTT INDUSTRY


by

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## ABSTRACT

### A STUDY ON THE FACTORS AFFECTING THE ADOPTION OF AI BASED CHURN PREDICTION MODELS IN OTT INDUSTRY

In the study A Study on the Factors Affecting the Adoption of AI-Based Churn Prediction Models in the OTT Industry, an in-depth analysis is conducted to uncover the critical determinants influencing the integration of artificial intelligence (AI) for churn prediction within the Over-the-Top (OTT) media services sector. The research employs a robust methodology, incorporating Partial Least Squares Structural Equation Modelling (PLS-SEM) and Importance-Performance Map Analysis (IMPA) to dissect the data obtained from industry professionals. A purposive sampling technique was utilized for the study, targeting individuals familiar with churn prediction models. The sample size, determined using G* Power software, was set at 600 respondents to ensure statistical accuracy and robustness of the results, surpassing the minimum required size of 436.

Central to the findings is the significant role of organizational factors, underscoring the necessity of an enabling internal environment for the adoption of AI-driven solutions. This includes aspects like company culture, management support, and readiness for technological advancements. The study also highlights the considerable influence of perceived usefulness and ease of use on the adoption decision, stressing the importance of user-centric design and clear benefits in technology acceptance.

In contrast, technology factors, though relevant, exhibit a lower impact on adoption decisions, suggesting that technical attributes alone are not the primary motivators for adopting these models. External factors like market trends and regulatory considerations also show moderate importance, indicating their secondary role in the adoption process.

The study concludes by emphasizing the need for OTT organizations to focus on enhancing internal readiness and clearly articulating the practical benefits of AI technologies. These insights offer a strategic direction for OTT service providers and technology developers, pointing towards a balanced approach that considers both organizational readiness and the tangible benefits of AI in churn prediction.

***Keywords:*** Artificial Intelligence, Churn Prediction, OTT Industry, Organizational Factors, Technology Adoption

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# Chapter 1 - Introduction

## 1.1 Introduction

The Over-The-Top (OTT) industry in India has experienced significant growth and transformation, especially in the context of the global COVID-19 pandemic. This growth can be attributed to various factors including advancements in technology, changes in consumer behavior, and the evolving landscape of digital media.

A pivotal factor in the rise of the OTT industry in India is the widespread availability and affordability of high-speed internet, largely driven by major telecommunication players (PwC India, 2021). This technological democratization has made streaming services accessible to a wider audience, contributing to the popularity of platforms such as Netflix, Amazon Prime, and local services like Hotstar.

The pandemic has accelerated the shift from traditional television to digital platforms. With people confined to their homes, there was a notable surge in the consumption of digital content (Gupta & Singharia, 2021). This shift is not merely a temporary change but signifies a more permanent alteration in consumer preferences and media consumption habits.

Indian consumers show a diverse preference for content, ranging from international to regional cinema. The increasing production of local content tailored to Indian audiences has been crucial in attracting and retaining subscribers (Basu et al., 2023). This localization strategy, coupled with competitive pricing models, has enabled OTT platforms to expand their market share in India.

Moreover, the OTT platforms have effectively leveraged data analytics and artificial intelligence to enhance user experience and engagement (Kumar et al., 2023). By utilizing consumer data, these platforms are able to offer personalized content recommendations, thus improving customer satisfaction and reducing churn rates.

The regulatory environment in India has also played a role in shaping the OTT industry. While there have been discussions around the need for regulation, the industry currently benefits from a relatively flexible regulatory framework, allowing for innovation and growth (Ramli et al., 2022). The OTT industry in India is at a crossroads, balancing technological advancements, changing consumer preferences, local content creation, and regulatory considerations. This dynamic industry is poised for further growth, transforming the way Indian audiences consume media.

The significance of churn prediction models in the OTT industry, particularly in India, is increasingly vital. These models help platforms anticipate and address reasons for customer attrition, thus ensuring a steady subscriber base. Churn prediction models utilize data analytics to identify patterns and factors leading to customer departure (Kumar et al., 2023). By analyzing viewing habits, subscription durations, and other user interactions, OTT platforms can develop targeted strategies to retain their audience. This approach is crucial in a competitive market like India, where customer loyalty can be influenced by factors such as content relevance, service quality, and pricing strategies. Effectively predicting and managing churn is thus essential for sustaining growth and profitability in the dynamic OTT landscape (Gupta & Singharia, 2021).

Advancements in churn prediction models, particularly those powered by AI, have been significant in recent years. These models leverage machine learning algorithms to analyze complex datasets, allowing for more accurate and nuanced predictions (Kumar et al., 2023). Recent developments include the use of deep learning techniques, which can process vast amounts of unstructured data, such as social media activity or customer service interactions, to identify potential churn triggers (Gupta & Singharia, 2021). Additionally, AI-based models can adapt and learn from new data, continually refining their predictions. This adaptability is crucial in the ever-changing OTT market, where consumer preferences and behaviors evolve rapidly.

**1.2 Research Problem**

The research problem for the study titled "A Study on the Factors Affecting the Adoption of AI-Based Churn Prediction Models in OTT Industry" is multifaceted and complex. It delves into understanding the varied aspects that impact the implementation and effectiveness of Artificial Intelligence (AI) in churn prediction within the Over-The-Top (OTT) media services sector. Despite the apparent advantages of AI in enhancing customer retention and understanding, its adoption across OTT platforms remains inconsistent and varied.

This disparity in adoption raises several questions. What are the technological barriers that prevent some OTT platforms from integrating AI-based churn prediction models? The study needs to examine if there are gaps in technological infrastructure or expertise that hinder the adoption of these advanced systems.

Another critical aspect is the availability and quality of data. AI models require large volumes of high-quality data to function effectively. The research must explore how data collection, management, and privacy concerns impact the adoption of AI models. Are platforms struggling with insufficient data, or are there concerns about data privacy and security that make them hesitant to adopt AI?

The organizational culture within OTT platforms also plays a significant role. How receptive are these organizations to adopting new technologies? The study might uncover resistance to change or a lack of understanding about AI's potential benefits, which could be significant barriers to its adoption.

Furthermore, the regulatory environment is a crucial factor. With increasing scrutiny over data usage and AI, how do regulations impact the decision to adopt AI in churn prediction? This aspect of the research would involve examining existing policies and potential regulatory challenges that OTT platforms might face when implementing AI-based models.

Cost implications cannot be overlooked. AI systems can be expensive to implement and maintain. The study should assess if the financial investment required for AI-based churn prediction models is a deterrent for some OTT platforms, especially smaller or newer ones with limited budgets. Moreover, the effectiveness of AI in predicting churn in a dynamic industry like OTT media services is itself a subject of study. How accurately do these models predict customer behavior, and what is their impact on customer retention and overall business performance?

In conclusion, the research problem is centered on understanding the diverse and intricate factors that influence the adoption of AI-based churn prediction models in the OTT industry. By unravelling these factors, the study aims to provide insights that could facilitate more effective and widespread use of AI in customer retention strategies, thereby shaping the future of the OTT industry in a data-driven era.

### 1.3 Need and Significance of the Study

The need and significance of the study titled "A Study on the Factors Affecting the Adoption of AI-Based Churn Prediction Models in OTT Industry" are substantial and multifaceted. Firstly, the OTT industry is experiencing exponential growth globally, with a particularly rapid expansion in emerging markets. As the market becomes more saturated and competitive, understanding customer behavior and effectively managing churn becomes paramount for the sustainability and profitability of OTT platforms.

This study is vital in providing a comprehensive understanding of the challenges and barriers to adopting AI-based churn prediction models. Despite the potential of AI to revolutionize customer retention strategies, many OTT platforms have not fully embraced these technologies. Identifying the factors hindering this adoption is crucial for industry stakeholders to address these issues and harness the full potential of AI.

Moreover, as AI technology evolves, it becomes increasingly important to understand its practical implications in real-world settings. This study will offer insights into how effectively AI can predict customer churn and the accuracy of these models in different market contexts. This knowledge is invaluable for OTT platforms in optimizing their customer retention strategies and improving overall business performance.

Furthermore, the study will contribute to the broader discourse on AI and data management in the digital age. With growing concerns about data privacy and security, understanding how these issues impact the adoption of AI in the OTT industry is essential. The study's findings could inform policy decisions and regulatory frameworks governing the use of AI and data in digital media services.

Lastly, the study holds significant academic and practical value. Academically, it contributes to the burgeoning research on AI in media services, while practically, it offers actionable insights for OTT platforms looking to leverage AI for competitive advantage. The comprehensive understanding gained from this study can guide OTT platforms in making informed decisions about investing in AI technologies, ultimately leading to more sophisticated, customer-centric business models in the OTT industry.

## 1.4 Research Purpose

The research purpose of this study is to thoroughly examine the factors influencing the adoption of churn prediction models in the OTT industry and to understand the interactions among these factors. The focus is on identifying and analyzing aspects such as technological capabilities, data management, organizational culture, and market dynamics that impact the integration of these models. Additionally, the study aims to explore how these elements interact, revealing the complexities and interdependencies within the adoption process. This comprehensive analysis is intended to provide valuable insights for strategic decision-making in the rapidly evolving OTT sector.

## 1.5. Research Questions

RQ1: What are the key factors influencing the adoption of churn prediction models in the OTT industry?

RQ2: How do these factors interact with each other in the adoption process?

# Chapter II – Literature Review

### *Reiner and Skiera (2014)*

All participants in pay-per-bid auctions must make a payment for each bid. However paying the bidding fees without getting the auction item in return frequently leads to considerable discontent among losers, leading to acrimonious conversations and high churn rates. Pay-per-bid auctioneers developed the Buy-Now function, which enables losers to apply all or a portion of the bidding fees they paid during an auction towards purchasing the auction item, in order to lessen these unfavourable reactions. they find that overall, the Buy-Now feature encourages more aggressive bidding behaviour, draws in more bidders, fosters customer loyalty, and generates a higher profit per auction using unique data, including individual customer bidding histories and cost data from more than 6,800 pay-per-bid auctions. Although they discover an increase in the average number of bids per bidder, the Buy-Now feature reduces the number of bidders and the profit per auction for voucher auctions that simulate common value auctions. Theoretically, they also demonstrate that a bidder is capable of pursuing a risk-free bid plan. They discover through actual research that bidders hardly ever employ this tactic.

### *Jahromi, Stakhovych and Ewing (2014)*

It is now generally acknowledged that businesses should focus more on keeping current clients than finding new ones. To do this, it is necessary to identify consumers who are likely to defect so that they can be approached with customised incentives or other special retention offers. Predictive models that can identify clients with increased odds of defecting in the very near future are required for such efforts. Many predictive models have been developed to model customer churn in B2C contexts, but the B2B context in general, and non-contractual settings in particular, have gotten less attention in this regard, according to a study of the existing literature on customer churn models. This paper suggests a data-mining approach to estimate non-contractual client churn in B2B scenarios in order to fill up these gaps. The ability of several modelling approaches to forecast real churners is compared. The best data mining method (boosting) is then used to create a retention strategy that maximises profits. Findings show that the model driven approach outperforms often employed managerial heuristics in terms of churn prediction and devising retention measures.

***Chung, Fung and Patel (2015)***

According to the empirical literature on investing performance, among institutional investors, only hedge funds have consistently outperformed them. They investigate if this stylized fact is still true when they concentrate on long equities holdings. Hedge fund long-equity holdings can produce a considerable excess return (gross alpha) of 4.1% annually in our sample period of 1997–2006, in contrast to other six groups of institutional investors' low gross alphas of 0.3–1.8% annually. Only hedge funds are likely to generate net excess profits from equities selection given realistic execution and administrative costs. Small hedge funds that experience strong positive alphas are those with high churn rates, while those with low churn rates do not. Hedge funds with the highest superiority also tend to have the highest turnover rates and benchmark weight deviations (high active share). Hedge funds perform worse than other institutional investors in terms of illiquidity, which is consistent with their higher turnover because the latter would result in high trading costs if carried out with illiquid equities. Unlike other institutional investors, hedge funds exhibit superior timing of their loading on the market risk factor, and their superior stock-picking alpha lasts across the three eras of our sample period.

***Mann and Jha (2015)***

The research is based on the standard of services provided by various mobile service providers and the degree of consumer satisfaction. Ten years ago, the government introduced mobile phone services and allowed commercial operators to use them. With this government action, numerous large and small businesses entered the market. Yet, ten years later, just half of the businesses are still operating in the sector. The rate of customer churning equalises or balances the rate of addition of new subscribers. The Telecom Regulatory Authority of India (TRAI) claims that mobile telephony service providers have fallen short of the standards for consumer satisfaction. Businesses continually look for fresh approaches and strategies to both keep their current clientele and draw in new ones in an effort to lower the problem of customer turnover. The study's goal was to evaluate the standard of services offered by basic and cellular mobile service providers in order to gauge how well they were received by their clients. The purpose of this study was to evaluate the general level of customer satisfaction with regard to consumption, billing issues, network accessibility, and other factors.

***Moeyersoms and Martens (2015)***

“High-cardinality attributes, such as family names, ZIP codes, or bank account numbers, are categorical attributes that contain a very large number of different values”. Such traits could be quite instructive in a predictive modelling context because it might be helpful to know if people “pay with the same bank account number” or reside in the same village. “High-cardinality variables are rarely used in predictive” modelling despite this apparent and significant advantage. “The main reason for this is that including these attributes using conventional transformation methods either makes it impossible to” build prediction models using most classification techniques “(when using semantic grouping of the values) or will significantly increase the dimensionality of the data set (when using dummy encoding)”. (1) The introduction of a number of potential transformation functions from various contexts and domains that enable the incorporation “of high-cardinality information in prediction models”.

(2) They demonstrate that the addition of such features does in fact greatly “improve the prediction performance of the model using a special data set from a large energy business with more than 1 million” consumers. Additionally, (3) they actually show that, contrary to "conventional" data, more data produces superior prediction models. As a result, we also make a contribution to big data analytics.

***Backiel, Baesens and Claeskens (2016)***

In order to stay profitable, mobile phone carriers must concentrate on client retention in a crowded market. This study looks into how social network data may be included “into churn prediction models to increase their profitability, timeliness, and accuracy. Conventional models are constructed using consumer attributes, however for prepaid clients, these data are” frequently insufficient. Instead, analysis can be done on call record graphs that are up to date and comprehensive for all clients. The call graph was constructed using a process, and from it, pertinent features were extracted for use in “classification models. With a telecom data set with 1.4 million users and more than 30 million calls each month, the technique's scalability and applicability are shown. The models are assessed using lift curves, ROC plots, and anticipated profitability. The findings demonstrate how leveraging network features over local features can increase performance while maintaining excellent interpretability and usability”.

***van Eijkel, Kuper and Moraga-González (2016)***

Companies “may sell forward for risk hedging purposes only, for risk hedging plus strategic considerations”, or for both in forward and spot markets under oligopolistic competition, according to Cournot models of oligopolistic interaction. This research provides “evidence that strategic factors play a significant role in explaining the observed firms' hedging” activities by using data from the Netherlands wholesale “natural gas market where we examine the number of players, spot and forward sales, churn rates, and prices. Our test for strategic behaviour is based on the theoretical relationship between the number of sellers and the incentives to sell forward: if risk-hedging is the only factor influencing firms' decisions to sell forward, then" the number of firms engaged in hedging activity should decrease; "otherwise, if strategic factors are significant, then firms' incentives to sell forward should rise in the number of competitors".

***Chen (2016)***

Because online consumers are so erratic, managing client attrition can be challenging. Every online business aspires to be able to identify churn at an early stage. It offers the opportunity for both financial gain and expense savings. Churn prediction models make an effort to coordinate consumer habits, "transactions, and demographics in order to lessen the likelihood of churn within a predetermined period of time". The majority of modern approaches, however, rely on high-dimensional "static data analysis, and the model parameters are" calculated using large numbers of customers. It is impossible to create a dynamic, personalised "prediction model at the individual level. In order to estimate the customised parameters for the purpose of" individual monitoring, this work suggests a unique "mechanism based on the gamma CUSUM chart in which just inter-arrival time (IAT) and recency need to be collected". The data used in this study came from a Taiwanese online dating service. "The exponential CUSUM chart from Gan (1994), the CQC-v from Xie et al". (2002), and the CQC from Chan et al. are contrasted with "the gamma CUSUM chart" (2000). According to the findings, a gamma CUSUM chart's accuracy rate (ACC) is 5.2% higher and its average time to signal (ATS) "is around two days longer than what the best CQC-v requires".

***Tamaddoni, Stakhovych and Ewing (2016)***

A primary priority now is customer retention. “Implementing a successful retention campaign, however, is a difficult process that depends on a company's ability to precisely identify both at-risk and valuable clients. We compare the effectiveness of various parametric and nonparametric churn prediction models using real and simulated data from two online stores in order to determine the best modelling strategy. The results demonstrate that the boosting methodology, a nonparametric approach, provides improved predictability across the majority of conditions (i.e., variable sample sizes, purchase frequencies, and churn ratios). Additionally, logistic regression is more effective in situations or environments where churn is less common. Finally, parametric probability models perform better than other methods in situations where the size of the client base is quite small”.

***Thaichon and Jebarajakirthy (2016)***

“The goal of this paper is to examine how customers' perceptions of quality” affect their propensity to repurchase “home internet services. In particular, it was discovered that information quality and privacy impacted customers' loyalty through perceived value” and commitment, both of which were connected to customer behaviour. “Design, methodology, and approach — A model is suggested in order to meet the goals of the research. The discussion follows a review of the available research and the development” of hypotheses linked to each construct. “A survey was carried out online. The total number of valid samples was 2059. Results - When compared to privacy, information quality was a better predictor of commitment and value”. Furthermore confirmed were the beneficial indirect impacts “of information quality and privacy on behavioural loyalty. Originality/Value - The research” offers useful conclusions that may be applied to the creation of marketing plans that will keep clients “in the residential internet market. Also, the current problem of a high client churn rate can be fixed. In summary, the study supports the notion that an internet service provider's success and long-term survival” depend on placing customers' privacy at the centre of business operations.

***Indrawati and Indriasari (2015)***

High Speed Internet (HSI) revenue growth in an Indonesian telecommunications company has a tendency to lag behind monthly sales growth. This was a sign that a number of clients left the company without paying for the service; as a result, “the revenue from sales did not increase in step with the rate at which sales were increasing. In order to lower the level of churn that took place, research” on client loyalty is required. This study used customer data from a big data project that used an optimised churn prediction method to identify clients who remained steadfast despite being expected to leave. In this study, a customer loyalty model was applied, and the “independent variables that had a positive impact on customer loyalty were corporate image, service quality, customer happiness, commitment, perceived value, switching cost, or trust”. 929 clients were given surveys to complete, which were disseminated both online “(using a Google form and the phone) and offline (during customer visits). The 929 clients” who remained steadfast for the following three months were chosen based on the outcome of a big data project's attrition prediction. Just 482 of the customers who completed the questionnaire provided meaningful responses. The SmartPLS 3.0 software “was used to examine the 482 valid data. The findings showed that factors such as service quality, client satisfaction, commitment, perceived value, switching cost, and trust had a” favourable impact on client loyalty. However the corporate image element did not, at a 95% significant level, have a beneficial impact on customer loyalty. The study indicated that the most important element influencing consumer loyalty was commitment. This research recommended boosting service quality in order to promote customer “loyalty since the commitment variable had the highest score for influencing customer loyalty and since commitment was influenced by customer satisfaction through service quality”. Based on the descriptive results, “the company must provide better service than other operators by enhancing HSI speed and stability, quickly and accurately fixing HSI interference, providing service in accordance with service level guarantees, and providing service as promised in terms of time and quality”.

***Fathian and Azhdari (2017)***

Client segmentation and offering products depending on their wants are “two of the most significant difficulties in customer relationship management”. In reality, technological advancements, a growth in the number of new clients and rival businesses, as well as a wider range of products, will all have an impact on how customers behave over time. Conventional segmentation models can't anticipate these shifts in customer behaviour because they are unchanging over time, thus they overlook them. This problem is particularly important in the telecom industry because of the high turnover rates. For the purpose of this study, we employed temporal fuzzy clustering to identify major alterations in consumer behaviour for a telecom company over a period of 10 months. “This study's objective is to identify the variables that influence the structural and progressive changes in the clustering model. Also, we have offered a technique based on Frechet distance to identify patterns in client usage. The results showed that there are seven distinct customer behaviour patterns, two of which lead to the customer drop or churn, assuming that integrating the temporal clustering with trajectory analysis is an effective technique to distinguish consumers' activity among the clusters”. These patterns can be leveraged to create the best services possible while lowering the risk and expense of client churn.

***Gordini and Veglio (2017)***

Through expanded opportunities for information sharing, product discovery, and purchase, e-commerce has increased the ease of switching between enterprises while also raising the danger of customer turnover. “By evaluating the forecasting abilities of a novel model, the support vector machine (SVM) based on the AUC parameter-selection technique, we create a churn prediction model specifically customised for the B2B e-commerce market in this work (SVMauc). SVMauc's predictive abilities are compared to those of logistic regression, neural networks, and conventional support vector machines. Our study demonstrates that the parameter optimization process is crucial to the prediction performance, and the SVMauc outperforms the other approaches when applied to noisy, unbalanced, and nonlinear marketing data”. Consequently, our results support the notion that in the B2B e-commerce sector, “a data-driven approach to churn prediction and the creation of retention strategies beats routinely employed managerial heuristics”.

***Coussement, Lessmann and Verstraeten (2017)***

“The goal of data preparation is to transform independent (categorical and continuous) variables into a format” suitable for additional analysis. To improve “the prediction performance for the frequently used logit model”, we investigate various data-preparation methods. “In this study, which is based on churn prediction modelling, an improved logit model is compared to eight cutting-edge data mining methods using common input data, including actual cross-sectional data from a significant European telecommunications operator. The findings support the conclusions that are made. I The area under the receiving operational characteristics curve and the top decile lift show improvements of up to 14.5% and 34%, respectively, in the area where analysts better accept that the data-preparation technique they select genuinely influences churn prediction performance. (ii) The improved logistic regression is competitive with both single and ensemble data mining algorithms that are more sophisticated”. The essay finishes with several managerial recommendations and ideas for additional study, along with proof that the findings are transferable to other company environments.

*Holtrop, Wieringa, Gijsenberg and Verhoef (2017)*

Churn management systems for companies that prioritise serving customers heavily rely on attrition prediction. In order to improve churn forecasts, methodological advancements have placed a focus on the utilisation “of customer panel data to model the dynamic evolution of a customer base”. However due to pressure from the public and policymakers to reduce “the storage of customer data, businesses have begun to "self-police" by limiting data storage, making panel data methods impractical. By creating a system that captures the dynamic evolution of a customer base without relying on the availability” of historical data, we address these issues. Instead, our method relies only on knowledge of previous model parameters and uses a recursively updated model. When historical data is available, this generalised “mixture of Kalman filters model maintains the accuracy of churn forecasts in comparison to other panel data approaches. Applications in the insurance and telecommunications industries establish greater predicted performance in the absence of historical data as compared to more” straightforward benchmarks. These enhancements result from the fact that the suggested method achieves data minimization and data anonymization while capturing “the same dynamics and unobserved heterogeneity found in consumer databases as advanced methods”. They draw the conclusion that maintaining privacy need not compromise analytical processes.

*Lee, Kim and Lee (2017)*

Using the availability heuristic “approach, the aim of this work is to” determine how word exposure frequency affects online news. This stands out from the majority of churn prediction research that emphasise “subscriber data. Design, methodology, and approach - This study used data mining technology in conjunction with logistic regression, decision tree graphing, neural network models, and a partial least square (PLS) model” to identify words that churn generate. It also “examined the churn prediction through words presented in previous studies”. Results - Prediction rates in this investigation were comparable “to those provided by subscriber data-based analysis. Additionally, this study combines decision tree graphing and PLS modelling to determine which words give favourable or negative influences” because earlier studies could “not clearly reveal the effects of the factors”. Originality/value - These results suggest an increase of psychological studies, advertising effects, and churn prediction. Additionally, it makes specific recommendations for enhancing business competitiveness, which benefits both company growth and efficiency across the board.

***Ojiaku and Osarenkhoe (2018)***

The presence “of mobile data services has increased competition and reorganised the mobile” telecommunications sector, leading to lower revenue from voice services in particular and a high churn rate. As a result, mobile service providers look for strategies to draw in and keep mobile data consumers in order to boost income. “In the context of mobile data service, this study looks into the factors” that influence customers' brand preferences and intents to stick with particular mobile service providers. The influence of prior experience on behavioural outcomes is also covered in this study. Regression analyses were used to analyse data “from 304 clients of mobile data service providers. Findings show that brand choice is influenced by brand image, but not by pricing or promotion, while brand choice is influenced by brand image”, price, and continuance intentions. Consumers' past experiences have a big and unfavourable impact on their brand choice, but not on their intention to stick with it. The study's value and implications are examined.

***Dominique-Ferreira (2018)***

Reason: Because customers extensively rely on intermediaries in both the claims management and purchase decision-making processes, “the insurance market has significant churn rates. This essay aims to look into the preferences of customers in terms of the purchasing decision-making process”, as well as the role that insurers and middlemen play in customer happiness. Design/methodology/approach: The initial phase involved choosing the most crucial characteristics for Portuguese insurance consumers. An ad hoc questionnaire was used to collect information from Portuguese clients of vehicle insurance, and “three focus groups were held (using B2C and B2B sectors)”. The multidimensional scaling unfolding model and structural equation models were used. Findings: By their influence over customer happiness, claims handling, “and the purchasing process, intermediaries play a significant role in the retail insurance distribution channels” (premium acceptance). Practical implications: “Insurers should strengthen their collaborations (back office support) with intermediaries” given the impact that intermediaries have on client satisfaction. Originality/value: By offering empirical proof of the effect of intermediaries on customer satisfaction, “the study adds to the retail distribution literature of the insurance industry”.

***Newton, Nowak and Kelkar (2018)***

This study's goal is to look into the variety of reasons “why wine club members leave and join other organisations. Design/methodology/approach: Via an online poll of 399 former wine club members who had recently cancelled their membership”, data on US wine consumers was obtained for this quantitative research study. “Data are examined using descriptive statistics, factor analysis, hierarchical multiple regression, and analysis of variance in line with literature on customer attrition rates in subscription marketplaces”. Findings: According to “the results provided by respondents, higher levels of perceived product quality, fair pricing, variety seeking, and commitment to customer service both at the start” of a wine club membership and at the end are associated with “higher levels of customer satisfaction and a desire to recommend the club to others even after quitting. The good news for wineries is that consumers are more likely to recommend a wine club if at least a year has gone since they opted to stop, even if variety seeking is more typical among seasoned wine drinkers”. Relevance in practise: “The findings have implications for wine club managers looking to increase wine club retention and offer suggestions for reducing customer attrition rates. Originality/value: This essay offers original research on the various reasons why wine club members leave”. A member's happiness with “their wine club and their desire to recommend it to others are influenced by aspects like product quality, fair pricing, service commitments, and variety-seeking behaviour”, according to the study that has been done so far. In an effort to better understand “wine club members' switching patterns and determine what the wineries may do to increase patron loyalty”, the authors have made an effort to incorporate all these variables into a single study.

***Ascarza (2018)***

Businesses across a range of industries are increasingly taking a proactive approach to minimising customer churn. Typically, “this involves identifying customers who are most likely to leave and concentrating retention efforts on them. Although there is a wealth of literature on creating churn prediction models that pinpoint consumers most at danger of leaving, no research has looked at whether it is actually best to target such people”.” The author shows that consumers identified as having the highest churn risk are not always the optimum targets for proactive” churn programmes by combining two field studies with machine learning techniques. “This conclusion not only goes against conventional knowledge, but it also raises the possibility that retention programmes can fail not because businesses provide the incorrect incentives, but rather because they do not follow the proper targeting guidelines”. So, regardless of their risk of churning, businesses should concentrate their modelling “efforts on identifying the observed variability in response to the intervention and targeting customers based on that sensitivity". This strategy has been empirically shown to be substantially more effective than the conventional practise of focusing on customers who have the highest churn risk. In a broader sense, the author urges businesses and academics utilising randomised "trials (or A/B tests) to go beyond the average effect of treatments and" to take advantage of the observed variation in customer response to choose customer targets.

***Zhu, Baesens, Backiel and Vanden Broucke (2018)***

Predicting customer attrition is significantly hampered by class inequality. To address this problem, numerous "data-level sampling techniques have been developed. In this study", we thoroughly compare the churn prediction ability of numerous cutting-edge sampling strategies. One of the primary performance indicators is a recently created maximum profit criterion, which provides further cost-benefit analysis. The outcomes of the experiment "demonstrate that the influence of sampling techniques depends on the evaluation measure that is being used, and that the impact pattern is connected to the classifiers". The reaction patterns are thoroughly investigated, and appropriate sampling tactics are suggested for each circumstance. In addition, we go over how the sample rate was set for the empirical comparison. Our conclusions provide a valuable framework "for the application of sampling techniques in the context of churn prediction".

***Safiranita, Ramli, Permata, Adolf, Damian and Palar (2019)***

"Over the Top (OTT) is a media platform that offers multimedia" services over operator-owned networks and hooks up to telecoms operator infrastructure. These services can include "video, audio, voice, telecommunications, news, or other commercial" offerings like a marketplace or online shops. Examples include Whatsapp, Instagram, YouTube, Facebook, and Google. The term "over the top" (OTT) describes "content providers who distribute streaming media as a stand-alone product directly to viewers over the Internet, eschewing telecommunications, multichannel television, and broadcast television platforms that typically act as a controller or distributor of such content. Another definition of OTT is the delivery of one or more services through an IP network" by a telecommunications service provider. It encompasses "a range of telco services, such as cloud-based services, communications, and content. The term "OTT," which stands for "Over The Top," is used in broadcasting and technology business reporting to describe audio, video, and other media that are transmitted over the internet as a stand-alone product without requiring users to sign up for a traditional cable or satellite pay TV service like Comcast". With its extensive content library, this market-disrupting OTT streaming player has won over the internet-savvy generation, especially the millennials, since it entered the market. Its OTT platform keeps raising the bar for offering excellent user experience and high-quality content. According to a recent research, the business holds an average market share of 12% in industrialised nations like the United States, where it ranks as the second-largest OTT provider.

***Tambde and Motwani (2019)***

The essential resource known as an employee is a person who works for a company. If one of them unexpectedly leaves the company, it might have a huge impact and cost the individual organisation a lot of money. Also, hiring would require both time and money, and the newly hired employee would need some time to make a particular business profitable. Based on the available analytical data, this model will help anticipate the rate at which people will leave their positions and utilise various machine learning algorithms to reduce prediction error. Customized or individual employee forecast varies depending on the working environment. The associated knowledge and understanding are still scattered, despite the fact that it is now clear that employee churn forecast responds to wage "differently based on their location, lifestyle, and surroundings. By developing an expert prediction system", we hope to address issues related to organisations' ignorance of employee behaviour, raise awareness of the value of employees within enterprises, reduce unneeded employee churn, and promote both individual and joint progress.

***Sujata, Aniket and Mahasingh (2019)***

Customers are the lifeblood of any business, and finding and keeping new customers is the biggest difficulty for any established company. “Improving the customer experience is one of the numerous approaches to lower the churn rate and boost” client retention. When companies expand, so does the number of their customers. As every consumer is unique and requires a different set of incentives to interact with the company, we must comprehend them all separately. “Artificial intelligence systems can bridge the gap between a company and a customer, generating vast amounts of data that can lead to a deeper understanding of the customer's preferences. It is important to comprehend these artificial intelligence capabilities, how they can help firms keep customers, and how they can support improved customer engagement”. But this important scientific field receives little attention in academic studies. So, “this study aims to close this gap by offering a conceptual” framework for comprehending how tools for artificial intelligence might improve customer experience. The approach of a narrative literature review has been used to conceptualise the model. The study has implications for practitioners “who create and develop AI tools to improve customer experience, managers who plan their companies' information technology strategies, academics who explore new technologies in the marketing domain, and society at large” because it will help to enhance customer experience and increase customer satisfaction.

***Pamina, Dhiliphan, Rajkumar, Suganya and Femila (2019)***

In order for a firm to succeed in the market, keeping and satisfying its important clients is one of its biggest problems. To address this issue in many applications, “numerous machine learning techniques are emerging to create various client retention models”. Because of its great relevance, this movement is more apparent in the telecom sector. An extensive study of “machine learning-based churn prediction in the telecom sector” from 2000 to 2018 is presented in this article. Also, they identified the issues and difficulties with telecom churn prediction and provided recommendations and remedies. They think this paper will be useful for researchers or data analysts in the telecom industry as they choose the best and most relevant methodologies and develop a better, more innovative model “for churn prediction in the future”.

***Amin, Shah, Khattak,Moreira, Ali, Rocha and Anwar(2019)***

In order to successfully predict customer churn in situations when one firm (the target) lacks sufficient data, researchers have developed the field of cross-company churn prediction (CCCP). Prior to developing a “CCCP model, the cross-company data is often translated into a set of comparable target company data with a normal distribution. The data transformation technique in CCCP, however, is still not apparent”. Also, there hasn't been a thorough investigation of how “data transformation techniques affect the performance of CCCP models when utilising various classifiers” in the telecommunications industry. “In this study, we developed a model for CCCP using data transformation techniques (i.e., log, z-score, rank, and box-cox) and presented not only a thorough comparison to validate the impact of these transformation techniques in CCCP, but also evaluated the performance of underlying baseline classifiers (i.e., Naive Bayes (NB), K-Nearest Neighbor (KNN), Gradient Boosted Tree (GBT), Single Rule Induction” Using publicly accessible datasets relating to the telecommunications industry, we conducted experiments. “The outcomes showed that the majority of data transformation techniques, such as log, rank, and box-cox, considerably enhance CCCP's performance. The Z-Score data transformation approach in this study, however, was unable to outperform the other methods in terms of results”. Also, it is examined “if the CCCP model based on NB outperforms on converted data, and how well DP, KNN, and GBT performed on average, as opposed to SRI classifier's lack of meaningful outcomes in terms of the generally used evaluation measures (i.e., probability of detection, probability of false alarm, area under the curve and g-mean)”.

***Shetty,Varsha, Vadone, Sarode and Kumar (2019)***

When some customers stop being devoted to a company, it is known as customer attrition or customer churn. If a customer's transactions end after a predetermined amount of time, it is said that churn has occurred in the context of retail organisations. Businesses with high churn rates suffer enormous losses because it has been found “that attracting new customers is more expensive than keeping the ones” they already have. Hence, they should be able to track churn rates in order to calculate client churn for businesses. These churn rates provide a firm with a number of variables to take into account when calculating client retention success rates and formulating improvement initiatives. The Pareto/NBD model is used to forecast client attrition. After predicting which clients are most likely to leave, it is necessary to separate them based on their prior purchase behaviour. Product classification is modelled using Natural Language Processing. Customer segmentation is done via semi-supervised learning. This entails segmenting data using k-means clustering and assigning a score using the RFM model. Then, techniques like logistic regression, SVM, and SGD classifier are used to predict clusters. These techniques are combined to create an effective suggestion system that aims to win back the loyalty of churning customers who were valuable to the business, boosting sales for shops.

***Ferreira, Telang and De Matos (2019)***

They research how consumers make decisions about “which tariff plan to select and whether or not to switch providers when their peers leave the mobile business”. They create a theoretical model that illustrates the circumstances under which customers stick with their carrier and the circumstances under which they switch when their friends do. They then characterise the path to death of the consumers with an unparalleled level of detail using a vast and comprehensive anonymised longitudinal panel of call detailed data. They investigate the network topology that may be derived from this data in order to provide tools for the endogenous buddy churn that occurs frequently in network situations. As a result, we can econometrically determine how “peer influence affects our setting. We discover that, on average, every extra buddy who leaves causes the monthly churn rate to rise by 0.06 percent. Our dataset's observed monthly churn rate is 2.15 percent”. Additionally, they discover “that companies who offer pre-paid tariff plans with the same rates for calls made both inside and outside the carrier” keep customers who might otherwise leave. “Without this tariff plan, the monthly churn rate” in our environment may have reached 8.09 percent. They carry out a series of robustness checks, paying close attention “to how they define friends in the social network, and they demonstrate that our findings hold true. Our study demonstrates how contagious churn undervalues the value of customers and, in particular, the value of customers who have more friends”. As a result, managers should actively consider the social network's structure when deciding which customers to prioritise for retention campaigns.

***Ahmed (2019)***

“This article examines the effects of customer turnover factors on boosting customer loyalty” to Egyptian telecom companies. Using a descriptive approach, this is accomplished. 1500 distinct emails from consumers of “telecom service providers who had previously utilised their services were chosen at random. The surveys were emailed out and self-administered for data collection, with a response rate of 25.6%. On the responses, linear regression” analysis was applied. “The findings indicated that there is a statistically significant association between customer turnover variables and customer loyalty, which might be improved upon and lead to higher levels of loyalty to Egypt's” telecom companies. The study's conclusions suggest that as a competitive strategy in the market for telecom services, providers can manage their interactions with customers better. By managing client churn, it can lower the churn rate and boost customer loyalty. Copyright

***Sivasankar and Vijaya (2019)***

The method of feature selection involves removing unimportant information from the dataset while retaining a respectable level of classification accuracy. The effectiveness of the final categorization can be significantly impacted by the chosen features. “In this study, a methodology is proposed that consists of two phases: choosing the attributes to use, and categorising those traits. The size of the attribute set and misclassification error can be decreased in phase one by using a filter and wrapper approach for attribute selection with random over-sampling (Ros)”. In the second step, classification methods including “decision trees (DT), K-nearest neighbour (KNN), support vector machines (SVM), naïve bayes (NB), and artificial neural networks” use the specified qualities as inputs (ANN). “In order to assess the effectiveness of the suggested system, actual churn, false churn, specificity, and accuracy are examined. It is discovered that the aforementioned methodology performs well for churn prediction and is appropriate for the telecommunications industry”.

***Amin, Al-Obeidat, Shah, Adnan, Loo and Anwar (2019)***

Churn and non-churn customers typically have similar characteristics, making Churn Customer “Prediction (CCP) a difficult task for decision-makers and the machine learning community. It is clear from various research on customer churn and related data that a classifier exhibits varying levels of accuracy for various zones of a dataset”. In such cases, it is simple to see a correlation between the classification accuracy level and the predictability of the classifier. “The expected classifier's accuracy can be predicted even before the classification if a mechanism can be devised to assess the classifier's certainty for various zones inside the data”. This work presents a “novel CCP approach based on the notion of distance factor-based classifier certainty” estimation discussed above. The dataset is separated into two groups for forecasting customers who will display churning and “non-churning behaviour: I data with high certainty, and (ii) data with low certainty. The data are sorted into distinct zones based on the distance factor”. The Telecommunication Industry (TCI) datasets were evaluated using “various state-of-the-art evaluation metrics, such as accuracy, f-measure, precision, and recall. The results showed that I the distance factor is strongly correlated with the classifier's certainty and (ii) the classifier achieved higher accuracy in the zone with a higher distance factor's value (i.e., customer churn and non-churn with high certainty) than those placed in the zone with a smaller (i.e., customer churn and non-churn with low certainty)”.

***Vezzoli, Zogmaister and Van den Poel (2020)***

“In order to attract new customers and keep existing” ones, businesses now approach marketing differently as a result of the liberalisation of the European energy market. Practitioners work to forecast which customers will churn (i.e., depart) and to comprehend the drivers of this intention. This project creates a churn prediction model using data-mining approaches to meet this demand. “The goal of the study is to find the data” that predicts churn and, as a result, to provide light on the psychological causes of churn. Using a dataset made up of 81,813 energy supplier customers, each with a single home electricity contract, the authors developed eight predictive models utilising decision trees, random forest, and logistic regression. It was discovered that logistic regression performed better than the other approaches. By addressing a posteriori psychological justifications for consumers' churn behaviour, the debate concentrates on the pertinent churn predictors. By addressing theoretical psychological underpinnings, the study offers new insights into the causes of customer turnover and a data-mining technique that is resilient to contextual changes.

***Kaur, Arora and Bali (2020)***

The adage "Customer is King" "has completely changed due to a confluence of technical advancements and the retail industry's increasingly competitive climate. On marketing concepts like the market basket model, value-based customer segmentation, campaign planning, etc., it has been observed that the combination of technologies with analytical concepts of video analytics, social media analytics, wireless analytics, and smart vision systems can impact customer satisfaction and lower the customer churn rate". Customer satisfaction will increase as a result of a successful amalgamation of these concepts, and retailers will gain an advantage in a cutthroat market. The purpose of this article is to comprehend how data analytics and technology breakthroughs have affected the retail industry and to develop "efficient merchandising and marketing strategies in order to attract and keep as many customers as possible".

***De Caigny, Coussement, De Bock and Lessmann (2020)***

Including "textual data into customer churn prediction (CCP) models adds value, according to this study. It builds on earlier research by comparing convolutional neural networks (CNNs) to current best practises for assessing textual data in CCP", and it verifies a methodology for include textual data in predictive models using actual "data from a European financial services firm. First, the findings support" earlier studies that found a CCP model's prediction ability is enhanced by the addition of textual input. Second, CNNs perform better than the CCP's existing best "practises for text mining. Third, while textual data are a valuable source of information for CCP", models for churn prediction that solely rely on unstructured textual data cannot compete with those that employ standard structured data. Practitioners can immediately use a computation "of the extra profit obtained from a customer retention campaign by including textual information to assist them in making more informed decisions about whether to invest in text mining".

***Lee, Moon and Yin (2020)***

The major goal of "this research is to build a comprehensive set of innovation processes that take place at the ecosystem level using academic research" as a foundation. By applying the four collaboration techniques, the study investigates the culturally and creatively motivated "over-the-top (OTT) platform that includes a diverse network of ecosystem" participants. Design/methodology/approach: The literature review that examines numerous ecosystem-related themes is the first step in our investigation "(e.g. service innovation, innovative ecosystem). The study also presents a novel conceptual framework that explains how cooperations take place in ecosystems". The OTT platforms are then the subject of a qualitative and exploratory case study in a worldwide context. Results: The framework's use demonstrates "how co-innovative business ecosystems exhibit co-evolution through various structures and trajectories. To deepen and widen the industry integration, an ecosystem" might develop by absorbing additional industries (also known as horizontal growth or broadening strategy). Originality/value: "The value of this research extends to other related industries where diverse actors such as technology firms, Internet firms, direct consumers, government, and even the society impact the type of product and service and shape the evolution of the entire ecosystem because it uses an exploratory approach to begin the discussion on how co-innovation and co-evolution occur at the ecosystem level, particularly in the industry that is driven by" culture and creativity.

***Vélez, Ayuso, Perales-González and Rodríguez (2020)***

“On the basis of analytical models created to anticipate both their churn likelihood and Net Promoter Score, businesses often have to make pertinent judgements about the loyalty and retention of their clientele (NPS). Even while these models must be able to forecast the future, interpretability is equally critical because judgements based on their findings must be correctly explained. In order to facilitate improved decision-making, this work proposes a novel methodology for creating analytical models that balance prediction performance with interpretability. It then fits logistic regression models using a modified stepwise technique for variable selection, which automatically chooses input variables while maintaining their previously proven business logic. In conjunction with this process, a brand-new technique for modifying independent variables is suggested in order to better handle ordinal targets and steer clear of some logistic regression problems with outliers and missing data. In the NPS forecasting assignment of an international university talent challenge offered by a well-known global bank, the combination of these two approaches with some competitive machine-learning methods gained the top spot. A case study is used to describe the use of the suggested methodology” and the outcomes it produced for this situation.

***Fudurić, Malthouse. and Lee (2020)***

“Over-the-top (OTT) platforms like Netflix and Hulu have drawn a lot of” users over the years and seriously disrupted the media and advertising sectors. “Using big data from one of the top US multi-system operators (MSOs), which offers cable TV, phone, and Internet services to numerous towns”, this study investigates the root cause of such a disruption. To be more precise, “the dataset enables us to simulate the viewing habits of 267,276 distinct households, which together viewed 270,718 distinct programmes, and investigate the effects of online video consumption, different genres, and use of extra cable services on cord-cutting.

The results indicate that video on demand and time spent watching various genres, particularly live sports and news, are the most significant predictors of cord cutting”. Finally, they go into how the study will really be used by advertising, content producers, and content distributors.

***Ahn, Kim and Lee (2020)***

Identifying the characteristics that foretell client attrition behaviour in the brokerage and investment banking industries is the aim of this article. Design/methodology/approach: “The authors examine 458,098 retail consumers' full stock trading histories and customer profiles from a Korean brokerage business. The authors create statistical classification techniques for customer attrition prediction models and further investigate the applicability of these models”. Findings: According to the findings of three independent “binary selection models, customer transaction patterns” are a useful explanation for the decline in active retail customers over time. The study's findings show that in the securities sector, characteristics with a “monetary value are the most important for forecasting client attrition”. Study limitations/implications: By presenting the first extensive “field-based evidence that supports the applicability of the canonical recency, frequency, and monetary (RFM) framework in the investment banking and brokerage sector, this study adds to the body of knowledge on customer attrition. By identifying the characteristics that predict customer attrition behaviours in the securities business”, the findings expand on earlier “survey-based studies in the financial services” sector. Relevance in practise: “Practitioners in financial service firms” can simply operationalize the results for attrition prediction. Further evidence that the characteristics identified “in this study are suitable for target marketing comes from estimates that the ex post density of inactive customers in the top 10% most-likely-to-churn category is five to six times the ex ante unconditional attrition ratio. Originality/value: Although the securities sector is one of the most information-intensive industries, in-depth empirical research into customer attrition has lagged”, in part because there aren't enough data on securities transactions and customer demographics. By utilising a sizable field data set, the current study closes this knowledge “gap in the literature and provides a foundation for more in-depth research” on the factors that influence customer attrition in the financial services industry.

***Britto andGobinath (2020)***

“One of the crucial difficulties in customer relationship management” is churn prediction (CRM). It is now more crucial to keep current customers than to find new ones. The review of customer churn prediction across a variety of industries, including “telecommunications, retail banking, e-banking, the energy industry, insurance, and more”, is presented in this paper. The study displays a sizable number of characteristics that other academics used to build their models of customer attrition. It demonstrates different methods that have been applied to churn prediction up to this point. For the churn detection, modelling techniques “like Logistic Regression, Neural Network Model, Random Forest, Decision Tree, Support Vector Machine, and Rough Set Approach are used”. The results show that, when compared to other similar approaches in prediction, the customer churn forecast made using predictive analytics will yield more accurate results. Predictive analytics can be used to predict customer turnover and increase customer retention.

***Bauman and Taylor (2020)***

“The purpose of this study is to look into the factors that influence a wine club member's decision to stay in the club. This study also looks at the prospective departure and retention rates of wine club members” and offers information on the sociodemographic characteristics and variations among wine club members. “Design/methodology/approach: In order to develop the” hypotheses that were evaluated in this study utilising several linear regression analyses, the preceding literature was consulted. 352 valid surveys were collected from the "wine club members of a winery in Fredericksburg, Texas", using an internet survey. The researchers looked at how well "wine club members' intentions to stay in the wine club were predicted by perceived service quality, vineyard wine club policy, customer loyalty, and brand attitude". Findings: It was discovered that brand attitude and customer loyalty significantly predicted whether "wine club members intended to stay in the club, accounting for almost 49% of the variance explained". The intention of wine club members to continue membership, however, was not found to be significantly predicted by views "of service quality or vineyard wine club policy". Also, it was discovered that household income positively correlated with the intention "of wine club members to stick around. Research" constraints and implications Initially, this study used self-reported metrics. Second, the study only included "wine club members from one winery, which reduced its generalizability. Thirdly, this study focused on the factors that influence wine club members' intention to stay" rather than their reasons for leaving. In the end, this research's key implications include showing the "significance of brand attitude and customer loyalty as antecedents of wine club members' intention to stay in the wine club" and offering insights into the prospective "retention and churn rates of "wine club members. Originality/value": Previous studies have not yet looked at the variables that influence wine club members"' intention to stay in the club. The two strong predictive antecedents that prevent wine club member turnover are therefore demonstrated in this paper. Further information about wine consumer behaviour "in the context of direct-to-consumer marketing" is also revealed by this research.

***Hemalatha. and Mahalakshmi (2020)***

Due to the large customer base, "the telecom industry generates enormous amounts of data on a regular basis". Business experts and decision-makers underlined the fact that adding new consumers appears to be "more expensive than keeping existing ones. CRM (customer relationship management) and business analysts must identify the reason" why customers leave and validate behavioural trends from the data on current turnover customers. This research foresaw the development of "a churn prediction model that applies clustering and classification techniques to identify churning consumers and identify" the driving reasons behind customer churn in the telecom industries. The weighted oversampling technique and association attribute ranking model are used to choose features. The suggested method first uses the Adaptive Logitboost (ALB) classification algorithm to classify churn customer data in order to more accurately categorise the instance. A crucial relationship management procedure to stop churners is the creation of retention policies. These models classify client data using a requirement similarity matrix after executing the classification procedure in order to get information. The primary source of churn can be identified using this model's validation of churn factors. "CRM may increase productivity by offering suitable promotions to a group of consumers based on associations" between their behavioural patterns after identifying key churn drivers from customer data. As a result, the company's marketing initiatives are enhanced. Metrics including "precision, accuracy, F-measure, recall, and receiver operating characteristics (ROC)" region are used to calculate the anticipated churn prediction model. Findings show that customer profiling using requirement similarity matrix and anticipated churn prediction provide better categorization than ALB. Additionally, it contributes to client churn by creating relevant pattern associations.

***Lim, Yim, Khuntia and Tanniru (2020)***

Internet health infomediaries are becoming a vital component of the healthcare industry to support and guide people's decisions about their health and wellness. "The active and long-term engagement of patients is essential to the commercial success and efficacy of health infomediaries. An infomediary cannot survive without the continued participation of current users", even when the expansion of its user base is anticipated to offer value by broadening the variety of information that may be communicated. “Understanding the operational workflow operations of an infomediary that can” result in patients' ongoing engagement is a difficulty. An infomediary needs to understand what drives participants to sign up for it as well as what keeps them interested during different involvement phases or transitions in order to increase engagement. In this study, we apply a Markov Chain modelling method to investigate the underlying mechanism of patient involvement as well as numerous transition phases in an online health infomediary. We also analyse user activity data. Over the course of a year, we monitored 127,610 users and more than 1 million activities on a website that provides patients with support for “cosmetic and reconstructive surgery. Cosmetic and reconstructive surgery decisions are health and well-being decisions that patients make based on their current” condition as well as other people's knowledge and experience. This study investigates the significance of the health information intermediary context. Using information on more than 500,000 activities, we took a sample of “the activities of 32,505 active users”. By simulating longitudinal transition probabilities across various levels of engagement, we examined the dynamics of user behaviour. To acquire detailed insights into user involvement, additional analysis “and robustness tests using text-mined data from the users' activities are implemented. Our study offers a number of useful recommendations for the development and administration of an online health infomediary”.

***Rani and Kant (2020)***

Knowledge is learned using both labelled and unlabeled input in semi-supervised learning. With the use of labelled data, supervised classification foretells the labels of unknown data. It is a difficult effort to collect the labelled data in a enough quantity and at a reasonable price. This study compares the six most popular “machine learning classifiers for predicting churn in the telecommunications industry. We also suggest a semi-supervised learning approach” with a pseudo label that would use a large amount of unlabeled data in conjunction with sparsely labelled data to justify an improvement in classifier performance. Using a telecom dataset for churn prediction, “six supervised algorithms, including SVM (Support Vector Machine), Random Forest, Logistic Regression, AdaBoosting, Gradient Boosting, and eXtreme Gradient Boosting, are implemented and evaluated using cross validation technique”. In the second stage, semi-supervised learning is used to assess how well all classifiers have improved. Empirical findings show the proposed model's suitability for these six baseline classifiers. “Gradient Boosting and eXtreme Gradient Bossting classifiers with semi-supervised learning and approximate accuracy of 99.24% and 99.62%, respectively”, are the top classifiers overall.

***Sucu. and Unusan (2021)***

Customer retention is crucial in today's fiercely competitive climate since “acquiring new customers is more expensive and difficult for organisations than keeping the ones” they already have. In order to reduce churn while working with limited resources, “it is critical to identify and analyse consumers whose loyalty is decreasing and who” have a propensity to depart. In the market for mobile communications, this problem is particularly prevalent. This study employs a binomial logit model to analyse survey data from 637 Turkish mobile users “to identify the causes and effects of customer churn”. According to “the findings, network quality, billing, tariff level, tariff plan, and education level are among the variables that determine customer churn and are linked to the inclination to switch. Our findings” show how the mobile telecoms industry's managers and rule-makers can be affected.

***Yousaf, Mishra, Taheri and Kesgin (2021)***

This study extends “the expectation-confirmation model (ECM) to include constructs such as neutral confirmation, customer-to-customer (C2C) interactions, and perceived content quality as antecedents to perceived enjoyment, perceived usefulness, user satisfaction, continuance, and recommendation intentions using data from India and the USA”. The remaining hypotheses are validated in both nations, with the exception of the effects “of C2C interactions on perceived enjoyment and perceived usefulness on recommendation intentions. The amplitude of the roads leading from neutral confirmation and C2C interactions to perceived usefulness as well as the paths leading from perceived enjoyment and satisfaction to continuation intentions” vary between countries.

***Martínez-Sánchez, Nicolas-Sans and Díaz (2021)***

“The transition of the audio-visual consumption model is being led by OTT platforms. These platforms are becoming more popular with audiences, which has effects on two different levels. The existing television model is changing, and established leaders are losing their hegemonic positions. In addition, OTT platforms like Netflix, HBO, Amazon Prime, and, more recently, Disney + are competing with one another to dominate the subscription industry. Facebook and Instagram in particular are a component of the promotional strategy used by all platforms in this race to try to entice new users. In this sense, the goal of this paper is to analyse the social media methods used by the various OTTs in the Spanish market” and evaluate how the launch of Disney+ would affect things. The study uses a quantitative methodology and analyses factors including publishing frequency, content distribution typology, and user interaction across various social networks. The findings help us comprehend the current landscape of these platforms' influence in the Spanish environment.

***De Caigny, Coussement, Verbeke, Idbenjra and Phan (2021)***

Decision-making in “business-to-business (B2B) is heavily reliant on analytics and predictive” modelling. They present uplift modelling as a pertinent prescriptive analytics method in light of this. “The uplift logit leaf model in particular provides a segmentation-based technique that blends interpretability with prediction performance. The uplift logit leaf model outperforms three other widely used uplift models in our study when applied to a real-world data set of 6432 consumers of a European software supplier". A case study that demonstrates the usefulness of the output obtained "from the uplift logit leaf model also" highlights this point. So, this new tool offers innovative "insights in the form of segment-level, global, and customised visualisations that are particularly applicable to industrial marketing" situations. "Overall, the results support the validity of uplift modelling for enhancing management decisions for B2B client retention".

***Srivastava and Eachempati (2021)***

"The employee records dataset from kaggle.com will be used to explore the factors that affect employee attrition rate in this research. Additionally, it compares ensemble machine learning approaches like Random Forest and Gradient Boosting to real-time employee data from a mid-sized Fast-Moving Consumer Goods (FMCG) company in order to determine the predictive power of Deep Learning for employee turnover prediction. A regression model and a multi-criteria fuzzy analytical hierarchy process (AHP) model that" computes weights and takes into consideration the relative relevance of each variable are used to further validate the results. "Deep Neural Networks (91.2% accuracy) are a better predictor of churn than Random Forest and Gradient Boosting Algorithm (82.3% and 85.2%, respectively), according to the empirical results of the machine learning models. For human resource (HR) managers working in an organisational" setting, these findings are insightful. The model can be calibrated by the human resources department of a firm to improve employee retention and incentives.

***De Bock and De Caigny (2021)***

Customer retention management is a significant business area that largely relies on cutting-edge “statistical and machine learning algorithms to support operational decision-making”. Predicting client attrition is an essential technique for encouraging customer retention. It “provides the opportunity to obtain insights into why consumers are at risk and enables early detection of customers who are at risk of leaving the organisation”. Thus, customer churn prediction models should add model insights to supplement predictive performance. This paper presents “rule ensembles and their extension, spline-rule ensembles, as a potential family of classification algorithms to the customer churn prediction arena”, motivated by their capacity to balance robust “predictive performance and interpretability. Spline-rule ensembles combine the simplicity of regression analysis with the adaptability of a tree-based ensemble classifier. They do, however, ignore the relationships between potentially at odds model elements, which can add needless complexity to the models and impair their capacity to be understood. Spline-rule ensembles with sparse group lasso regularisation (SRE-SGL), a unique algorithmic extension”, is suggested as a solution to this problem in order to improve interpretability through structured regularisation. The higher prediction “performance of spline-rule ensembles with sparse group lasso over a collection of well-but-powerful benchmark methods is shown in experiments on fourteen real-world customer turnover data sets from various industries in terms of AUC and top decile lift; (ii) demonstrate that spline-rule ensembles with sparse group lasso regularisation significantly outperform conventional rule ensembles while performing at least as well as conventional spline-rule ensembles; and (iii) use a case study on customer churn prediction for a telecommunications company to illustrate the interpretability of a spline-rule ensemble model and the benefit of structured regularisation in SRE-SGL”.

***Slof, Frasincar and Matsiiako (2021)***

“Customer relationship management has become a” key part of telecommunication service providers' marketing strategies as a result of cheap switching costs and fierce competition. “Telecommunication service providers are eager to lower the churn rate since the expenses of recruiting a new client are five times greater than the costs of sustaining an existing customer”. To solve this issue, a thorough understanding of customer churn behaviour is necessary. Lowering the turnover rate can result in large revenue increases and give an advantage over the competition. “In this study, the authors use a duration model to forecast the likelihood” that clients of a Dutch telecom company will leave. Using a competing risks approach, we simultaneously anticipate customer churn and the cause of that churn. We use Latent Dirichlet Allocation to incorporate topics that were extracted “from the telecommunication service provider's important textual data, which is based on transcripts of calls between customers and the customer support centre”, as variables in our models (LDA). “They compare four models and discover that the ones that include topic factors typically produce the most accurate churn predictions. Also, the analysed models outperformed the benchmark model, which was the model being used by the telecommunications service provider at the time”.

***Li, Hou, Wu, Zhao, Xie and Zou (2021)***

China's national “broadcast service providers have been engaged in a bitter conflict with a” variety of new suppliers from every link in the supply chain. Although there have historically been benefits, “the rate of client churn has been rising recently. National broadcast service providers, like cable network businesses, should anticipate customer” turnover before the competition does in order to better respond to market competition. “According to a positivist perspective, customer churn is associated with viewing frequency, consumption volume, and payment practises. Customer watching intensity and customer churn are only slightly affected by watching preference (as the only available resource). In-depth interviews were done to examine the relationships between variables and to” look at user retention tactics. In the current era of competition, this study gives examples of similar large traditional firms.

***Fanea-Ivanovici and Baber (2021)***

The most popular crowdfunding categories are movies and web shows, and project creators have used a variety of strategies. Filmmakers may offer set “or flexible budgets, use reward-based or equity-based crowdfunding”, and use specialist or generic crowdfunding platforms to raise money. Production may be fully or partially financed through crowdfunding. There is currently no established model for financing the creation of films and web series. Content-based web series have grown in popularity recently “on over-the-top (OTT) services like Netflix and Amazon Prime”. This study's goal is to close this conceptual gap and offer a film “and web series crowdfunding model that can be implemented and used for the good of all stakeholders”: the future audience as a whole, as well as the creators, backers, distributors, platform owners, etc. The model consists of six different “sorts of flows—information/content, funds, audition, decision-making, content, promotion, and rewards”—and nine chronologically linked phases. The conceptual model put forth here “is based on a critical analysis of the literature already in existence in the field, primarily qualitative analyses completed on professionally produced and crowdfunded films” that were successful and unsuccessful in relation to the functionalities of the current technical platform.

***Ardovino and Delmastro (2021)***

In this research, we examine the impact of shifting market dynamics on customers' switching preferences “in the Italian mobile phone market (churn rate)”. In order to achieve this, we look at a market environment in which a limited oligopoly was disturbed by a structural rupture. “The Italian mobile phone market underwent significant changes during the analysis period (2015–2018): while on the one hand, transactions led to a merger between two of the major operators, on the other hand, the merger was approved subject to the entry of a new operator into the market, in an effort to preserve the positive effects of competition. Such evolution represents the ideal condition to test the impact of structural market changes in the competition game, in terms of features of the players, but not in terms of their number. To examine such scenario, we use data related to two different surveys (before and after M&A and new entry events) in order to empirically assess the effect of such changes on consumers' (switching) choices. The empirical models consider the impact of individual socio-demographic and economic characteristics as well as a set of variables related to "choice theory" as proxies of transaction costs, information asymmetries, and implied value of service". The character of the game is altered as a result of the change in market participant typology (but not quantity), leading to a significant rise in both consumer "and social welfare (with redistributive effects in favour of the most vulnerable subjects)".

***Loria and Marconi ((2021)***

The value of a system is determined by how many people are drawn to and actively use it. By alerting designers and algorithms, timely churner detection in gamification can result in more effective apps. Even though churn prediction in entertainment games has been thoroughly studied, gamified systems frequently use simpler mechanics, which results in a smaller number of features than in fully "featured games. In this work, we investigated whether a Random Forest model for churn prediction in a gamified application can be trained using a limited set of players' telemetry data representing in-game activity". They specifically looked at various sampling and data preparation methods. Then, a validation set comprised of "data from an online free-to-play (F2P) game was used". Findings demonstrate how in-game activities may be used to accurately forecast churn. In addition, they discovered that players' propensity to quit the game is inversely correlated with the amount of time they devote to the game and gamified system.

***Iyer and Siddhartha (2021)***

“Instead of viewing traditional television, reports show that 49% of adults in India spend at least 2-3 hours accessing OTT media. Brands have been adjusting to the new patterns that this study looks at as a result of such changes in how the general public is exposed to content. Based on the Technological Acceptance Model, this study was done to determine how consumers felt about and accepted brand placement in the novel media format of web series (TAM). This study used a self-report questionnaire that was modified from F Davis's Perceived Usefulness, Perceived Ease of Use, and User Acceptance of TAM questionnaire. It was based on a survey of 278 people from Urban India settings (1989)”. The research backs up TAM and acknowledges that brand recall is directly correlated with “the frequency of viewing Web Series” (R = 0.57, p.001). When audiences have already formed favourable opinions of the brand, product/brand placement increases “engagement with the placement and results in brand” recognition for unknown or disliked brands “(t (277) = 27.11, p =.01). This study also demonstrates that the TAM is a useful model that can be used to analyse how frequency and duration of viewing influence attitudes towards brands and the positioning of those brands in web series. Brand placement in web series is seen as helpful and heavily influences brand memory. As a result, marketers should strategically consider including brand placement in web series in their marketing communication plan, particularly given the importance of this media and other associated types of advertisement for brands to meet the communication problems facing their industry”.

***Maldonado, Domínguez, Olaya and Verbeke (2021)***

“This research suggests a novel method for churn prediction in the mutual fund sector that is profit-based. In order to meet various segments” with significantly different average customer lifetime values, the maximum profit metric is reformulated (CLVs). In binary classification contexts, the suggested “multithreshold framework for churn prediction seeks to optimise the revenue from retention campaigns. Using data from a Chilean mutual fund business with variable and varied individual CLVs, the multithreshold framework is empirically evaluated. In comparison to other metrics, our results show the benefits of the suggested technique in producing the best profit”. Our system, which can be used to any churn prediction assignment even if it is described in the case of investment companies, makes a significant addition to business analytics decision-making.

***Mittal. and Sinha (2021)***

“Learning outcomes: Following are the learning outcomes: understand the relevance of project management as an integrated approach for managing projects in an exceptional situation. Address the problems connected to managing modern projects such as shorter product life cycles, changing client preferences and last-minute risks. Assess the role of sub-domains of project management such as project prioritising, project negotiation, project portfolio system, project risk assessment and management and project stakeholder management. Case overview/synopsis: It is the year 2020, and the entire world is striving to cope up with the crisis created by the corona virus (COVID-19) epidemic”. Everything that was once normal has stopped. The importance of creating creative “strategies to adapt to the new normal situation has been realised across all industries. This case details the struggles of TVR Cinemas, a Tiya Group business unit that handles the production and distribution of Hollywood and Bollywood films in India”. Multiplex industry is severely harmed by the Indian subcontinent being under lockdown. The corporation must come up with new strategies to compete in the market given the higher standards for hygiene, social isolation, and a "stay home stay safe policy." In this case, students are asked “to put themselves in the position of the company's project manager, Mr. Ramchandani, and offer advice on how to release seven unfinished Bollywood movie projects, choose the best over-the-top (OTT) partner for tie-ups, and develop tactical moves to restore the company's reputation by launching their own OTT platform. Academic difficulty level: The scenario is helpful for teaching the fundamentals of project management as well as making decisions for projects" in a challenging circumstance. Students at the undergraduate, graduate, and executive levels can utilise this case to practise "project management, project risk management, and negotiation management skills. Further materials Educators" alone have access to the teaching notes. CSS 9: Operations and logistics is the subject code.

***Sarkar and De Bruyn (2021)***

Businesses frequently work with high-dimensional data in predictive modelling that spans a variety of "channels, websites, demographics, purchase kinds, and product categories. Conventional customer response models heavily rely on feature engineering, and the success of these models depends on the analyst's ability to" develop accurate predictors based on their domain-specific knowledge. But conventional models get exponentially more difficult as data complexity rises. In this study, the authors show "that long-short term memory (LSTM) neural networks, which only accept raw data as input", are capable of making very accurate predictions of consumer behaviour. In our initial use, a model outperforms benchmarks as expected. "An LSTM model competes against 271 hand-crafted models that employ a wide range of characteristics and modelling techniques in a second, more realistic application". It defeats 269 of them, most of them decisively. LSTM neural networks are great options for simulating consumer behaviour in complicated situations utilising panel data "(e.g., direct marketing, brand choices, clickstream data, churn prediction)".

***Koul, Ambekar and Hudnurkar (2021)***

"The aim of this study is to identify, rank, and create composite relational aspects that affect millennial consumers' decision to subscribe to an OTT platform service on an access basis".

For a business planning to increase its client base or for a business trying to keep its current consumers, it is important “to understand what elements drive the subscription of a service in the competitive and growing Indian market of OTT platforms”.

Design/methodology/approach: The strategy involves identifying the elements that influence customer purchasing decisions and asking survey respondents to rank them in terms of how important they are when deciding whether to subscribe to an OTT platform service. In this study, “the primary data were gathered using a questionnaire”. Participants in the poll were chosen using "purposive sampling" “based on their age group and their past or present use of at least one OTT platform service. The survey was made available to millennial viewers in Tier I and Tier II cities with strong mobile internet connectivity”. Findings: As a consequence of this research, components are ranked according to how important millennial consumers believe they are, and then combined to create composite factors with similar replies. Practical ramifications: This research gives information consumers the chance to focus on the aspects that turn out to be most crucial to them and plan or anticipate their strategy and future research investigations accordingly. Originality/value: A similar study for OTT platforms located in the US has been done. The significance of this research, which is focused on Indian platforms and customers due to the country's expanding OTT market.

***Vo, Liu, Liand Xu (2021)***

“In the financial services sector, it's critical to keep customers. In order to forecast client churn concerns, machine learning has been applied into customer data analytics. Even though they are effective, current systems typically only leverage structured data, such demographics and account history. Unstructured data, such as customer interactions, can be used for data mining to yield more insightful results, but this potential has not been fully realised. In this study, they provide a model for predicting customer attrition based on spoken phone conversation data, which is unstructured data. They conducted extensive experiments on a large call centre dataset comprised of two million calls from more than two hundred thousand customers". The findings demonstrate that by combining "interpretable machine learning with personality traits and consumer segmentation", our approach is capable of reliably predicting client churn risks and producing insightful data. They talk about how managers can use these information to create retention plans that are specific to particular client groups.

***Dhini and Fauzan (2021)***

The ability to quickly switch providers in order to achieve higher quality has led to a shift in customer opinion towards better service from internet service providers. If internet service providers want to keep their consumers, they must identify the risk of churn as soon as possible. "This study used customer data from one of the largest fixed broadband providers in Indonesia as a case study" to forecast churn using recent advances in machine learning methodologies. Extreme gradient boosting and random forest were two methods used in this study to achieve ensemble learning, which combines meta-algorithms to enhance model performance (XGBoost). The outcomes demonstrate that "XGBoost is the best algorithm for predicting customer attrition", while ensemble learning models beat traditional techniques. Clients are grouped as having a high, medium, or low chance of leaving the company as a result, and the business can establish specific retention measures for each customer cluster.

***Dumitrache, Nastu and Stancu (2020)***

The vast number of studies "on the issue of customers switching from one competing telecoms service provider to another published" in the previous 10 years demonstrate how serious this issue has grown within this sector and beyond. "The goal of this study is to identify which variables", out of the many that are included in the data set for postpaid customers, are significant contributors to the issue of customer churn at other Romanian mobile telecommunications providers. They require technologies that can evaluate the data in order to help us comprehend and “address the issue of churn in the telecoms industry. As a result, they employ three feature selection tools—Permutation Importance, Partial Dependency Plot, and SHAP—and a Balanced Random Forest for the churn model”. They categorise the predictive indicators using the churn model and use them to determine the relevance, predictive power, and distribution of each characteristic's influence. “The number of months since the last offer was changed from the account, the number of minutes used outside the company, the value of the invoice, the age of the customer, and his time with this telecommunications operator” are the drivers regarding churn issue, according to the Permutation Importance. For each of the listed indicators, the partially dependent plot identifies the churn risk areas encountered by the Romanian telecoms firm, “such as: clients with younger ages or with out-of-date offers (unchanged for almost two years)”. A substantial number of minutes obtained from competitor networks, a short time in the network, or a long time since the last offer all contribute to an increase in the projected churn per client, according to SHAP.

***Langerová, Starzyczná and Zapletalova (2021)***

“The article seeks to assess the degree of the analytical component of CRM in SMEs in Czechia and its effect on boosting the profitability of the businesses. Primary quantitative study was done for the empirical element”. Analytical activities were chosen as the topic for the quantitative research. The Moravian-Silesian Region's SMEs were the focus of the study. 1 067 people filled out the survey questionnaire. “The PDCA method (Deming cycle), used to assess process quality, was updated to assess the extent of the usage of particular analytical activities. This method was chosen as a result of the Anglo-Australian examination of relationship marketing that is based on quality management”. “The mode served as the basis for applying the PDCA approach”. This article offers an alternative viewpoint on CRM level evaluation. How much analysis was done was the subject of a research topic. This strategy “highlighted the highest level of customer satisfaction analysis”, client segmentation, and sales evaluation—all fundamental marketing operations. CRM is unable to function without these tasks. The ability to predict client churn and establish a system for gauging customer loyalty revealed the lowest level. The primary objective of CRM is to create lasting relationships, which should enhance businesses' financial performance. In order to express the connection between the intensity of particular analytical operations and rising corporate profitability, five hypotheses were developed. “Regression analysis was used to confirm the hypothesis. The profitability of businesses was impacted by all analytical operations”.

***AL-Najjar, Al-Rousan and AL-Najjar (2022)***

“The percentage of clients that discontinue utilising a bank's services is known as the credit card customer churn rate”. As a result, banks will receive an early warning to modify their service to “that consumer or to offer them new services if they construct a prediction model to predict the predicted status for the customers. The goal of this study is to construct a feature-selection strategy and five machine learning models to predict credit card client attrition. Three models were used to choose the independent variables: feature selection, two-step clustering with k-nearest neighbour, and selection of all independent variables. Also, the Bayesian network, the C5 tree, the chi-square automatic interaction detection (CHAID) tree, the classification and regression (CR) tree, and a neural network were chosen as five machine learning prediction models. The results of the investigation demonstrated that any machine learning model could forecast the model of credit card user attrition. Also, the outcomes demonstrated that, when compared to the other three constructed models, the C5 tree machine learning model performed the best. The findings showed that the total number of transactions, the total credit card revolving amount, and the change in transaction count were the top three factors required in the building of the C5 tree customer churn prediction model. Lastly, the findings showed that the prediction models performed better when the multi-categorical variables were combined into a single variable".

**Chen, Zhang, Zhao, and Xu (2022)**

The financial system of today's globe depends heavily on the insurance sector. Car insurance clients' churn management is a top goal because it makes up a significant portion of insurance firms' revenue and keeping regular customers has proven to be cost-effective. In the meantime, customer turnover will define a company's financial situation and reflect the quality of its management and service. "In order to model the client churn issues and identify the critical variables that influence clients' decisions, this paper proposes a new model that combines the Cox model with variable penalties (Lasso, SCAD, and MCP). The model is based on the personal information and behaviour data that were provided by a major insurance company in China". This methodology has been shown to be effective in determining client churning and comparing fines. The most significant aspect of customer churn issues is revealed by the variable penalty model, which can offer a solid foundation for insurance firms' product development. MCP produces the most sparsity, but as a result, some information is lost. They advise employing SCAD in the model because it strikes a compromise between information reservation and sparsity. Also, a novel method for creating "a dynamic threshold of churning probability is suggested, which businesses can utilise to manage their clientele more adaptably. By doing this, clients who are likely to leave can be detected beforehand", and client management costs can be adjusted accordingly.

***Kour and Chhabria (2022)***

The available literature on "Video on Demand (VoD) has mainly ignored the stakeholder perspective in favour of the consumer viewpoint. This study seeks to close this gap by comprehending, from the supplier's perspective", the techniques to improve the experience and engage customers. “The study's goal is to discover and examine the tactics used by over-the-top (OTT) platforms to maintain customer loyalty in the VoD market. Design/methodology/approach: The authors conducted 16 in-depth interviews with industry” professionals working for Indian OTT platforms as well as individuals in charge of various marketing-related jobs “using a qualitative approach and inductive qualitative design”. Topics covered in the data collection included engagement, platform, customer value provided, consumer experience, and industry landscape stickiness. Meaningful semantic components were discovered using thematic analysis. Results: This study discovered that platform expansion as value enhancers, “consumer sense-making and engagement, consumer engagement, and consumer experience were the primary techniques implemented in the Indian context, which contributed to a platform's stickiness. Study limitations/implications: This study provides policymakers with information about how content, digital platforms, media professionals, and managers are influencing” consumer behaviour. Practical implications: This study offers guidance to media professionals, managers, and leaders of digital platforms “who are influencing customers through platform tactics. Social implications: The” study may aid businesspeople and marketers in comprehending the viewpoints of those involved in India's VoD sector. “Research on the idea of stickiness, which may or may not be equated with loyalty, is encouraged by the study. In order to encourage clients to return to the same platform in the near future”, it is crucial to concentrate on quality, regularity, and consistent reminders.

***Gattermann-Itschert and Thonemann (2022)***

Companies can target high-risk consumers with proactive retention strategies thanks to the ability to predict customer attrition. They create a churn prediction model and use it in a field research “for a non-contractual business-to-business (B2B) wholesale context. Our study demonstrates that contacting the clients with the highest estimated churn probabilities” considerably lowers population turnover when compared to random targeting. They show that this has a favourable financial impact on the growth of revenue as well. They add to the literature by highlighting the key “elements in addition to testing B2B churn prediction and retention in the real world”. In addition to the usual features of recentness, frequency, and monetary worth They demonstrate the significance of features unique to customer relationship management, such as the most recent time a customer spoke with a field person. they offer a method for utilising current customer service procedures to integrate proactive churn management into operations.

***Chawla, Shaw, and Choudhary (2022)***

Virtual streaming platforms “are the main source of entertainment in the modern world”. Online streaming platforms gradually overtake conventional entertainment channels as consumers switch over as they provide more inventive options. The number of users in the streaming industry grew dramatically during the COVID-19 period. “As a result, streaming services are now widely seen as the future of the entertainment sector”. OTT services have lately acquired popularity, especially during the epidemic, for a variety of reasons, including supplying high-quality content and connecting people through different streaming platforms. “The goal of this study is to pinpoint the elements that affect consumers' happiness with a streaming service in Kolkata, West Bengal, and to determine the connections” between these characteristics and various streaming services. Methodology: The survey was conducted in Kolkata, West Bengal, “with the aid of a standardised questionnaire and casual interactions with the users. Findings: This study found that” "Fringe Benefits" and "Refreshment" were the two key variables that most significantly influenced consumer happiness. It was discovered that the component "Fringe Benefits" had a significant impact. Moreover, correspondence analysis could be used to link customer pleasure to the calibre of services offered to streaming platforms. Several online streaming services were found to be wellliked, providing “high-quality content with a variety of options, few advertising, and high-quality and extensive features at an affordable price. Also, we utilised cluster analysis to identify three clusters that affected viewers of different ages while they watched on different streaming websites”. "Gen Z Socializing," "Gen Y Entertaining," and "Gen X Quality Essence" were the names of these clusters.

***Eisenbarth, Cholez and Perrin (2022)***

To distribute transactions and blocks amongst nodes, “public blockchains like Ethereum rely on an underlying peer-to-peer (P2P) network. With the growth of blockchain applications and the value of cryptocurrencies, they have evolved into crucial infrastructures” but are still understudied in depth. In this research, they suggest looking at the Ethereum P2P network's dependability. To gather data on the peers making up the network, we created our own trustworthy crawler. While the network might demonstrate a fast and significant growth “in size and peers are disproportionately concentrated on a small number of ASes, our data analysis regarding the geographical distribution of peers and the churn rate reveals good network features”. they then look for any odd trends that would indicate “a Sybil attack. They discover that many nodes in the network have several identities and may pose a threat. They suggest an architecture to identify suspicious nodes and revoke them” in order to lessen upcoming Sybil attacks. “It is based on a monitoring system, a smart contract to spread the information, and an outside revocation tool to assist customers in cutting off their connections to suspect peers. Our test on the Ethereum Test network” demonstrated the viability of our approach.

***Oloyede (2022)***

Because marketing is frequently viewed “as a cost centre inside many organisations, corporations utilise marketing attribution models to hold the marketing department accountable for the money and resources they use. Marketing" attribution models are used by marketers for two reasons. First, to defend the funds allocated to marketing initiatives and operations, and second, to pinpoint which marketing avenues and strategies deliver the desired effects. To justify spending or demonstrate results, marketing teams still have trouble using marketing attribution models. Data integrity problems, a lack of understanding on "how to use marketing attribution tools successfully, and the sheer complexity of the buyer's journey" are the three main reasons why marketers find it difficult to adopt attribution models.This study makes the case that the real issue with attribution reporting is how marketers see its use. Additionally, it is suggested that those causes are merely signs of a more serious issue with marketers' methods for attributing marketing success. Marketers must modify the "focus of their attribution models to centre on customer metrics rather than business" results if they hope to successfully use attribution. Return on investment (ROI) is frequently used as a benchmark in marketing attribution; nevertheless, ROI is a company consequence, not a customer statistic. Marketers will get the informed results they want by concentrating on customer KPIs like brand awareness, brand engagement, and churn rate. By determining "the attribution model's objective and then matching the appropriate marketing data to the desired result", it is possible to acquire insight from an attribution model.

***Feng, Su, Feng and Li (2022)***

More and more providers of information products switch to "a subscription-based business model and" provide customers with a selection "of subscription lengths for the same product. In order to compare the single- and two-option menus, this study uses a horizontal differentiation model" in which the only difference between the subscription options is the duration of the renewal period. "The latter provides both the short- and long-length options", but the former only provides one. According to analytical findings, "the unit misfit cost, which evaluates consumers' disutility per unit distance between the real and ideal subscription durations, and the basic value of the product are crucial elements in establishing the” best layout for the subscription “menu. When both the basic value and the unit misfit cost” are greater than a predetermined threshold, “the two-option menu outweighs the one-option menu. More research is done on the effect of consumer attrition rate on subscription menu design”. When the rate of consumer turnover rises, it is increasingly likely that a two-option menu will be the popular option. “Moreover, the unit misfit cost affects how much the rising consumer turnover rate affects pricing. Vendors should increase the price for the short-length option and the price discount level for the long-length option only” if the unit misfit cost is sufficiently low given the increased consumer churn rate; otherwise, the best pricing choice will remain the same. “The appropriate number of periods for the long-length choice are discussed in relation to the product value, customers' cognitive cost, and unit misfit cost after endogenizing the length of the long-length option”. It is also investigated whether a multiple-choice menu with more than two selections is appropriate.

***Bhattacharyya and Dash (2022)***

From the early 2000s, “the importance and volume of the literature on customer churn behaviour in telecommunications have increased. In order to review pertinent papers published by these journals on customer churn research in telecommunication, this study ran a quantitative bibliometric retrospective of selected journals that satisfied the criteria for the ABDC journal quality list. This review provides light on the publication trends, publications, stakeholders, popular research approaches, and themes of interest throughout three decades using bibliometric data from 175 research articles found in the Scopus database (1985–2019). The results of this review indicate that there are ten major categories of scholarship that collectively represent the current level of contributions: churn prediction and modelling, feature selection techniques and comparison, customer retention strategy and relationship management, service recovery, pricing and switching cost, legislation, legal, and policy, word-of-mouth and post-switching behaviour, new service adoption, brand credibility, and loyalty. The majority of the literature now in publication makes full use of quantitative techniques. The study's main argument is that academics have neglected the metatheoretical repercussions of depending entirely on a logical positivist paradigm for far too long. We also emphasise future areas for study and the necessity of expanding feature selection and modelling in customer churn studies”.

***Valluri, Raju and Patil (2021)***

In a specific group of subprime borrowers, “this article examines the application of a customer character model as a predictor of used auto loan churn. The 4 Cs of capacity, collateral, credit, and character of churn prediction are compared to the customer character model (i.e., restricted model). The findings show that the whole model and the customer character model are different. A variety of supervised classification techniques, including logistic regression (LR), linear discriminant analysis (LDA), decision trees (DTs), and random forests (RFs), are also used and their prediction accuracy is evaluated. The most effective performance is reported by the RF classification measures. Also, many classification techniques point to the significance of certain client character traits. So, from a practical standpoint, it is advised to conduct efficient borrower character screening to establish customer profiles more precisely for the objectives of target marketing and client retention. This study adds to our understanding of subprime lending markets and sheds” new light on machine learning-based credit scoring.

***Tariq, Babar, Poulin and Khattak (2022)***

“The proposed model's goal is to help” e-businesses forecast consumers who would churn using “machine learning. The purpose” of this study “is to observe consumer behaviour and make decisions” in line with it. Design/methodology/approach: “The 2-D convolutional neural network is utilised in the suggested model (CNN; a technique of deep learning). Data load and preprocessing layer and 2-D CNN layer" are the two distinct phases that make up the proposed model's layered architecture. The data is also processed in a parallel setting "using the Apache Spark parallel and distributed framework By utilising Telco Customer Churn, training data is extracted from Kaggle". Findings: The proposed model's accuracy rating is 0.963 out of 1, indicating that it is reliable. "Also, the training and validation loss, which is 0.004, is incredibly low. The true-positive values are 95% and the true-negative values are 94%, according to the results of the confusion matrices. But it still works because the false-negative rate is only 5% and the false-positive rate is only 6%. Originality/value: This study emphasises a thorough explanation of the preprocessing needed for the CNN model". In order to make an effective customer churn prediction, the data set is examined more extensively.

***Xiahou and Harada (2022)***

For e-commerce businesses to develop efficient client retention strategies and put them into practise, it is crucial to predict customer turnover. This work suggests "a loss prediction model based on the combination of k-means customer segmentation and support vector machine (SVM) prediction, taking into account the characteristics of longitudinal timeframes and multidimensional data variables of B2C e-commerce customers' shopping habits. The technique identifies the primary customer groups and divides the consumer base into three categories. To forecast customer attrition, the support vector machine and logistic regression were evaluated. The findings demonstrate the importance of k-means clustering segmentation by demonstrating a significant improvement in each prediction index following customer segmentation. SVM predictions were more accurate than those made using logistic regression". The findings of this study are important for B2C e-commerce businesses managing client relationships.

***Pekel Ozmen and Ozcan (2022)***

One of a company's most valuable resources is its workforce. The performance of a corporation is substantially impacted by the turnover of valuable staff. For businesses, the development of technologies that can forecast staff attrition is crucial. Machine learning algorithms currently have significant prospects for the diagnosis of employee churn. Deep learning models have taken the role of classical categorization methods in modern times. In order to forecast staff attrition in the retail industry, “a convolutional neural network (CNN) model was initially applied to a set of numerical data. Eventually, a new hybrid extended convolutional decision tree model (ECDT) was proposed by enhancing the CNN algorithm” because the data loss in data transformations is too great. In order to increase the classification accuracy of ECDT, grid search optimization was finally used to create a novel model (ECDT-GRID). In terms of classification accuracy, “numerical results showed that the proposed ECDT-GRID model performed better than the CNN and ECDT models and fundamental classification algorithms”. This model also provided a useful methodology for predicting employee churn.

***Basu, Mandal, Murti and Makany (2023)***

“The COVID-19 pandemic disrupted the entertainment industry globally and put a stop” to outdoor activities. As a result, customers started using streaming video and music services for their entertainment needs. In order to prevent income losses and protracted delays, a number of movie companies have chosen the digital distribution option on “over-the-top (OTT) platforms. Yet in order to match the theatrical experiences, these non-theatrical OTT film releases need to try” out new tactics. In order to establish credibility in a cutthroat entertainment market, this exploratory study seeks to shed light on the question of “whether Immersive Cinema may be utilised to simulate the real world through digital simulation on

OTT platforms. In order to understand viewpoints about Immersive Cinema consumption on OTT platforms and its potential as compared to conventional theatrical releases, they conducted semi-structured, qualitative interviews with 21 consumers and focus groups with 14 MBA students. The results of this study can be used by OTT platforms to curate their new movies as a direct replacement for theatrical releases".

***Gupta (2022)***

Client attrition is currently a significant issue "for e-commerce businesses. To accurately anticipate customer turnover in e-commerce applications", e-commerce enterprises must have a customer churn prediction model. An innovative idea for a "fading channel patch-based heat map for convolutional neural network deep learning models has been put forth in this study. Using benchmarked Brazilian e-commerce data heat maps, the current work aims to train the fundamental, two-layered, and three-layered convolutional neural network churn prediction models. Prediction is performed using a pre-processed, balanced dataset of 14,188 data samples" from online shoppers. The models are tested on 30% of the data after being trained on 70% of the data (9932 samples) (4632 samples). The constructed models are trained using the heat maps, which are created and contain the qualities and pertinent purchase data for each consumer. For model evaluation, the performance metrics accuracy, "lift, true positive rate, and false-positive rate are used. The correctness of the models created in this work is also compared to the models" already in use that have been created by other researchers in the past. In comparison "to the three-layered and basic convolutional neural network models, it is discovered that the two-layered model has superior accuracy and performance. In comparison to current machine learning and convolutional neural network models, the accuracy of the two-layered convolutional neural network model is higher. Hence, this work suggests a precise two-layered churn prediction model for e-commerce. The authors want to increase accuracy in the future by utilising an ensemble convolutional neural network. Also, the authors are aiming to train the created models" using many datasets.

***Ganeson, Lew. and Abdul Razak (2022)***

As there are no requirements for customers to be loyal to a specific online business, the identification of retainable online non-contractual clients is important for the functioning and expansion of non-contractual online enterprises. So, the goal of this research article was to suggest a churn window for non-contractual transactions. Secondly, a prediction model based on the previous purchase patterns of the average client was given. Second, a new churn window was suggested based on trends in consumer purchase history. Customers typically have a distinct churn window based on their buying habits. This contrasts with the conventional concept of churn window, which applies a set churn window to all consumers regardless of each one's unique purchase history. The proposed churn window model offers more accuracy than the conventionally defined window, which is applied uniformly to all consumers, according to the results. This leads to the conclusion that the suggested prediction model and the churn window model may be helpful in assisting non-contractual internet firms' marketing strategies and initiatives.

***Ahn (2022)***

Human activity tends to peak at particular times and then decline for extended amounts of time. "This study shows that an entropy measure of non-Poisson trading patterns has advantages over the canonical recency, frequency, and monetary value framework in the financial services industry by analysing detailed trading records as well as the demographic profiles of 486,049 customers from a major securities company. The clumpiness measure of trade clustering" significantly contributes to explaining customers' future churning, according to "the LASSO logistic regression, the information gain metric in gradient boosting decision trees, and the relative importance technique in neural networks”. Furthermore, It seems that freshly created statistical learning methods have a stronger impact on churn prediction mistakes reduction. To more accurately estimate client lifetime value, machine learning methods in combination with a metric-based parsimonious RFMC methodology might be utilised.

***Sarpong,Maclean and Hassan (2022)***

They examine “the high churn rate in the UK financial services business using the Notsie story, a West African literary folklore, as” a lens from the Global South. they investigate why former financial complaint handlers regularly left their well-paying employment by using the fabled accounts of these individuals as a prism for a Notsie story. Our research demonstrates how an unrelenting focus on efficiency leads to managerial tyranny—a collection of impulsive, repressive organisational actions that together cause “high turnover. The wisdom of our Notsie narrative perspective focuses on relationality, the skillful ways of relating that forge connections between people, and what it means for the Notsie kingdom to be doomed to collapse without its people. This wisdom appears to be overlooked and undervalued in western ways of knowing, which are rooted in individualism, rationality, and instrumentalism”.

***Duan and Ras (2022)***

“It is widely acknowledged that one of a company's most significant” assets is its customer base. Reduced client outflow is crucial for businesses, for this reason. “In this paper, they concentrate on identifying the clients with a high probability of attrition and offer reliable and valid suggestions” to reduce client turnover. In order to do this, they created and put into use a recommender system that may offer suggestions for improving customer churn rate. From 2011 to 2017, “they used transactional and survey data from the heavy equipment maintenance and servicing sector. A Charlotte, North Carolina-based consulting firm gathered this data. Customers provide their views, feelings, expectations, and complaints as freeform text in the survey data. To learn more about how customers felt about the service, they used aspect-based sentiment analysis on the review text data. Actionable solutions for lowering customer churn are identified via action rule mining and meta-action triggering mechanisms”.

***Rajeswari and Suganthi (2022)***

With a growing subscriber base, Indian mobile carriers aim to hold the second-largest position in the global ranking. Although customer turnover rates are high, mobile carriers confront intense competition in a lively market environment. The study was carried out to establish metrics and confirm “the degree of customer turnover in the Indian mobile communications” industry. “In order to verify the accuracy and validity of the customer turnover scale, structural equation modelling was used to collect data from a total of 1,102 consumers. In the Indian telecom industry, issues like price, corporate image, service quality, and customer relationship management have” become crucial in determining how often customers churn. Despite creating proactive measures through investments and creating client retention campaigns, mobile carriers They were powerless against the rising turnover rates. “This study suggests a validated scale to anticipate customer attrition in the expanding Indian mobile services market, together with the exponent in prevalent churn rates. The contribution to the thorough development of the customer churn scale in the Indian mobile services sector” would be covered by this special study.

***Dhiman, Singh and Sarmah ((2022)***

“The current study attempts to measure the determinants of continuous intention of over-the-top (OTT) platforms. In the present context, stimulus–organism–response (S–O–R) model was applied to identify the determinants of continuous intentions. The data were collected from users of the existing OTT platforms. To test the proposed model, we applied the partial least square structural equation modeling (PLS-SEM) technique in accordance with the objective and hypotheses. The proposed model explains 45% of perceived value and 41% of continuance intentions, respectively. The results indicated that there are four significant relationships and one insignificant relationship. To be clear, perceived customisation benefits, perceived ease of use, perceived mobility benefits, perceived value substantially influences the continued intention of OTT platforms, and entertainment value was shown to be unimportant compared to perceived value. This study” gives marketers numerous hints about how to influence consumer behaviour and determine the elements influencing OTT platform decision-making. According to the current study, continual intentions might be framed through providing value.

***Patnaik, Patra, Mahapatra and Baral (2022)***

The current era of quick technology advancements and the increasing rate of internet adoption have made it easier for people to pursue their preferred forms of entertainment. “Over-the-Top (OTT) media services have advanced by changing the media landscape during the COVID pandemic. A sizable portion of the global public now accepts OTT thanks to smart phones and easy access to broadband. The handheld OTT” gadget is evolving as consumers' preferred method of video consumption in India as well. Yet, there are several drawbacks to this new form of communication, primarily in terms of socioeconomic and technological problems. Together with identifying the expanding OTT demand, the present study focused on the difficulties associated with implementing this quickly becoming a favourite media platform. Three key elements, including "user behaviour," "technology flexibility," “and "customer-centric content," were found to be the primary influences of OTT content after a study of the data gathered from respondents in the twin cities of Odisha (Cuttack and Bhubaneswar)”. The regulatory bodies and OTT media players can both benefit from the study's insights in terms of promotion and strategy formulation.

***Ramli, Ramli, Ramadayanti, Lestari and Fauzi (2022)***

As expected, the establishment of communications rules has drawn attention from the public because it can offer a number of protections. “The Indonesian Job Creation Law has also brought forth new ramifications for the telecom companies in the form of government assistance. It is anticipated that the Indonesian telecommunications operator system will be able to develop and supply the best facilities in keeping with community needs based on the values of fairness, impartiality, and non-discrimination as well as maintaining service quality”. “The introduction of a new pattern of collaboration with the Over-The-Top (OTT) service, which has been gaining popularity, has also been made possible as a result of this. The goal of this study”, which employs “a normative research methodology and online data collection techniques, is to produce an analysis”, promote socialisation, and educate the public about the development of telecommunications operations principles and how they are applied “in the Job Creation Law and its Implementing Regulations”.

***Fridrich and Dostál (2022)***

A strong customer base must be kept in e-commerce retail through effective retention management. The goal of retention is supported by efforts to anticipate churn, which rely on dependent and independent factors. Sadly, there doesn't seem to be general agreement on “a user turnover model. Our aim is to present a model based on both conventional and novel” qualities and investigate its characteristics via auxiliary assessment. The most effective modelling pipelines and a permutation technique are used to determine the importance of each individual variable. they also employ a unique method based on relevance ranking and information retrieval to quantify “the effects on the performance and quality of a feature set”. SVM-RBF, GBM, and LR learners are used in the pleasing pipelines that the performance benchmark demonstrates. The solutions heavily rely on user behavior's traditional recency and frequency factors. The potential of subtler factors defining user preferences or date-time behavioural patterns is interestingly exploited by SVM-RBF and GBM. The gathered data may also help with business decisions related to churn prediction efforts, including designing retention campaigns.

***Nata, Antonio and Monika (2022***)

“The over-the-top (OTT) streaming platform market is a new” development that has given the film business a new challenge. A satisfying watching experience for moviegoers is essential for success in the fiercely competitive “OTT business. In the setting of the OTT platform, this study sought to investigate the predicate of the viewing experience as well as the mediating function of viewing towards behavioural goals in Indonesia. This study uses social media exposure and fear of missing out (FOMO)” in addition to viewing experience to forecast behavioural intentions. The empirical data that was collected through purposive sampling was examined using the PLS-SEM approach. An online survey that was issued to all eligible sample participants yielded a total of 438 responses. The findings show that movie qualities have the biggest impact on the viewing experience. “With an R-squared value of 0.629”, the viewing experience also mediates behavioural intentions, indicating a significant impact. The study findings' theoretical and managerial ramifications are examined. “The study also sought to determine how good viewing habits, social media exposure, and fear of missing out influence consumers' intentions to recommend movies, platforms, and subscriptions”. Finally, this study evaluated which viewing experience antecedent has the greatest influence on creating a positive viewing experience.

***Shabankareh, Shabankareh,Nazarian, Ranjbaran and Seyyedamiri (2022)***

Organizations constantly battle to keep their existing consumers while also acquiring new ones “using a variety of strategies in today's competitive market. Customer turnover is a significant issue for a variety of businesses and industries”. Despite their first efforts to gain customers being successful, businesses eventually discover that their present clients may defect to their competitors. “Organizations will be able to ensure their future performance by modifying their customer relationship management policy” by identifying churn candidates. This study used data mining algorithms to combine new methods for early churn identification while analysing the data of the telecommunications sectors. According to research, the best results can be obtained by combining “support vector machines (SVMs) and the chi-square automatic interaction detection (CHAID) decision tree”. The outcomes demonstrate that the suggested churn prediction solution is accurate as suggested. Moreover, stacking helped to enhance results for detecting client churn.

***Chalaby (2016)***

In this paper, “the globalisation of television is examined using the global value chain (GVC) framework, and it is asserted that this process has been fueled by the dynamics of a recently developed TV content value chain. As the supply chain became more globalised and businesses sought to gain a competitive edge by becoming global in their industry, distinct segments began to emerge. This article focuses on four aspects of the TV content value chain and makes the case” that the internationalisation of the chain's segments is what led to the millennial global shift in the TV industry by demonstrating the expansion of transnational TV networks and formats. The article concludes by arguing that industrial aggregation “should be understood in the context of Internet disruption and global production dispersion inside growing value chains”.

***Chen, Kuo and Chen (2018)***

The demand for digital media "has increased significantly over the past ten years because of the popularity of" multimedia and the network's ever-increasing capacity. In today's e-commerce, "the digital media with protected contents—such as images, movies, audios, and 3D model materials—are more significant. One developing e-commerce strategy in recent years is the delivery of digital media content utilising an OTT (over-the-top) platform. The transaction platform for both content producers and content providers to publish their DMC goods is always provided by the traditional website for digital media content (DMC)". After making a purchase, customers (clients) might browse the website's attractive products and download DMCs. Nonetheless, the platform still accepts traditional forms of payment, such as ACH, credit cards, and debit cards, for the transaction of these copyrighted DMCs (Automated Clearing House). The revolutionary secure private OTT (p-OTT) network that "is proposed in this study uses blockchain technology to handle transactions with reliable and adaptable services". Smart contracts are one of the main components of the blockchain technology. As a result, a pre-defined data contract template might be provided for each DMC product. "Real data contract (RDC) will be produced and output by smart contract following the negotiation process using smart contracts. The content producer or provider might easily put his transaction policy" into practise using the preset template of the data contract. Additionally, they create "a shadow key pair for each reserved DMC for a transaction period as well as an online authentication key for each member". Thus, using blockchain technology, this article provides a safe OTT paradigm. By performing a smart contract, they demonstrate "that it is not only a safe OTT platform but also a flexible transaction".

***Bouquillion (2019)***

A preliminary finding is simple to draw: digital platforms are crucial to the economy of the cultural industries. The transnationalization of the audiovisual industry “has largely been facilitated by digital channels. The deployment of Over-The-Top (OTT) platforms has resulted in the establishment of a liberal offer”, partially from "new entrants" in the markets, particularly in France and India. They are international digital players, such as Amazon and Alibaba, or national telecoms industry players. “The deployment of OTT has heightened tensions surrounding public policy issues in both France and India. These challenges involve a complex interplay between global logic and its national character”. National players “in France” are requesting fewer regulatory requirements as a result of the entry of transnational players, particularly Netflix. The changes go hand in hand with the process of globalisation, which results in a redistribution of power that benefits both transnational and domestic entities, namely telecom providers.

***Safiranita, Ramli, Permata, Adolf, Damian and Palar (2019)***

“Over the Top (OTT) is a media platform that offers” multimedia services over operator-owned networks and hooks up to telecoms operator infrastructure. These services can include “video, audio, voice, telecommunications, news, or other commercial” offerings like a marketplace or online shops. Examples include Whatsapp, Instagram, YouTube, Facebook, and Google. The term "over the top" (OTT) describes “content providers who distribute streaming media as a stand-alone product directly to viewers over the Internet, eschewing telecommunications, multichannel television, and broadcast television platforms that typically act as a controller or distributor of such content. Another definition of OTT is the delivery of one or more services through an IP network” by a telecommunications service provider. It encompasses “a range of telco services, such as cloud-based services, communications, and content. The term "OTT," which stands for "Over The Top," is used in broadcasting and technology business reporting to describe audio, video, and other media that are transmitted over the internet as a stand-alone product without requiring users to sign up for a traditional cable or satellite pay TV service like Comcast". With its extensive content library, this market-disrupting OTT streaming player has won over the internet-savvy generation, especially the millennials, since it entered the market. Its OTT platform keeps raising the bar for offering excellent user experience and high-quality content. According to a recent research, the business holds an average market share of 12% in industrialised nations like the United States, where it ranks as the second-largest OTT provider.

***Hutchins,Li and Rowe (2019)***

"Over-the-top (OTT) Internet and mobile video streaming services are expanding, which is a significant change in how worldwide media sport is distributed, transmitted, and consumed. The way live sports are experienced and shared across television, computer, game console, tablet, and smartphone screens is changing thanks to the intervention of heavily capitalised firms like Tencent Video, DAZN, and Amazon Prime Video. This article describes three services (Tencent Video, DAZN, and Amazon Prime Video) that are available across Asia, the United Kingdom, Europe, the Americas, and Australasia, and defines and analyses six key characteristics of OTT live sport streaming. It claims that, first, live sport streaming is a crucial method through which television content and viewing behaviours are eroding the bounds of broadcast media while also continuing to support these behaviours. Second, it is suggested that these services are establishing new norms regarding how media sport is accessed and curated. As a result, their arrival signals a historic shift in the global marketplace for sport coverage rights and the media systems through which live content circulates. This idea is based on Amanda D. Lotz's conceptualization of portals".

***Nijhawan and Dahiya (2020*)**

"The extraordinary global pandemic known as COVID-19 has altered how audiences consume media. The adoption of OTTs emerged during this time as an evident trend. Several statistics demonstrate the expanding market and customer demand for the variety of content offered on OTT platforms. OTTs give users advantages they've never had before, like a variety of content, simple access, and device and medium options (hand phone, laptop, tablet or TV screen). The days of squabbling over who got to watch what on the family's one home device, the TV, are long gone. With this study, the researchers examined the dynamic OTT space, examined the evolution of OTT in India, and evaluated some firsts like the release of blockbuster movies on services like Netflix and Amazon, the return of vintage programming from the DD era to Hotstar, etc. Although there is no censorship in the OTT domain, it was essential to examine the effect of increased content consumption on psychographics across generations (children, adults, and elderlies) in order to complete the study. With this context, the researchers worked on the goals and attempted to assess the role played by the pandemic in evolving OTT media consumption trends; a qualitative mapping of increase in OTT adoption - Pre and Post COVID 19 in India; study underlying trends around increasing consumer appetite for the medium; and analyse psychographic impact on children, adults, and elderlies - listing benefits and drawbacks for freely available content with little censorship. To extrapolate the data, the researchers blended a qualitative and quantitative technique. In order to map and analyse the audience, a survey was also undertaken. In addition to" the original data, relevant trends were accumulated by analysing the content of news stories, industry research papers, and international publications.

***Malewar and Bajaj (2020)***

“By using the unified theory of acceptance and use of technology 2 (UTAUT2) paradigm, the research tries to discover characteristics that encourage consumers in India to adopt and use OTT video streaming services. The study also made an effort to examine the moderating effects of experience, gender, and age”. 277 users of Indian OTT video streaming services who participated in the study as responders provided their primary data via a questionnaire. Software known as “SmartPLS 3.3.2 was used to analyse the data. Performance expectations, price value, habit, and content accessibility are the main factors that influence the adoption and use of OTT video streaming platforms. The study affirms the UTAUT2 model's applicability in the current situation”. The study also demonstrates how age, experience, and gender in relation to OTT video streaming platforms have a moderating effect on model constructs from the UTAUT2. “In India, the OTT platform business is expanding rapidly and is anticipated to pick up steam in the years to come”. Therefore, it is crucial to understand consumers' behavioural intentions. “The study's findings will aid managers in better understanding and formulating various strategies for OTT video streaming platform users. The study is the first ever attempt to use the UTAUT2 model to best understand research and observe the acceptability of OTT video streaming apps”.

***Jose and Azevedo (2020)***

“The goal of this study is to suggest a model of” self-regulation that is implemented for Brazil's OTT video streaming services. The suggested approach aims to offer an alternative to the current regulatory inequity, in which Law No. 12,485 regulates Cable TV and its equivalents, “while Video Streaming OTT services are made available to the general public with no regulatory burden. Methodology: This research proposes a recommended approach for the regulation of Video Streaming OTT platforms in Brazil based on the imposed self-regulation model as outlined by Ayres and Braithwaite through a literature assessment of the Responsive Regulation Theory". Findings: An imposed self-regulation model for video streaming over-the-top services (OTTs) emerges as a workable substitute "for the current regulatory imbalance between such services and cable TV in light of the Brazilian legal system and the effective use of negotiational legal mechanisms". Originality: In a first for Brazil, this article suggests a concept of enforced self-regulation in place of legislation governing OTT video streaming services. The famed "success of such platforms in the Brazilian market and the ongoing global discussion about the regulation of OTT services determine the importance of this research".

***Goyal, Singh and Inder (2020)***

"The goal of over-the-top (OTT) platforms like Netflix has" always been to increase audience and improve the content. To give viewers a taste of the film's content, trailers are posted on websites like YouTube. The suggested system extracts emotional components "(Valence-Arousal) from reaction videos of people watching the trailers using convolutional neural networks. To determine the connection between the quality of the trailer's content and changes in Netflix stock value", 109 movie trailers were evaluated. It was observed that the quality of the content and the change in stock price are directly proportional.

***Lee,Moon and Yin (2020)***

"The main goal of this research is to build a generalised set of innovation processes that take place at the ecosystem level using academic research" as a foundation. By applying the four collaboration techniques, the study investigates the culturally and creatively motivated "over-the-top (OTT) platform that includes a diverse network of ecosystem" participants. Design/methodology/approach: The literature review that examines numerous ecosystem-related themes is the first step in our investigation "(e.g. service innovation, innovative ecosystem). The study also presents a novel conceptual framework that explains how cooperations take place in ecosystems”. The OTT platforms are then the subject of a qualitative and exploratory case study in a worldwide context. Findings: The framework's application demonstrates “how co-innovative business ecosystems exhibit co-evolution through various structures and trajectories. To deepen and widen the industry integration, an” ecosystem might develop by absorbing additional industries (also known as horizontal growth or broadening strategy). Originality/value: “The value of this research extends to other related industries where diverse actors such as technology firms, Internet firms, direct consumers, government, and even the society impact the type of product and service and shape the evolution of the entire ecosystem” because it uses an exploratory approach to begin “the discussion on how co-innovation and co-evolution occur at the ecosystem level, particularly in the industry that is driven by” culture and creativity.

***Garcia-Ruiz. and Perez-Escoda (2020)***

“The digital transformation creates societies built on connected and participatory logics”, in which members of the network can engage equally from mobile devices. Continuous contemplation “on communication and education as determining factors in the growth of society is forced by the increasingly” normalised virtual engagement, which was reinforced following the most recent occurrences of worldwide imprisonment by “the Covid-19 pandemic. The question of whether people are using the proper” actions and practises for this consequent critical and democratic involvement arises “in the face of inexorable technological penetration and connectivity”. This monograph is provided in this setting “where communication and education are entwined to provide particular contributions in four areas: 1) Communication” as it relates to education: transmedia skills and journalism in the classroom; “2) social networks as platforms for communication and education: bots, misinformation, rumours, and digital skills; 3) new connected generations; and 4) emerging actors in communication and education: youtubers, OTT platform gamers, and family responsibility".

***Ramos, Alaejos, Prieto and Prieto (2020)***

"The patterns of content consumption and reception in the family" context as well as the development of young people's media literacy have been impacted by the convergence of many media "and the entry of the Internet into the audiovisual market". Even while the statistics for young children's linear television viewing have not altered, it is evident that audiovisual platforms are becoming more and more common in Spanish families, and parents and other adult guardians play a crucial part in this development. "Based on a descriptive study conducted with 431 parents or tutors, the goal of this research is to establish the usage patterns of these platforms by Spanish preschoolers and primary school" students as well as to analyse family mediation strategies in the new media convergence environment. It was carried out using the Qualtrics methodology tool, which applied a questionnaire using a snowball sampling. "Although the most common regulation in both age groups is linked to the time that the parents or guardians allow the children to pass through the different devices, rather than in the restrictions around the contents", significant changes in parental mediation were observed after the results were analysed, "in accordance with the children's progressive increase in age. Children's programmes and films predominate at the youngest ages, and there are no appreciable variations in the types of audiovisual items they consume on linear television and OTT platforms". It was carried out using the Qualtrics methodology tool, which applied a questionnaire using a snowball sampling. "Although the most common regulation in both age groups is linked to the time that the parents or guardians allow the children to pass through the different devices, rather than in the restrictions around the contents", significant changes in parental mediation were observed after the results were analysed, "in accordance with the children's progressive increase in age. Children's programmes and films predominate at the youngest ages, and there are no appreciable variations in the types of audiovisual items they consume on linear television and OTT platforms".

***Kanade (2020)***

Video streaming services are what keep the modern world moving. Video streaming suppliers let the users to access "the digital content on televisions, desktops, laptops, phones, electronic gadgets, etc". According to the type of subscription a user chooses, "the video streaming platforms operate on a monthly subscription model, whereby the streaming services obtain licencing rights to the digital material and further make the content available to the customers. Delivery of consumer-preference-based digital content appears to be causing a paradigm shift in video streaming services as over-the-top (OTT)" platforms become more and more popular in the world of video streaming services. "The transmission station that broadcasts the composite video signal accommodates different video channels on different frequency windows by using modulation techniques, but the consumer can only watch one piece of material at a time. The study describes a unique genetic algorithm-based method for embedding multiple video frames into a single video stream" so that many consumers can simultaneously see multiple preference-based video contents.

***Fudurić, Malthouse and Lee (2020)***

"Over-the-top (OTT) platforms like Netflix and Hulu have drawn a lot of" users over the years and seriously disrupted the media and advertising sectors. "Using big data from one of the top US multi-system operators (MSOs), which offers cable TV, phone, and Internet services to numerous towns", this study investigates the root cause of such a disruption. To be more precise, "the dataset enables us to simulate the viewing habits of 267,276 distinct households, which together viewed 270,718 distinct programmes, and investigate the effects of online video consumption, different genres, and use of extra cable services on cord-cutting. The results indicate that video on demand and time spent watching various genres, particularly live sports and news, are the most significant predictors of cord cutting". Finally, they go into how the study will really be used by advertising, content producers, and content distributors.

***Bouquillion (2020)***

This chapter's goal is to highlight the difficulties in implementing "over-the-top (OTT) offers in India's audio-visual industry. To define its boundaries, the concept of OTTs must first be defined precisely, and the components of the audio-visual field that will be covered" must then be clarified. First, because OTTs use telecommunications networks to function, they can operate in compliance with "national regulatory frameworks, particularly Broadcasting Acts. Being significant bandwidth consumers, OTTs" frequently run afoul of telecom companies, sometimes even having their streaming services stopped. "But by the end of 2010, in many nations, including to a certain extent India, the different actors involved seemed to have arrived to a level of accord. Second, user-generated content (UGC) audio-visual content is not the subject of this chapter; rather, we concentrate on "professionally" produced audio-visual OTT suppliers, that is, commercially produced content" that is paid for in a variety of ways by the OTT platform.

***Sadana and Sharma (2021)***

"The purpose of this paper is to examine how young consumers in India are switching from traditional Pay TV services (Cable TV/DTH) to the top over-the-top (OTT) platform as their preferred source of entertainment" and what factors, in addition to content gamification, are crucial in shaping such preferences. The study adheres to the use and gratifications theory and niche analysis "theoretical framework. Design/methodology/approach: The study creates a conceptual framework for comprehending consumer preferences that lead to the switch from traditional media to new. By using exploratory and confirmatory factor analysis, this study proposes a method for comprehending the pertinent implications in customer replies to a structured online survey distributed among various age groups". Logistic regression is a statistical approach used to better understand the relationships between measured variables and constructs. Findings: "Empirical findings and discussion suggested that there are five elements that influence customers' entertainment choices, including content and viewing habits, service costs, adjustments caused by incentives or offers, convenience, and connectivity. The strength of these variables, which made content and watching habits, service costs, and convenience the three most crucial variables, was confirmed by logistic regression". Research constraints and "implications This study examines the forces that are revolutionising the entertainment sector and can be used to create a pleasant and interesting consumer experience in the future. Originality/Value: This study's findings are useful for internet streaming services, video-on-demand services, cable TV operators, and content" creators in the entertainment industry. The research is original in nature.

***Kamath, Ganguli. and George (2020)***

In India, sports are growing popularity and people are becoming more and more interested in sports outside cricket. Even though there are currently many sports leagues operating in India, the Indian Premier League (IPL) commands an unrivalled level of attention and viewership. "This is demonstrated by social media posts and the rising TV and Over-the-Top (OTT)" platform viewing. This study looks into how closely supporters are connected to the players of their preferred team. By the extraction of tweets from the IPL player auctions occurred during the preseason of the thirteenth IPL season, they analyse the fan perspectives. As a sign of their strong team identification, “the fans were quite active on social media, sharing their opinions about the several players up for auction and accessible to their team”. The same was supported by 15,374 tweets that were extracted and analysed in total. Additionally, using the “System Dynamics (SD) methodology, they create a causal loop connecting the different important elements in the IPL ecosystem, which could assist the league and team managers in better understanding the significance of fan attachment” to players. The System Dynamics methodology is used for the first time in an IPL study to support the results of twitter analytics.

***Blasco, Castellà and Raso (2020)***

“Introduction: This study aims to explore the impact of the Covid-19 pandemic on media habits and consumption in Spain, one of the most severely affected countries. Methodology: A representative online survey of the Spanish population (N = 1,500 participants) was conducted from March 13 to 30, 2020, coinciding with the first weeks of home confinement. The sample was studied according to two variables, gender (Women N = 750; Men N = 750) and age (18-39 years individuals, N = 720; over 40 years individuals N = 780) to detect the most relevant specificities of each group. The sampling error is ± 4.38% to 95% confidence”. Findings show that, prior to digital media, television is the most popular medium for learning about the virus. It should be mentioned that television shows with an infoshow feel draw larger audiences than the standard newscasts. “Internet, social networks, radio, information from family or friends, and the conventional press” are the least used media to learn about the Covid-19's development. Although while listening to the radio may not seem like a big deal for staying informed, it is the most reliable source of media, along with television. “The use of over-the-top (OTT) platforms has also increased significantly” over this time. Discussion: Television regains the younger target demographic that it appeared to have lost to digital media. Conclusions: A media environment that is both complicated and competitive is solidifying.

***Rodriguez-Vazquez, Silva-Rodriguez, Direito-Rebollal and Garcia-Orosa (2020)***

The live, social, and audience involvement offers during the special information show on March 26, 2019, “election night in La 1 of TVE and La sexta are analysed” using a mixed technique. They proposed the idea that the competition from VoD-OTT platforms has altered how people watch television. This empirical work's goals are to identify “the multichannel information strategy used by the aforementioned stations and to ascertain the audience's” reaction. Elections and other political events spark a lot of talk and keep viewers tuned into traditional and social television.

***Capapé (2020)***

“Some of the popular streaming services available in Spain” are Netflix, HBO, and Filmin. The audiovisual market has changed “as a result of technological advancements and” customer behaviour. The possible changes in televisual usage during the past ten years will therefore be investigated in this research. The goal is to comprehend how linear TV and the emergence of OTT services interact. Findings from two separate timeframes—"2006 to 2014 and 2015 to 2019—will be considered. The growth of internet services and its effects on the televisual” sector will be examined concurrently.

***Yousaf, Mishra,Taheri and Kesgin (2021)***

This study extends “the expectation-confirmation model (ECM) to include constructs such as neutral confirmation, customer-to-customer (C2C) interactions, and perceived content quality as antecedents to perceived enjoyment, perceived usefulness, user satisfaction, continuance, and recommendation intentions using data from India and the USA”. The remaining hypotheses are validated in both nations, with the exception of the effects of “C2C interactions on perceived enjoyment and perceived usefulness on recommendation intentions. The amplitude of the roads leading from neutral confirmation and C2C interactions to perceived usefulness as well as the paths leading from perceived enjoyment and satisfaction to continuation intentions” vary between countries.

***Martínez-Sánchez, Nicolas-Sans and Díaz (2021)***

“The transition of the audio-visual consumption model is being led by OTT platforms. These platforms are becoming more popular with audiences, which has effects on two different levels. The existing television model is changing, and established leaders are losing their hegemonic positions. In addition, OTT platforms like Netflix, HBO, Amazon Prime, and, more recently, Disney + are competing with one another to dominate the subscription industry. Facebook and Instagram in particular are a component of the promotional strategy used by all platforms in this race to try to entice new users. In this sense, the goal of this paper is to analyse the social media methods used by the various OTTs in the Spanish market” and evaluate how the launch of Disney+ would affect things. The study uses a quantitative methodology and analyses factors including publishing frequency, content distribution typology, and user interaction across various social networks. The findings help us comprehend the current landscape of these platforms' influence in the Spanish environment.

***Izquierdo-Castillo and Latorre-Lázaro (2021)***

The media landscape in Spain is heavily patriarchal. Female leadership roles are still underrepresented in the media. This study looks at how this fact may be inferred from the quick concentration “of streaming platforms and the intensification of their production strategy in national marketplaces”. The major objective is to ascertain the effect that “these new players have on the leadership and employability of women in the Spanish sector. International over-the-top (OTT) platforms that also create their own content in Spain are" researched for this aim. By specialisation and level of responsibility, the diversity of labour structures is examined using "as a sample the original Spanish productions released between 2015 and the start of 2020. The" findings indicate a minor improvement in the employability of women in the media business, despite the fact that it is still heavily masculinized.

***Kanwar and Singh (2021)***

"In India, the media is an integral component of daily life. Because the vast majority of people globally rely on various media platforms to receive information for entertainment purposes and to promote awareness of several other events" taking place across the world, the effects of media can be comprehended. Denis McQuail (2000) asserts that the media is in charge of educating, developing systematic exposure, and forming beliefs and values. Also, "according to the BARC (Broadcast Audience Research Council) Study from 2019, web series are referred to as popular shows with strong viewership that have a wide range of themes" that touch on various socio-cultural facets of society's daily lives. Several Over the Top (OTT) entertainment systems that broadcast continuously exist. This essay aims "to evaluate web series in the context of Indian society. By depicting them as helpless, meek, and victims, Indian media have portrayed the stereotyped image of women and have been oppressing women in numerous ways". The current study attempts to explore how gender representation in modern and digital platforms is still influenced by the patriarchal system. Based on the problem description, the researcher will use qualitative theme analysis to investigate the evolving feminine characteristics of the main female characters in seasons 1 and 2 of the online series Four More Shots Please.

***Fanea-Ivanovici and Baber (2021)***

The most popular crowdfunding categories are movies and web shows, and project creators have used a variety of strategies. Filmmakers may offer "set or flexible budgets, use reward-based or equity-based crowdfunding", and use specialist or generic crowdfunding platforms to raise money. Production may be fully or partially financed through crowdfunding. There is currently no established model for financing the creation of films and web series. Content-based web series have grown in popularity recently "on over-the-top (OTT) services like Netflix and Amazon Prime. The purpose of this study is to close this conceptual gap and offer a crowdfunding model for films and web series that can be used and applied to the advantage of all stakeholders, including creators, backers, distributors, platform owners, and the full potential audience. The model consists of six different sorts of flows—information/content, funds, audition, decision-making, content, promotion, and rewards—and nine chronologically linked phases. The conceptual model put forth here is based on a critical analysis of the literature already in existence in the field, primarily qualitative analyses completed on professionally produced and crowdfunded" films that were successful and unsuccessful in relation to the functionalities of the current technical platform.

***Puthiyakath and Goswami (2021)***

"Over-the-top (OTT) platform usage has rapidly expanded in India after the" COVID-19 outbreak and the ensuing nationwide lockdown. The traditional TV networks have experienced a significant influence from the rising use of video streaming during pandemics. This study aims to investigate the rivalry, compatibility, "and competitive supremacy of OTT and TV in delivering customer happiness. The study used the niche theory to empirically compare the satisfaction levels provided by OTT and TV, their similarity, and their competitive advantage in seven micro-dimensions of satisfaction. The study's data was acquired from 223 online users in India. The study's findings show that OTT offers greater levels of satisfaction across all seven types of gratification, with the" convenience dimension showing the biggest difference. "The niche overlap measurements revealed that while TV and OTT offer satisfaction in the relaxation dimension, there is the least amount of resemblance between them in the convenience aspects. The competitive advantage of OTT outpaced TV in every way, with relaxation showing the biggest difference".

***Lee, Lee, Joo and Nam (2021)***

"The growth of the early paid Over-The-Top (OTT) video streaming sector in 50 countries is examined in this study. The panel data analysis results indicate that the market entry of Netflix, the size of the traditional pay TV market, broadband infrastructure, and competition among OTT platforms are factors in the early market growth of paid OTT video streaming services like subscription video-on-demand (SVOD) services. The findings also show that in many nations, the markets for paid OTT video streaming and traditional pay TV subscriptions" initially grow simultaneously. Yet, the results also show a negative correlation "between Netflix's introduction into the market and the growth rate of traditional pay TV services'" subscriber revenues. "The findings of this study have regulatory and industry implications for the expansion of the paid OTT video streaming market and the long-term health of the media sector".

***Iyer and Siddhartha (2021)***

"Instead of viewing traditional television, reports show that 49% of adults in India spend at least 2-3 hours accessing OTT media. Brands have been adjusting to the new patterns that this study looks at as a result of such changes in how the general public is exposed to content. Based on the Technological Acceptance Model, this study was done to determine how consumers felt about and accepted brand placement in the novel media format of web series

(TAM). This study used a self-report questionnaire that was modified from F Davis's Perceived Usefulness, Perceived Ease of Use, and User Acceptance of TAM questionnaire. It was based on a survey of 278 people from Urban India settings (1989)". The research backs up TAM and acknowledges that brand recall is directly correlated with "the frequency of viewing Web Series" (R = 0.57, p.001). When audiences have already formed favourable opinions of the brand, product/brand placement increases "engagement with the placement and results in brand" recognition for unknown or disliked brands "(t (277) = 27.11, p =.01). This study also demonstrates that the TAM is a useful model that can be used to analyse how frequency and duration of viewing influence attitudes towards brands and the positioning of those brands in web series. Brand placement in web series is seen as helpful and heavily influences brand memory. As a result, marketers should strategically consider including brand placement in web series in their marketing communication plan, particularly given the importance of this media and other associated types of advertisement for brands to meet the communication problems facing their industry".

***Mittal and Sinha (2021)***

Learning results: The learning objectives are as follows: acknowledge the importance "of project management as a comprehensive strategy for handling projects in a novel setting. Determine the challenges that come with managing projects in the modern day, such as shorter product life cycles, shifting consumer preferences, and last-minute risks. A project portfolio system, project negotiation, project prioritising, project risk assessment and management, and project stakeholder management" are a few examples of project management sub-domains to consider. Summary of the case: The globe is attempting to deal "with the crisis brought on by the corona virus (COVID-19) pandemic in the year 2020". Everything that was once normal has stopped. The importance of creating creative solutions to adapt to the new normal condition has been recognised across all industries. "This case details the struggles of TVR Cinemas, a Tiya Group business unit that handles the production and distribution of Hollywood and Bollywood films in India". Multiplex industry is severely harmed by the Indian subcontinent being under lockdown. With updated sanitary standards, social segregation, and a "stay home stay safe policy," the business must come up with new strategies to remain competitive. In this case, students are asked "to put themselves in the position of the company's project manager, Mr. Ramchandani, and offer advice on how to release seven unfinished Bollywood movie projects, choose the best over-the-top (OTT) partner for tie-ups, and develop tactical moves to restore the company's reputation by launching their own OTT platform. Academic level of complexity: The case is helpful for teaching the fundamentals of project management as well as making decisions for projects in an uncertain circumstance". Students at the undergraduate, graduate, and executive levels can utilise this case to practise "project management, project risk management, and negotiation management skills. Further materials" Educators alone have access to the teaching notes. CSS 9: Operations and logistics is the subject code.

***Gupta. and Singharia (2021)***

"The current investigation highlights the changes in consumers' media consumption in light of the ecosystem of technological developments in telecommunication and improved gadget capabilities. The transition from traditional media to over-the-top (OTT) media has led to a battle amongst streaming service providers to win over and keep subscribers, especially during the COVID-19 shutdown period. Given this development, the current study uses partial least squares structural equation modelling (PLS-SEM) analysis to determine the effects of two important antecedents, namely customer engagement (CE) and quality of service experience (QoSE), on users' propensity to continue using and subscribe to streaming services (WCS) in the future. The research also explores the indirect effects of habit and satisfaction on the aforementioned links. The implications of the study offer OTT platform providers the chance to take full advantage of the perceived change” at a time when the world is dealing with the effects of the epidemic.

***Koul, Ambekar and Hudnurkar (2021)***

“The aim of this study is to identify, rank, and create composite relational aspects that affect millennial consumers' decision to subscribe to an OTT platform service on an access basis”. For a business planning to increase its client base or for a business trying to keep its current consumers, it is important “to understand what elements drive the subscription of a service in the competitive and growing Indian market of OTT platforms”.
Design/methodology/approach: The strategy involves identifying the elements that influence customer purchasing decisions and asking survey respondents to rank them in terms of how important they are when deciding whether to subscribe to an OTT platform service. In this study, “the primary data were gathered using a questionnaire. Participants in the poll were chosen using "purposive sampling" based on their age group and their past or present use of at least one OTT platform service. The survey was made available to millennial viewers in Tier I and Tier II cities with strong mobile internet connectivity. Findings: The study's findings include a ranking of criteria according to how” crucial they are to millennial customers, who then combine these aspects into composite factors with resonant characteristics. Relevance in practise: With the use of this research, information users can focus on the elements that appear to be most important to them and plan or anticipate their strategies and further research investigations appropriately. Originality/value: For US-based OTT platforms, a study along similar lines has been done. The significance of this research is due to the expansion of the Indian OTT market and the fact that it is specific to Indian customers and platforms.

***Ying and Hung (2021)***

TV used to be thought of as a necessary component of every home. One important consumer behaviour used to be watching TV shows as a family. Yet, as a result of technological advancement, "the digital revolution, and the influx of Over-The-Top (OTT)platforms, consumer behaviour has started to change dramatically". Most of our time is spent on our smartphones and tablets. Multiscreen televisions are becoming the standard. Hence, the "IMD's 2019 "Digital Whirlpool" study states that "digital disruption has already happened in the media, entertainment, and telecoms industries" due to the impact of digital convergence. The following five services could be replaced by new ones if digital transformation is not completed in a timely manner ". You'll see that Taiwan has fewer cable TV subscribers now than it did in 2017. There were 5.23 million. It has completely decreased to the present low of 4.83 million in 2021 "due to the influence of internet platforms and online pirated content". Several TV stations have actively changed from internal thinking to exterior settings in response to the recent shift in TV advertising spending as well as the changes in viewers' viewing habits. The digital revolution of TV stations like "TVBS, Eastern Broadcasting Corporation (EBC), Sanli TV, and Ctitv has already started".

***Arora and Ahuja (2021)***

Social media marketing is expanding quickly. Marketers must stay up with tech-savvy customers and assist firms in growing through the use "of social media strategies. This article demonstrates how an Over-the-Top platform, such as Netflix India, leverages social media as a digital tool for boosting customer interaction and establishing reliable consumer-brand" partnerships. This article makes additional "attempts to categorise the content produced by Netflix India on its social media channels, including Understand how the amount of likes, comments, shares, and retweets (in the case of Twitter) linked to the most significant content typology effects the improvement of consumer engagement among the Netflix audience”. Twitter into distinct content typologies. “Following that, the research study divides the content produced by Netflix into three groups”: relational, promotional, and informational content. The study is also able to statistically demonstrate how more “likes, shares, comments, and retweets on relational content have a big impact on” how engaged Netflix's audience is with the brand.

***Sangra (2021)***

“Over time, the media has emphasised "hegemonic masculinity" and created a monochromatic image of males that is linear, flat, and consistent with the conventional concept of manliness. Such idealised portrayals of men feed prejudice against other genders, which has negative effects for men as well. With the introduction of Over the Top (OTT) platforms, which are challenging such representations”, there is a clear silver lining. In order to challenge "hegemonic masculinity," “these platforms lay out the fundamental tenets of the idea of social construction of reality”. In order to comprehend how Indian OTT material blurs masculine “images instead of what the cultural products are” expressing, this article tries to critically explore and assess how masculinity is represented in various Indian OTT platforms' content. In addition, the article analyses how the male protagonist characters are positioned in a way “that does not compartmentalise men's traits into the preexisting patriarchal male image and instead portrays them as authentic and relatable. This essay supports the discourse analysis approach. In order to test the hypothesis” that "Indian content on OTT platforms is blurring the one-tone representation of masculinity," three pieces of content from Indian OTT platforms—"Little Things" – “Seasons 1 and 2 on Netflix, "Made in Heaven" on Amazon Prime Video, and "Yeh Meri Family" on TVF Play—were chosen with the purposive sampling method. In order to challenge the patriarchal framework of gender and power for further progress in the study, the paper suggests a redesigned study of men and masculinity.

According to the report, OTT platforms have advanced gender equality by making a difference and increasing societal acceptance of variation in masculinity through” their depiction.

***Pattanayak and Shukla (2021)***

Over the top, or OTT, is a platform that does not need traditional cable or receivers for delivery. Without a multi-system operator, OTT refers to the delivery of audio and video through the internet. in charge of the content's dissemination and management. Viewers can save it for later watching and access it from any location, at any time. Data filtering systems that use various algorithms and “data to inform a specific consumer or viewer of the most” pertinent elements are called recommendations engines. “The recommender systems for OTT platforms are essential to providing perfect and high-quality content in response to the shifting demands of a sizable viewership. Collaborative filtering and content-based filtering are two of the main methods” that have been suggested for the construction of a recommendation system. Both approaches have their advantages, but they are frequently ineffective. To enhance performance, many hybrid tactics are taken into consideration. In order to assist consumers find interesting and useful material, leading OTT platforms use artificial intelligence, which is discussed in this paper along with various recommendation systems and how they relate to one another.

***Pérez, Ramos, Prieto, and Prieto (2021)***

In Spain, one out of every three internet-connected homes uses payment platforms to watch audiovisual content online, significantly changing traditional ways of consumption. “The purpose of this study is to determine how” children and young people in Spain use these OTT or “over-the-top platforms and applications (platforms and applications that provide video content over the internet” instead of television via cable or satellite), as well as to examine the development and trends in reception based on a descriptive study of 648 subjects aged between 3 and 18 that was conducted across Spain. Two independent online questionnaires were created for this aim using the methodological tool Qualtrics, one for parents of children ages 3 to 12 and another for teenagers ages 13 to 18. The answers' analysis supports the gradual renunciation of audio-visual consumption from conventional media among the age groups examined, particularly among teenagers, as well as the variety of devices used to experience information. The potential for trans-media product consumption related to audio-visual viewing on these platforms is also apparent, especially in the younger age groups, and interaction is growing, particularly in the older age group.

***Arslan and Tetik (2021)***

Due to the expansion of viewers, “the introduction of cable, digital, online, and OTT (over-the-top) platforms, as well as the” expanding global popularity of Turkish programmes, Turkish television has seen significant change in recent decades. As a result, TV material has gotten better and better. This article explores the growth of the Turkish television industry into one that creates programming that is sold internationally, as well as how discussions about high-quality television influenced these developments. The article also highlights significant shifts and suggests a novel periodization, dividing the development of television in Turkey into three distinct stages. The modern interpretation of "quality" is then demonstrated through the six seasons of the popular crime drama “Sfr Bir: Bir Zamanlar Adana'da (Zero One: Once Upon a Time in Adana, 2016–2019). After a transitional third season, the article contends that the series' final three seasons feature an institutionalised "quality" drama on a national OTT platform at the expense of its earlier authenticity and naturalism. The first two seasons of the series show off an independent, low-budget Web production based on a true story”.

***Llamas, Gelado, de la Calle and Pérez (2021)***

Consumer research suggests that over the course of Spain's more than 70-year television existence, the content interests of the Spanish audience for television have not altered significantly. Television, both free-to-air general television and now OTT platforms, is shaped by the viewing preferences of its audience, but it also has the power to have an impact on the viewers' own identities through the content it creates and makes available. With the devotion to new television formats and genres, television programming has been able to adapt to every historical-social environment, particularly with the appearance of the private channels. To confirm this situation and validate these consumption models, an ad hoc study composed of seven focus groups that fell within the General Media Study's age ranges was conducted. The results, which clearly address the age groups taken into account in the General Media Study, will shed light on a variety of topics, including how television programming is currently consumed, how viewers behave while watching television, and what the most popular formats and genres are.

***Mohan and Jadhav (2022)***

Without customers, no industry can prosper, and with customers come the possibility of customer churn. Many sectors are concentrating on understanding the reasons causing churn and creating strategies to accurately anticipate it because customer turnover has a direct influence on revenue. Customers have more options to choose from any service or product today than ever before. Customers today also benefit from several subscriptions to service providers in various industries. In this study, our objectives are to: I Identify the OTT platform customer churn-influencing factors; and (ii) Forecast customer turnover. Using a questionnaire, 317 respondents who subscribe to different OTT platforms provided the data for this study. The questionnaire data consists of 19 items, including demographic data, OTG platform usage, and customer satisfaction with OTT service. By combining feature ranking techniques from "Recursive Feature Elimination (RFE), Linear Regression, and Ridge Regression, we have" determined the factors affecting customer attrition in "Over-The-Top (OTT) platforms. To examine the effects of two recently introduced characteristics, multiple subscription and switching frequency, on the overall effectiveness of the customer churn" forecast, we employed hierarchical logistic regression. Last but not least, approaches "like Decision Tree, Random Forest, AdaBoost, and Gradient boosting are used to predict customer churn". They discovered that the random forest method produces more accurate predictions.

***Malhotra (2022)***

The global business arena has been widened by the digital economy to include portable devices enabling easier "access to consumer data and more trading opportunities". Internet user growth across a variety of "social media platforms has impacted not only trade but" also international "media and communication. The accessibility of digital technologies has" "spawned content makers all around the world as user-generated content sites like YouTube and TikTok show no signs of" slowing down. YouTube's reach goes beyond music and entertainment as "the second-most visited website in the world" and the leading OTT platform for media consumption in India. "YouTube is producing a paradigm shift in worldwide education, including cinematic pedagogy. YouTube is a content-sharing network that also provides opportunities for informal learning. The popularity of YouTube as an educational alternative among media and communication students in India is investigated in this research article using the Jungian theory of individuation and a schizoanalytical Deleuzian lens. In order to explore semiotic patterns in media consumption in terms of informal learning and meaning-making activities", the research design will use hybrid techniques. They comprise variable correlation analysis and descriptive analysis for specific variables. The research project will enable reproducible investigation "of informal learning paradigms made possible by digital technology and the consequent consumer surplus in addition to identifying YouTube trends in cinematic pedagogy among media and communication students in India".

**Summary of Literature Review**

"Over-the-top (OTT) platforms have experienced rapid growth in recent years", leading to an increased interest in understanding and predicting customer churn. Churn prediction models are vital for these platforms "to retain their customers and maintain a sustainable competitive advantage". Several studies have explored different churn prediction models "in the context of OTT platforms; however, there remains a research" gap in understanding the most effective techniques. Existing literature on churn prediction models for OTT platforms primarily focuses "on machine learning and deep learning techniques. Common machine learning models include logistic regression, decision trees, random forests, and support vector machines (SVM). On the other hand, deep learning techniques such as artificial neural networks (ANN), convolutional neural networks (CNN), and recurrent neural networks (RNN)" have also been employed for churn prediction.

"Feature selection and extraction play a critical role in the performance of churn prediction models". Some studies have emphasized the importance of using customer behavior data, including viewing habits, preferences, and usage patterns. Others have highlighted the significance of demographic and socio-economic factors in predicting churn. Despite the substantial amount of research on churn prediction models for OTT platforms, there remains a research gap in identifying the rate of adoption of AI based churn prediction models. A study by PwC India found that "the adoption rate of AI in the Indian media and entertainment industry, including the OTT sector, is relatively low compared to other countries" (PwC

India, 2021). The study suggests that limited budgets, a lack of understanding and awareness of AI, and the complexity of implementing AI solutions are some of the primary reasons for the low adoption rate.

Despite the challenges, using AI-based churn prediction models is crucial for the OTT industry to stay competitive in the market. AI models “can analyze vast amounts of customer data and identify patterns and trends that human analysts may miss”. This can help companies personalize their offerings, provide targeted recommendations to customers, and ultimately reduce churn rates.

The Indian “OTT industry has witnessed exponential growth in recent years, driven by” factors such as affordable internet access, a rapidly expanding smartphone user base, and a diverse content offering that caters to various regional languages and preferences. However, despite this growth, the industry faces challenges related to customer retention, as churn rates remain a significant concern. The unique market dynamics, high churn rates, growing competition, evolving consumer behavior, and technological advancements in the Indian OTT industry justify the need for research on the factors affecting the adoption of churn prediction models. Such research “can provide valuable insights for OTT platforms, enabling them to” better understand “their customer base, optimize their retention” strategies, and ultimately achieve long-term success in the market.

In conclusion, the existing literature on churn prediction models for OTT platforms provides valuable insights into the potential “of machine learning and deep learning techniques. However, there is a research gap in understanding the factors affection the adoption of such churn” prediction models by OTT companies, which becomes the objective this study.

# Chapter III – Methodology

## 3.1 Need and Significance of the Study

As the OTT market continues to experience remarkable growth, driven by advancements in technology and shifts in consumer preferences (Statista, 2021), it becomes essential for service providers to mitigate customer churn and maintain a competitive edge. Churn prediction models can play a critical role in identifying customers at risk of attrition, enabling businesses to take targeted actions to retain them (Kaya & Kahraman, 2020). Despite the substantial body of research on churn prediction in various industries, including telecommunications (Keramati et al., 2014) and banking (Amin et al., 2019), there is limited literature focusing explicitly on the OTT industry. This study aims to fill this knowledge gap by examining the factors affecting the adoption of churn prediction models in the OTT context. Given the unique characteristics of the OTT sector, characterized by its reliance on digital platforms, subscription models, and streaming services, it is essential to explore the industry-specific factors shaping the adoption of these models (Clement, 2021).

Furthermore, this study seeks to contribute to the literature by exploring the perceptions of employees in the OTT industry regarding the adoption of churn prediction models. As key stakeholders in the implementation and use of these models, employees' perspectives can provide valuable insights into the barriers and facilitators affecting the adoption process (Wamba et al., 2017). By examining employee perceptions, this research will offer a more comprehensive understanding of the factors influencing churn prediction model adoption and inform strategies for overcoming adoption barriers.

In addition, the study will complement existing research on the Technology Acceptance Model (TAM) (Davis, 1989), which posits that perceived usefulness and perceived ease of use influence technology adoption. By applying the TAM framework to the context of churn prediction models in the OTT industry, this study will contribute to the validation and expansion of TAM in a novel domain. The findings of this research will contribute to the existing literature on churn prediction and technology adoption while providing practical insights for OTT service providers seeking to optimize their customer retention strategies.

### 3.2 Research Question

RQ1: What are the key factors influencing the adoption of churn prediction models in the OTT industry?

RQ2: How do these factors interact with each other in the adoption process?

### 3.3 Theoretical Framework

The proposed theoretical framework consists of six constructs: organizational factors, technological factors, perceived usefulness, perceived ease of use, external factors, and adoption intention (Figure 1). These constructs have been selected based on an extensive review of the literature on technology adoption (Davis, 1989; Oliveira and Martins, 2011; Rogers, 2003; Venkatesh et al., 2003).

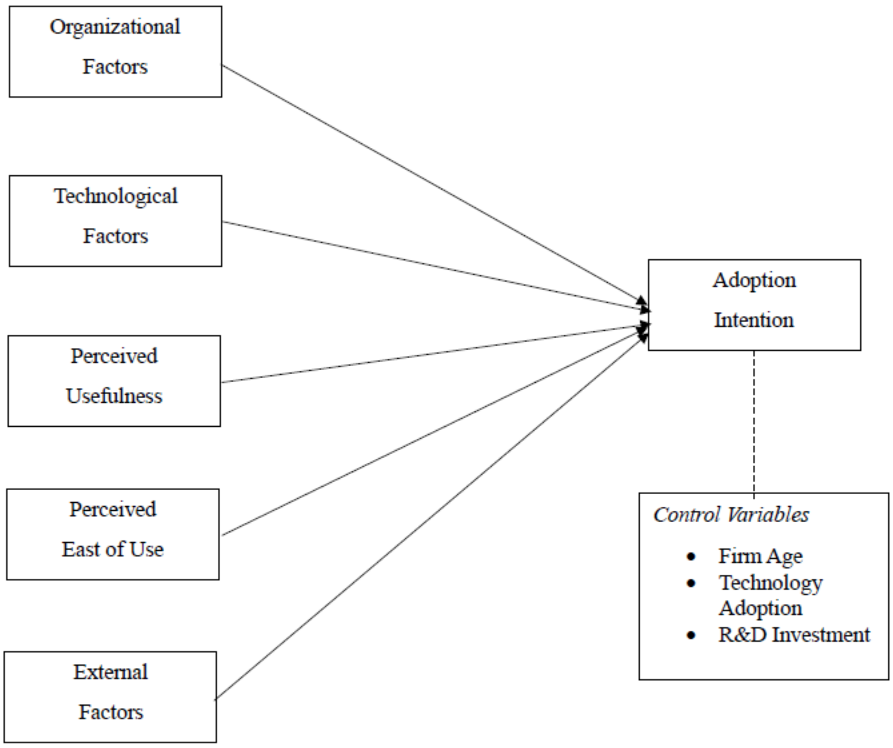
### 3.4 Study Variables

- *Organizational Factors:* Organizational factors play a critical role in the adoption of new technologies (Oliveira and Martins, 2011). In the context of OTT, we consider factors like company size, resources, management support, and organizational culture.
- *Technological Factors:* Technological factors, such as the compatibility, complexity, and relative advantage of a churn prediction model, have a significant impact on its adoption (Rogers, 2003). We argue that a churn prediction model is more likely to be adopted if it is compatible with existing systems, easy to implement, and offers a competitive advantage.

- *Perceived Usefulness:* Perceived usefulness refers to the degree to which a user believes that a technology will enhance their job performance (Davis, 1989). In the OTT industry, a churn prediction model's perceived usefulness can be gauged by its ability to improve customer retention and increase revenue.
- *Perceived Ease of Use:* Perceived ease of use is the extent to which a user believes that using a particular technology will be free of effort (Davis, 1989). The ease of use of a churn prediction model can influence its adoption in the OTT industry, as complex models may discourage potential users.
- *External Factors:* External factors, such as competition, market trends, and regulatory environment, can affect the adoption of churn prediction models in the OTT industry (Oliveira and Martins, 2011). For example, if the industry is highly competitive, companies may be more inclined to adopt advanced technologies to stay ahead.
- *Adoption Intention:* Adoption intention is the willingness of an organization to adopt a new technology (Venkatesh et al., 2003). This construct serves as the outcome variable in our framework, as it reflects the likelihood of adopting a churn prediction model in the OTT industry.

Further, Firm Age, Technology Adoption and R&D Investment were chosen as the control variables for the study (König et al., 2013; Cenamor et al., 2013; Chau and Tam, 1997).

**Figure 3.1: Theoretical Model of the Study**




## 3.5 Study Hypotheses

H1: Organizational factors have a significant impact on the adoption intention of churn prediction models in the OTT industry.

H2: Technological factors have a significant impact on the adoption intention of churn prediction models in the OTT industry.

H3: Perceived usefulness has a significant impact on the adoption intention of churn prediction models in the OTT industry.

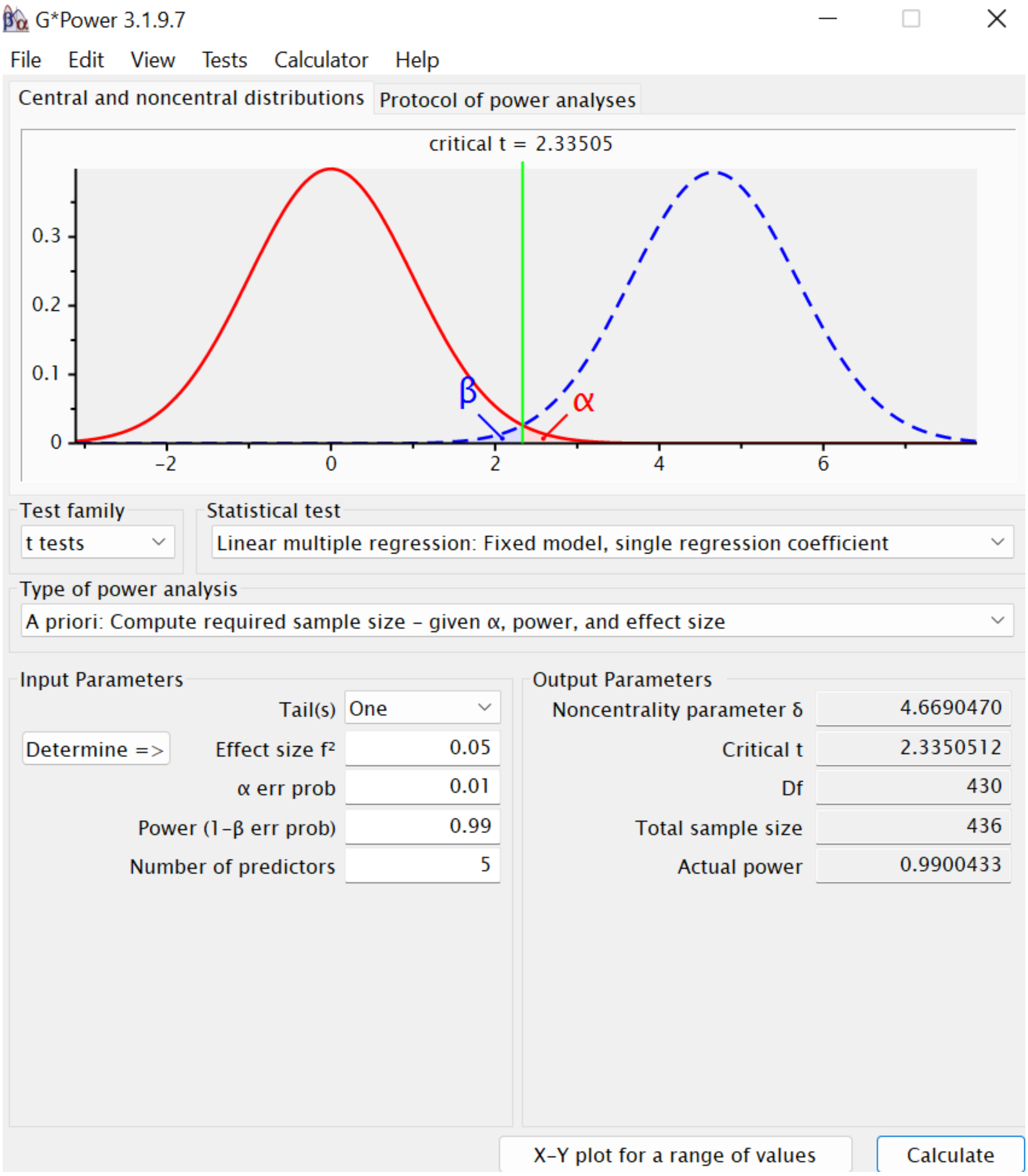
H4: Perceived ease of use has a significant impact on the adoption intention of churn prediction models in the OTT industry.

H5: External factors have a significant impact on the adoption intention of churn prediction models in the OTT industry.

### *Sample Size*

G* Power software has been used to compute the required sample size needed for the proposed research model and the results of the software are shown in Figure - 2.

**Figure – 3.2: Minimum Sample Size**



As the required sample size is 436, to ensure statistical accuracy of the model and to reduce Type I and II errors, the sample size is determined at 500. It is believed that the increased sample size will ensure the robustness of the results.

### 3.6 Sampling Technique

Purposive sampling technique is used for the study as the respondents must be aware of churn prediction models to answer the questionnaire.

### 3.8 Data

The study is mainly based on primary data. The opinions of the respondents are collected using a well-structured and pre-tested questionnaire.

### 3.9 Data Analysis

Due to the complexity of the model, PLS-SEM analysis is done using SMART PLS software.

# Chapter IV – Results and Analysis

In order to satisfy the objectives of the study, required data were collected from 600 respondents using a well-structured and pre-tested schedule questionnaire. It could be noted that, purposive sampling has been used for the study and all the respondents are cryptocurrency investors, as answering the questions required certain level of knowledge and understanding about churn prediction and AI.

## 4.1 Demographics

Table 4.1.1 offers a comprehensive overview of the demographic and organizational characteristics of 600 respondents across various cities in India, focusing on aspects such as location, gender, age, firm age, technology adoption, and R&D investment, crucial for understanding the dynamics in the OTT industry.

A significant portion of the respondents are from Chennai, representing 42% of the total, followed by 25% from Hyderabad. This heavy representation from these two cities suggests that the study might have a strong urban focus, particularly on these major tech hubs. Bangalore, Mumbai, and Delhi follow, with 16%, 9%, and 8% of the respondents respectively, indicating a wider geographical coverage but with less emphasis on these cities.

In terms of gender distribution, the sample leans towards a male majority, constituting 60% of the respondents, while females make up 40%. This disparity might reflect the prevailing gender demographics in the relevant sectors or could be indicative of the sampling methodology used.

The age profile of the respondents skews younger, with the most represented age group being 18-30 years, accounting for 24%. The next significant age group is those between 40 and 50 years, making up 35%, followed by those in the 30-40 year range at 25%, and the least represented group is those above 50 years, at 16%. This youthful tilt in the age distribution is typical of industries driven by technology and innovation.

When examining the age of the firms represented in the survey, a majority (68%) have been in operation for more than 20 years, indicating that the study predominantly includes well-established firms. This is a crucial factor, as longer-established firms may have different approaches and capacities for technology adoption compared to newer entities.

Regarding technology adoption, the responses suggest a balanced perspective between deliberate (44%) and quick (56%) adoption strategies. This distribution could be indicative of a cautious yet progressive approach to integrating new technologies within the OTT industry.

Finally, the data shows that a vast majority of the firms (84%) are categorized as having low R&D investment, contrasting with a smaller fraction (16%) that have high R&D investment. This finding is significant as it implies that most firms might have limited resources dedicated to innovation and research, which could influence their ability and readiness to adopt advanced technologies like AI.

In summary, the study's findings paint a picture of a sample predominantly comprising of older and established firms, with a male majority, based in major urban centers, and exhibiting a cautious approach to technology adoption. The low levels of R&D investment across most firms further provide context to the technological landscape in the OTT industry as perceived by the participants.

**Table 4.1.1 – Demographic Profile of Respondents**

| Place | | Gender | | Age | | Firm Age | | Technology Adoption | | R&D Investment | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Chennai** | 252 (42) | **Male** | 360 (60) | **18-30 years** | 144 (24) | **Greater than 20 years** | 412 (68) | **Deliberate** | 261 (44) | **High** | 97 (16) |
| **Hyderabad** | 150 (25) | **Female** | 240 (40) | **30-40 years** | 150 (25) | **Less than 20 years** | 188 (32) | **Quick** | 339 (56) | **Low** | 503 (84) |
| **Bangalore** | 96 (16) | | | **40-50 years** | 210 (35) | | | | | | |
| **Delhi** | 48 (8) | | | **Above 50 years** | 96 (16) | | | | | | |
| **Mumbai** | 54 (9) | | | | | | | | | | |
| **Total** | **600 (100)** | **Total** | **600 (100)** | **Total** | **600 (100)** | **Total** | **600 (100)** | **Total** | **600 (100)** | **Total** | **600 (100)** |

***Source:*** *Primary Data*

***Note:*** The figures in parentheses are percentage to the total

## 4.2 PLS-SEM Results

### 4.2.1 Assessment of the Measurement Model

“To assess the measurement models,  Hair et. al (2019) guideliness on how to report PLS-SEM results has been followed. In this study, the indivdiual indicator variables are reflective in nature and the assessment of reflective measurement models comprises of measuring the internal reliabiltiy, internal consistency, convergent validity and discriminant validity.

Internal reliability is ensured by looking into the indicator loadings, which are shown in Table” 4.2.1.

**Table 4.2.1: Indicator Loadings**

| Construct | Item | Loading |
|---|---|---|
| **Organizational Factors** | OF01 | 0.889 |
| | OF02 | 0.921 |
| | OF03 | 0.93 |
| **Technology Factors** | TF01 | 0.792 |
| | TF02 | 0.795 |
| | TF03 | 0.804 |
| **Perceived Usefulness** | PU01 | 0.886 |
| | PU02 | 0.885 |
| | PU03 | 0.894 |

| | | |
|---|---|---|
| **Perceived Ease of Use** | PE01 | 0.918 |
| | PE02 | 0.92 |
| | PE03 | 0.911 |
| **External Factors** | EF01 | 0.946 |
| | EF02 | 0.928 |
| | EF03 | 0.915 |
| **Adoption Intention** | AI01 | 0.847 |
| | AI02 | 0.905 |
| | AI03 | 0.914 |

*“**Source:** Primary Data*

***Note:*** PLS-SEM analysis is done using SMART PLS software

Indicator loadings explain the amount of variance shared between the individual variables and the construct associated with them. Indicator loadings ensures the indicator reliability of reflective measurement models. It can be seen in Table 4.2.1, that all the indicator loadings of our measurement models are more than the recommended critical value of 0.708 (Hair et. al, 2019). The critical value of 0.708 indicate that the associated construct explains more than 50% of the related indicator’s variance and thus provide adequate item reliability. Thus, we can say that our model has satisfactory indicator reliabilitiy”.

“After ensuring indicator reliability, the next step is to assess internal consistency and convergent validity. The composite reliabiltiy and ρA is used to assess the internal consistency of reflective constructs, and AVE (Average Variance Extracted) is used to assess the covergent validity of reflective constructs. Compositie reliabilty, ρA and AVE of our assessment model is shown in Table 4.2.2".

"It can be seen from Table 4.2.2, that both the composite reliabilty and ρA lies in between the recommended thresholds of 0.70 and 0.95. and all the AVE values exceed the recommended critical value of 0.5. Thus, we can say that our reflective assessment model has satisfactory level of internal consistence as well as covergent validity".

**Table 4.2.2: Reliability and Validity**

| Constructs | ρA | Composite Reliability | Average Variance Extracted |
|---|---|---|---|
| **Adoption Intention** | 0.868 | 0.919 | 0.791 |
| **External Factors** | 0.939 | 0.950 | 0.864 |
| **Organizational Factors** | 0.907 | 0.938 | 0.835 |
| **Perceived Ease of Use** | 0.910 | 0.940 | 0.840 |
| **Percieved Usefulness** | 0.868 | 0.918 | 0.790 |
| **Technology Factors** | 0.726 | 0.839 | 0.635 |

*"**Source:** Primary Data*

***Note:*** PLS-SEM analysis is done using SMART PLS software

The final step in the assessment of reflective measurement model is to ensure discriminant validity, which explains the extenet to which each construct is empirically separate from other construct. HTMT (Hetrotrait-monotrait) ratio is used to assess the discriminant validity of the model. The HTMT values are shown in Table 4.2.3”.

“HTMT is the mean correlation value of items across constructs in relation to the geometric mean of  average correlations for item measuring the same construct. When HTMT values are high, discriminat validity is said to be low. It can be seen from Table 4.2.3., that all the HTMT values of our reflective measurement model are significantly lower than the conservative threshold limit of 0.85. Thus, it can said that discriminant validity of our model is satisfactorily established”.

**Table 4.2.3: Hetrotrait-monotrait (HTMT) Ratio of Correlations**

| | Adoption Intention | External Factors | Organizational Factors | Perceived Ease of Use | Perceived Usefulness |
|---|---|---|---|---|---|
| **External Factors** | 0.416 | | | | |
| **Organizational Factors** | 0.479 | 0.321 | | | |
| **Perceived Ease of Use** | 0.445 | 0.560 | 0.374 | | |
| **Perceived Usefulness** | 0.466 | 0.424 | 0.337 | 0.453 | |
| **Technology Factors** | 0.420 | 0.438 | 0.550 | 0.506 | 0.386 |

***Source:*** *Primary Data*

***Note:*** PLS-SEM analysis is done using SMART PLS software

### 4.2.2 Assessment of the Structural Model

“To assess the structural model, the guideliness of Hair et. al (2019) has been followed. According to Hair et. al (2019), assessment of the structural model involves three important things viz., checking the collineartity issues, checking the relevance and significance of path coefficientts and checking the models’ explanatorty and predictive power. The results of our structural model were shown in Table 4.2.4 and the significance of the path coefficients with relevant hypothesis has been separately shown in Figure 4.2.1”.

VIF (Variance Inflation Factor) is used to check collinearity issues in the model. “It can be seen from Table 4.2.4, that the VIF values are close to 3. The largest inner VIF value of our model construct is 3.187 (Hair et. al, 2019). Thus, we can say that collinearity is not at critical level in the inner model and will not affect the regression results. Next, we examine path coefficients’ size and significance. With respect to control varaibles, Technology Adoption has significant impact on all the predictor constructs namely oranizatioanl factors ($\beta = 0.284$), technology factors ($\beta = 0.535$), perceived usefulness ($\beta = 0.601$), and perceived ease of use ($\beta = 0.477$), and external factors ($\beta = 0.548$); R&D has significant impact on three constructs namely perceived usefulness ($\beta = -0.43$), perceived ease of use ($\beta = -0.648$), external factors ($\beta = -0.579$), and firm age has significant impact on only two constructs namely perceived usefulness ($\beta = -0.43$), and perceived ease of use ($\beta = -0.648$), However, control variables doesn’t have any significant impact on the endogenous construct (adoption intention) of the model”.

“Figure 4.2.1 illustrates the size and significance of path coefficients between the endogenous and exogenous constructs. It can be seen from figure 4.2.1, that organizatioanl factors ($\beta = 0.264$), perceived usefulness ($\beta = 0.209$), perceived ease of use ($\beta = 0.142$), and external factors ($\beta = 0.13$)”, has significant positive correlation with the adoption intention.

Surprisingly, Technology Factors (β = 0.038) “doesn’t have any significant impact on the” adoption intention.

“A look into the $R^2$ values in Table 4.2.4 shows, organizational factors, perceived usefulness, perceived” ease of use and external factors “were the three major predictor constructs in explaining the adoption intention (0.319). As the $R^2$ value of the endogenous construct is more than 0.25, the model has achieved moderate-to-high level of success (Hair et al., 2019) in explaining the” adoption of churn prediction models.

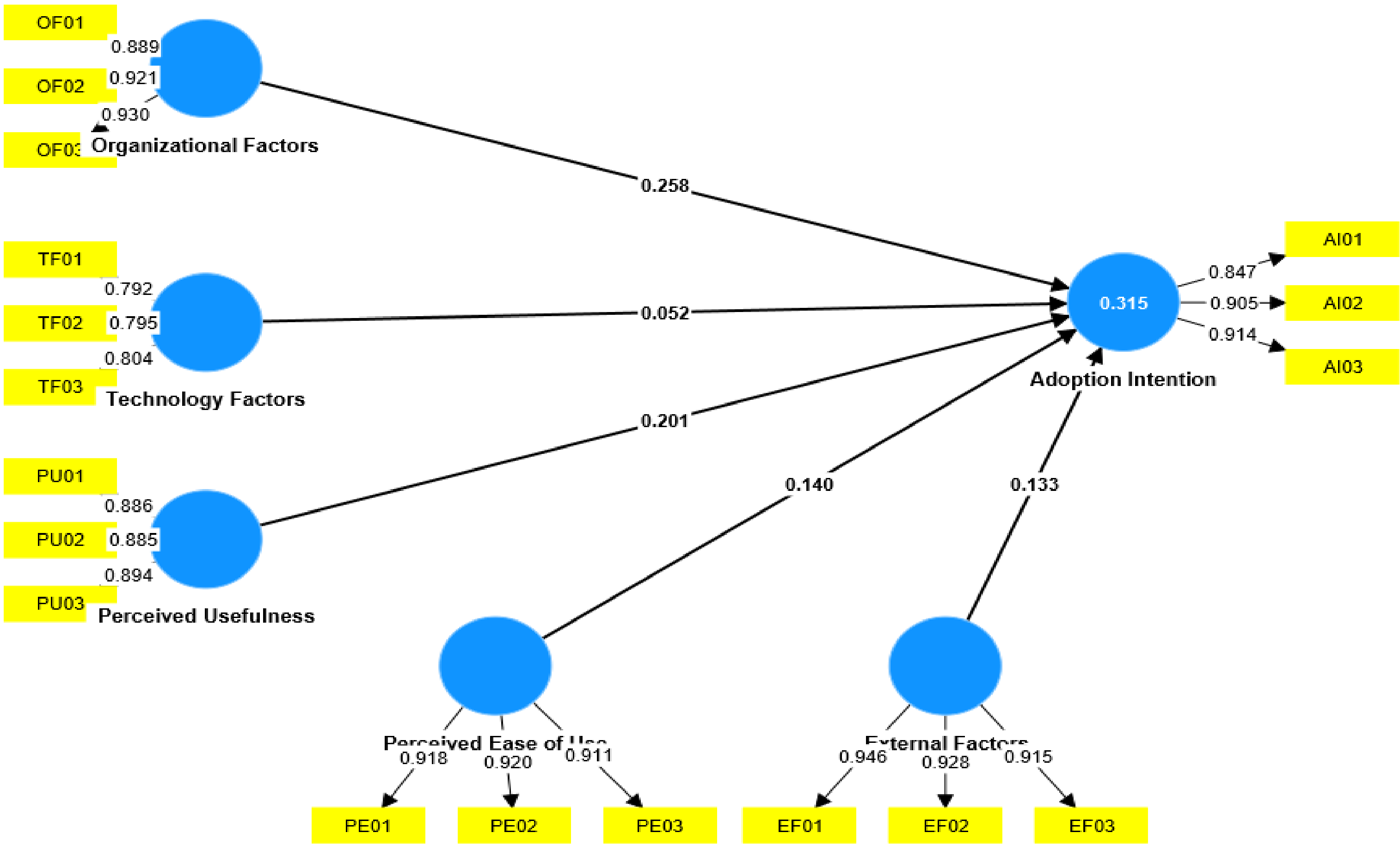
***Accepted / Rejected Hypotheses***

Based on the results from the study, the following hypotheses were accepted or rejected:

- **H1 (Organizational factors)**: Accepted, as there was a significant positive correlation (β = 0.264) with adoption intention.
- **H2 (Technological factors)**: Rejected, as there was no significant impact (β = 0.038) on adoption intention.
- **H3 (Perceived usefulness)**: Accepted, as there was a significant positive correlation (β = 0.209) with adoption intention.
- **H4 (Perceived ease of use)**: Accepted, as there was a significant positive correlation (β = 0.142) with adoption intention.
- **H5 (External factors)**: Accepted, as there was a significant positive correlation (β = 0.13) with adoption intention.

Therefore, H2 was the only hypothesis rejected, while H1, H3, H4, and H5 were accepted.

**Figure 4.2.1: Structural Model Results**




***Source:*** *Primary Data*
***Note:*** PLS-SEM analysis is done using SMART PLS software

**Table 4.2.4: Structural Model Results**

| Outcome | R Sq. | Predictor | Direct Paths & Hypotheses | B | CI | Significance? | $f^2$ | VIF |
|---|---|---|---|---|---|---|---|---|
| **Organizational Factors** | 0.015 | CV | Firm Age -> Organizational Factors | 0.122 | [-0.183; 0.429] | No | 0.001 | 3.187 |
| | | CV | R&D -> Organizational Factors | -0.292 | [-0.578; 0.001] | No | 0.007 | 1.732 |
| | | CV | Technology Adoption -> Organizational Factors | 0.284 | [0.034; 0.527] | Yes | 0.008 | 2.455 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Technology Factors** | 0.015 | CV | Firm Age -> Technology Factors | -0.076 | [-0.373; 0.216] | No | 0 | 3.187 |
| | | CV | R&D -> Technology Factors | -0.048 | [-0.272; 0.041] | No | 0.097 | 1.732 |
| | | CV | Technology Adoption -> Technology Factors | 0.535 | [0.290; 0.761] | Yes | 0.032 | 2.455 |
| **Perceived Usefulness** | 0.069 | CV | Firm Age -> Perceived Usefulness | 0.569 | [0.263; 0.880] | Yes | 0.023 | 3.187 |
| | | CV | R&D -> Perceived Usefulness | -0.43 | [-0.685; -0.165] | Yes | 0.016 | 1.732 |
| | | CV | Technology Adoption -> Perceived Usefulness | 0.601 | [0.366; 0.828] | Yes | 0.039 | 2.455 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Perceived Ease of Use** | 0.062 | CV | Firm Age -> Perceived Ease of Use | 0.236 | [-0.069; 0.539] | No | 0.004 | 3.187 |
| | | CV | R&D -> Perceived Ease of Use | -0.648 | [-0.924; -0.377] | Yes | 0.016 | 1.732 |
| | | CV | Technology Adoption -> Perceived Ease of Use | 0.477 | [0.266; 0.692] | Yes | 0.039 | 2.455 |
| **External Factors** | 0.057 | CV | Firm Age -> External Factors | 0.201 | [-0.7; 0.473] | No | 0.003 | 3.187 |
| | | CV | R&D -> External Factors | -0.579 | [-0.858; -0.301] | Yes | 0.028 | 1.732 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | CV | Technology Adoption -> External Factors | 0.548 | [0.356; 0.742] | Yes | 0.032 | 2.455 |
| **Adoption Intention** | 0.319 | OF | Organizational Factors -> Adoption Intention | 0.264 | [0.171; 0.356] | Yes | 0.078 | 1.309 |
| | | PU | Perceived Usefulness -> Adoption Intention | 0.209 | [0.111; 0.315] | Yes | 0.048 | 1.339 |
| | | PEU | Perceived Ease of Use -> Adoption Intention | 0.142 | [0.040; 0.240] | Yes | 0.019 | 1.565 |
| | | EF | External Factors -> Adoption Intention | 0.13 | [0.033; 0.223] | Yes | 0.017 | 1.486 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | TF | Technology Factors -> Adoption Intentiion | 0.038 | [-0.058; 0.133] | No | 0.001 | 1.484 |
| | | CV | Firm Age -> Adoption Intention | -0.232 | [-0.520; 0.045] | No | 0.005 | 3.276 |
| | | CV | R&D -> Adoption Intention | -0.156 | [-0.365; 0.062] | No | 0.003 | 1.732 |
| | | CV | Technology Adoption -> Adoption Intention | -0.087 | [-0.342; 0.160] | No | 0.001 | 2.455 |

***Source:*** *Primary Data*

***Note:*** PLS-SEM analysis is done using SMART PLS software

CI = 95% bootstrap two-tailed confidence interval, CV = Control Variable, OF = "Organizational Factors", TF = "Technology Factors", PU = "Percieved Usefulness", PEU = "Perceived Ease of Use, EF = "External Factors".

### 4.2.3 Predictive Relevance of the Model

Table 4.2.4 indicates that "the model has achieved moderate-to-high level of success (Hair et al., 2019) in explaining the adoption intention" of AI based Churn Prediction Models, "as the $R^2$ value of the endogenous construct (0.319) is more than 0.25. However, the $R^2$ statistics explains only the in-sample explanatory power of the model" (Saari et. al, 2021). In order "to assess the out-of-sample predict relevance of our model for" cryptocurrency adoption, $Q^2$ values has been obtained for major constructs using blindfolding technique "and the results are shown in Table 4.2.5".

**Table 4.2.5: Predict Relevance of the Model**

| Construct | $Q^2$ Predict |
|---|---|
| **Adoption Intention** | 0.294 |

*"**Source:** Primary Data*

***Note:** PLS-SEM analysis is done using SMART PLS software"*

"It can be seen from Table 4.2.5, that the $Q^2_{predict}$ value is" above zero. It could be noted that $Q^2_{predict}$ is used to verify that the predictions have outpaced the most naïve benchamark, which has been defined as "the indicator means from the analysis sample" "(Hair et. al, 2019). This proves the out-of-sample predict relevance of the model".

### 4.2.4 Importance-Performance Map Analysis (IMPA)

“In order to identify the impact and perforamnce of the constructs with respect to the endogeneous construct, importance-performance map analysis (IMPA) has been conducted with intention to use as the target construct and the results are shown in Table 4.2.6 and Figure 4.2.2. The results of IMPA demonstrate for which exogenous construct the total effects are important by explaining the variance of the endogenous construct (Saari et. al, 2021)”.

“In this study focusing on the factors affecting the adoption intention of AI-based” churn prediction models, “the Importance-Performance Map Analysis (IPMA) within the Partial Least Squares Structural Equation Modeling (PLS-SEM)” framework offers insightful interpretations. The IPMA results reveal “a nuanced understanding of how various predictor constructs contribute to” the adoption intention, the endogenous construct in this context.

The unstandardized total effect, representing the importance of each predictor construct, varies significantly, indicating a differential impact on the adoption intention. Organizational Factors emerge as highly influential, with an importance score of 0.258, suggesting that aspects such as company culture, management support, and organizational readiness “play a crucial role in the adoption of AI-based” churn prediction models. However, their moderate performance score of 46.083 indicates potential areas for improvement.

In contrast, Technology Factors, while essential, exhibit a relatively lower importance score of 0.052. This lower score, coupled with a performance score of 43.409, implies that while technological aspects like system quality and compatibility are relevant, they might not be the primary drivers in the decision-making process for adopting these models.

Perceived Usefulness stands out with a high importance score of 0.201 and the highest performance score of 48.062 among the predictors. This finding underscores that the perceived benefits and effectiveness of AI-based churn prediction models are not only crucial but are also well-regarded in the current scenario. It suggests that stakeholders generally recognize the utility of these models in predicting customer churn.

"Similarly, Perceived Ease of Use, with an importance score of 0.14 and a performance score of 45.841", indicates a moderate but noteworthy impact on adoption intention. This reflects the significance of user-friendly and accessible technology in influencing the decision to adopt AI-based solutions.

External Factors, encompassing aspects like market trends, competitive pressure, and regulatory environment, also hold moderate importance (0.133) and performance (45.107). This finding suggests that while external market and regulatory conditions are considered, they might not be the primary determinants in the adoption of these models.

The average importance (0.1568) and performance (45.7004) across all constructs provide a baseline for comparison. Constructs exceeding this average in importance and/or performance are particularly impactful or effective in their current state.

In conclusion, this study highlights that while all the examined factors contribute to the adoption intention of AI-based churn prediction models, their impact and current performance vary. Organizational Factors and Perceived Usefulness are pivotal, suggesting that efforts to enhance organizational readiness and highlight the practical benefits of these models could significantly bolster adoption rates. Technology Factors, "Perceived Ease of Use, and External Factors, while important, play a somewhat lesser role. These insights can guide targeted strategies to foster the adoption of AI-based" churn prediction models, ensuring that efforts are concentrated on the most influential areas.

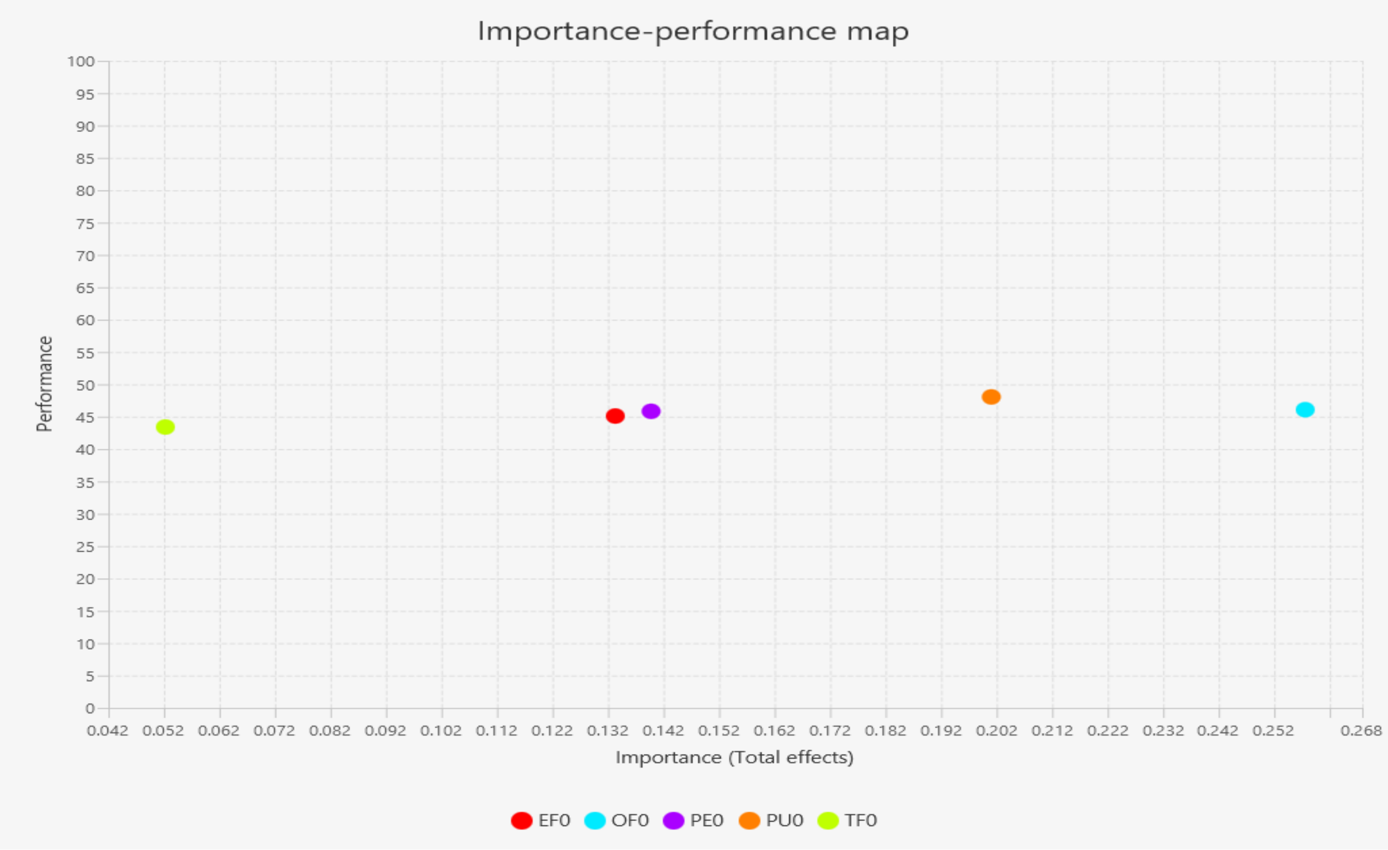
**Table 4.2.5: Importance-Performance Map Analysis**

| | Unstandardized Total Effect | Performance | LV Performance |
|---|---|---|---|
| **Organizational Factors** | **0.258** | **46.083** | - |
| **Technology Factors** | 0.052 | 43.409 | - |
| **Perceived Usefulness** | **0.201** | **48.062** | - |
| **Perceived Ease of Use** | 0.14 | **45.841** | - |
| **External Factors** | 0.133 | 45.107 | - |
| **Adoption Intention** | | - | 49.636 |
| **Average** | 0.1568 | 45.7004 | |

***Source:*** *Primary Data*

***Note:*** PLS-SEM analysis is done using SMART PLS software

**Figure: 4.2.2: Importance-Performance Map Analysis**




***Note:*** *EF0 = External Factors, OF0* = Organizational Factors, PE0 = Perceived Ease of Use, PU0 = Perceived Usefulness, TF0 = Technology Factors

# Chapter V - Discussion

## 5.1 Key Findings

“The key findings from the study” titled can be summarized as follows:

### 5.1.1 Structural Model Assessment:

- **Path Coefficients**: Significant impacts were observed from Technology Adoption on various predictor constructs like organizational factors, technology factors, perceived usefulness, ease of use, and external factors. However, control variables showed no significant impact on the endogenous construct (adoption intention).

- **Model's Explanatory and Predictive Power**: “The R2 value of the endogenous construct (adoption intention) is more than 0.25”, indicating moderate-to-high success in explaining the adoption of churn prediction models.

### 5.1.2 Importance-Performance Map Analysis (IMPA):

- **Organizational Factors**: High importance (0.258 importance score) but moderate performance (46.083 performance score), indicating significant influence but room for improvement.

- **Technology Factors**: Lower importance (0.052 importance score) and performance (43.409 performance score), suggesting they are not primary drivers in adoption.

- **Perceived Usefulness**: High importance (0.201 importance score) and the highest performance (48.062 performance score), indicating recognized benefits and effectiveness.
- **Perceived Ease of Use**: Moderate importance (0.14 importance score) and performance (45.841 performance score), reflecting the significance of user-friendly technology.
- **External Factors**: Moderate importance (0.133 importance score) and performance (45.107 performance score), suggesting consideration but not as primary determinants in adoption.
- **Overall Insights**: Organizational Factors and Perceived Usefulness are critical in driving adoption, while Technology Factors, "Perceived Ease of Use, and External Factors have a lesser impact".

These findings imply that "to enhance the adoption of AI-based churn prediction models in the" OTT industry, focus should be placed on improving organizational readiness, highlighting practical benefits, and ensuring user-friendly technology, while also considering external market conditions and technological aspects.

### 5.2 Organizational Factors

The adoption of AI-based churn prediction models in the Over-The-Top (OTT) industry is significantly influenced by various organizational factors. "Firstly, the complexity and adaptability of AI technologies" play a crucial role. Organizations need to have the requisite technical infrastructure and expertise to implement and manage these sophisticated systems effectively (Amin et al., 2019; Ahn, Kim, and Lee, 2020). Moreover, the quality of data available to these organizations directly impacts the accuracy of AI-based predictions. High-quality, comprehensive data sets are essential for training and fine-tuning AI models to predict customer churn accurately (Alkurd, Abualhaol, and Yanikomeroglu, 2020; Chen, Kuo, and Chen, 2018).

The organizational culture and employees' readiness to embrace AI technologies also significantly affect their successful adoption. A culture that fosters innovation and continuous learning is conducive to integrating AI into business processes (Barat et al., 2020; Bhattacharyya and Dash, 2022). Additionally, the strategic alignment of AI initiatives with the organization's overall goals and customer management strategies is critical. AI-based models should be aligned with the organization’s customer relationship management and retention strategies to be effective (Capapé, 2020; Chaturvedi and Verma, 2023).

Finally, the financial resources available to an organization influence the adoption of AI-based churn prediction models. Implementing AI technologies requires “significant investment in hardware, software, and human resources. Therefore, organisations” need adequate funding and a clear ROI plan to sustain these initiatives (Dixit, 2022; Goyal, Singh, and Inder, 2020).

In summary, the successful adoption of AI-based churn prediction models in the OTT industry hinges on several organizational factors, including technological infrastructure, data quality, cultural readiness, strategic alignment, and financial resources. These factors must be carefully considered and managed to leverage AI effectively in predicting and reducing customer churn.

### 5.3 Perceived Usefulness

The perceived usefulness of AI-based churn prediction models is a pivotal factor influencing their adoption in “the Over-The-Top (OTT) industry. The perception of these AI” models as beneficial and effective tools for predicting customer churn significantly impacts the willingness of organizations to invest in and implement them. This perceived usefulness stems from the potential of AI to provide accurate, timely, and actionable insights into customer behavior and preferences, which are critical for customer retention strategies in the highly competitive OTT market (Mohamed, 2019; Ahn, 2022).

Organizations in the OTT industry are more likely to adopt AI-driven solutions if they perceive these technologies as instrumental in enhancing their decision-making processes, improving customer engagement, and ultimately reducing churn rates (Amin et al., 2019; Alkurd, Abualhaol, and Yanikomeroglu, 2020). Furthermore, the effectiveness of AI models in processing large volumes of data to identify at-risk customers also contributes to their perceived usefulness, encouraging OTT providers to adopt such technologies for strategic advantage (Chen, Kuo, and Chen, 2018; Dhiman, Singh, and Sarmah, 2022).

In conclusion, the perceived usefulness of AI-based “churn prediction models plays a crucial role” in their adoption within the OTT industry. This perception is influenced by the models' ability “to provide valuable insights into customer behavior, enhance” decision-making, and contribute to effective churn management strategies.

## 5.4 Perceived Ease of Use

“The perceived ease of use of AI-based churn prediction models plays a crucial role in their adoption within the OTT industry”. This concept, as outlined by Davis (1989), “emphasizes the importance of user-friendly interfaces and straightforward operation in encouraging the use of new technologies”. In the OTT sector, complex systems that are difficult to navigate can be a significant barrier to the adoption of AI models (Chen, Kuo, and Chen, 2018). Moreover, seamless integration with existing systems is essential to ensure smooth operation and reduce learning curves, as highlighted by Mohamed (2019). Effective training and support are also critical in making these technologies more approachable, as argued by Dhiman, Singh, and Sarmah (2022). Furthermore, the complexity of the AI model itself can influence its perceived ease of use. Simplifying these models, while maintaining their effectiveness, can make them more accessible to a broader range of users within an organization, thereby enhancing their adoption and utilization in churn prediction strategies (Amin et al., 2019; Alkurd, Abualhaol, and Yanikomeroglu, 2020).

"One key aspect of perceived ease of use is the user interface". A well-designed, intuitive interface can make a substantial difference in how users interact with the AI model. This includes clear navigation, understandable outputs, and straightforward processes for inputting data and interpreting results. If users find the interface confusing or overly complex, they are less likely to utilize the model effectively, which can hinder its adoption.

Another crucial factor is the integration of AI models with existing systems and processes. In the OTT industry, companies often use a variety of software and data management tools. AI models that can seamlessly integrate with these existing systems are more likely to be adopted. This ease of integration reduces the learning curve for users and minimizes disruption to existing workflows.

Training and support are also important components of perceived ease of use. Providing comprehensive training and ongoing support can help users feel more comfortable and confident in using AI models. This includes not only initial training but also ongoing support to address any issues or questions that arise. Effective training and support can demystify AI technology, making it more approachable and less intimidating for users.

Finally, the complexity of the AI model itself can influence its perceived ease of use. Models that are too complex or require a high level of technical expertise may deter adoption.

Simplifying the models, without compromising their effectiveness, can make them more accessible to a broader range of users within an organization.

In summary, the perceived ease of use of AI-based churn prediction models is a critical factor in their adoption within the OTT industry. Key aspects influencing this perception include the user interface, integration with existing systems, training and support, and the complexity of the models themselves. By focusing on these areas, OTT companies can enhance the usability of AI models, thereby encouraging their adoption and effective use in churn prediction and customer retention strategies.

### 5.5 External Factors

External factors significantly impact the adoption of AI-based churn prediction models in the OTT industry. Regulatory environment, market competition, technological advancements, customer expectations, and economic conditions are key influencers.

Regulatory Environment: Stringent regulations regarding data privacy and usage can limit the extent to which OTT providers can utilize customer data for AI churn models (Ahmed, 2019). Compliance with these regulations is critical for legal operation and customer trust.

Market Competition: In a highly competitive market, the need to retain customers and reduce churn becomes more pressing. AI-based churn models offer a competitive edge by providing insights into customer behavior and predicting churn (Ahn, 2022).

Technological Advancements: Rapid advancements “in AI and machine learning technologies enhance the capabilities of churn prediction models”, making them more accurate and efficient (Alkurd, Abualhaol, and Yanikomeroglu, 2020).

Customer Expectations: Today's customers expect personalized and engaging experiences. AI churn models help OTT providers tailor their services to meet these expectations, thereby reducing churn (Amin et al., 2019).

Economic Conditions: Economic factors like consumer spending power and market dynamics influence the adoption of AI technologies. In tougher economic times, OTT platforms may focus more on retaining customers, thereby increasing the relevance of churn prediction models (Dixit, 2022).

In conclusion, external factors like regulatory constraints, market competition, technological progress, evolving customer expectations, and economic conditions "play a substantial role in the adoption of AI-based" churn prediction models in the OTT industry. These factors collectively influence how and why these models are utilized, underlining their importance in strategic decision-making.

### 5.6 Technology Factors

Contrary to expectations, technology factors do not significantly impact the adoption of AI-based churn prediction models in the OTT industry. This is primarily because the OTT industry is inherently technology-driven, and most players are already equipped with the necessary technological infrastructure and expertise. The industry's familiarity with advanced technologies means that the introduction of AI-based models does not present a substantial technological challenge. Additionally, the rapid evolution and integration of AI in various sectors have made these technologies more accessible and user-friendly, further minimizing the technological barrier to adoption. As such, factors like organizational readiness, market competition, and customer expectations "play a more pivotal role in influencing the adoption" of AI-based churn prediction models in the OTT industry.

# Chapter VI - Conclusion

## 6.1. Major Findings

“The study” reveals that in the OTT industry, technology adoption significantly impacts factors like organizational readiness, technology aspects, “perceived usefulness, ease of use, and external influences. Interestingly, control variables” don't significantly affect adoption intentions. The model effectively explains adoption tendencies with a moderate-to-high success rate. Organizational factors are highly important but require improvement. Technology factors, while less critical, still influence adoption. Perceived usefulness is both important and effective, whereas ease of use and external factors have moderate importance. These insights suggest that enhancing AI-based churn model adoption in OTT should focus on organizational readiness, highlighting practical benefits, and ensuring user-friendly technology, while also considering external market conditions and technological aspects.

## 6.2 Implications of the Study

“The implications of the study results are multifaceted and” provide valuable insights for the OTT industry in adopting AI-based churn prediction models:

1. Organizational Factors: The high importance and moderate performance of organizational factors suggest that companies need to focus on internal readiness and capabilities. This includes investing in the necessary infrastructure, training employees, and developing a culture that embraces AI and data-driven decision-making.

2. Perceived Usefulness: The significant impact of perceived usefulness indicates that organizations should not only invest in these technologies but also effectively communicate

their benefits. Demonstrating the practical value of AI-based models in reducing churn and enhancing customer satisfaction can encourage broader acceptance and utilization.

3. Technology Factors: Despite their lower importance, technology factors should not be overlooked. Ensuring that the AI models are compatible with existing systems and are technologically advanced to handle complex data analysis is crucial. This also involves staying updated with the latest AI advancements to maintain a competitive edge.

4. Perceived Ease of Use: “The moderate importance of ease of use” highlights the need for AI models to be user-friendly. Simplifying the interface and making the technology more accessible to non-technical staff can increase its adoption.

5. External Factors: The moderate impact of external factors suggests that while internal factors are primary, external elements like market trends, customer preferences, and regulatory environments should also be considered. Staying attuned to these external dynamics can help OTT providers better position their AI strategies.

6. Balanced Approach: The study implies a need for a balanced approach in adopting AI for churn prediction. While focusing on internal readiness and the utility of AI, companies should not neglect the ease of use and the broader market and technological environment.

7. Strategic Decision Making: These insights should inform strategic decision-making in the OTT industry. Adopting AI-based churn prediction models is not just about technological investment but also about aligning this technology with business strategies, employee capabilities, and market demands.

8. Future Orientation: The findings indicate that for long-term success, OTT companies must continuously adapt to changing technological landscapes and customer expectations, ensuring that their AI models evolve accordingly.

In conclusion, the study provides a comprehensive roadmap for OTT companies looking to implement AI-based churn prediction models. It underscores the importance of a holistic approach that encompasses organizational readiness, clear communication of benefits, technological integration, user experience, and an awareness of market dynamics.

**6.3 Recommendations**

“Based on the study's implications and results, the following recommendations can be made” for the OTT industry:

1. Enhance Organizational Readiness: Invest in training and infrastructure to support AI technology. Foster a data-driven culture to maximize the potential of AI-based churn prediction models.

2. Communicate Benefits Effectively: Clearly articulate the practical advantages of AI models to stakeholders to drive adoption and support.

3. Ensure Technological Compatibility: Regularly update AI models to ensure they align with current technological standards and integrate seamlessly with existing systems.

4. Focus on User-Friendly Design: Simplify interfaces and make AI tools accessible to all employees, not just technical staff.

5. Stay Attuned to Market and External Factors: Regularly assess market trends, customer preferences, and regulatory changes to adapt AI strategies accordingly.

6. Adopt a Balanced Approach: While prioritizing internal readiness and “perceived usefulness, also consider ease of use and external factors” in your AI strategy.

7. Strategic Integration: Align AI adoption with broader business strategies and customer management objectives.

8. Continuous Adaptation and Improvement: Keep evolving the AI models in response to new data, technological advancements, and customer feedback.

### 6.4. Conclusion

The study concludes that for effective adoption of AI-based churn prediction models in the OTT industry, emphasis should be on enhancing organizational readiness, effectively communicating the benefits of AI, ensuring technological compatibility, and focusing on user-friendly designs. It highlights the importance of a balanced approach, considering both internal capabilities and external market dynamics. Future research could explore "the long-term impact of AI adoption on customer retention and satisfaction, the evolution of AI capabilities in response to changing market conditions, and the role of emerging" technologies in enhancing churn prediction models. Additionally, examining the impact of cultural differences in AI adoption across various regions could provide deeper insights.

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## Annexure I – Questionnaire

**Demographics**

1. Place

    a) Chennai

    b) Hyderabad

    c) Bangalore

    d) Delhi

    e) Mumbai

2. Gender

    a) Male

    b) Female

3. Age

    a) 18- 30 years

    b) 30-40 years

    c) 40-50 years

    d) Above 50 years

4. Firm age (years in operation):

    a) Greater than 20 years

    b) Less than 20 years

5. Technology Adoption

    a) Deliberate

b) Quick

6. R&D Investment

a) High

b) Low

**Rate the Following Statement (1 – Strongly Disagree; 7 – Strongly Agree)**

| Construct | Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|
| **Organizational Factors** | **OF01** - Our company has sufficient resources to adopt AI-based churn prediction models. | | | | | | | |
| | **OF02** - Our company's organizational culture is open to adopting new technologies like AI-based churn prediction models. | | | | | | | |
| | **OF03** - Our company's management actively supports the adoption of AI-based churn prediction models. | | | | | | | |
| Technology Factors | **TF01** - AI-based churn prediction models are compatible with our existing systems. | | | | | | | |
| | **TF02** - Implementing AI-based churn prediction models is not complex. | | | | | | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **TF03** - Adopting AI-based churn prediction models offers a competitive advantage for our company. | | | | | | | |
| Perceived Usefulness | **PU01** - AI-based churn prediction models would significantly improve customer retention in our company. | | | | | | | |
| | **PU02** - AI-based churn prediction models would considerably increase our company's revenue. | | | | | | | |
| | **PU03** - AI-based churn prediction models would enhance decision-making processes in our company. | | | | | | | |
| Perceived Ease of Use | **PE01** - AI-based churn prediction models are easy to use. | | | | | | | |
| | **PE02** - AI-based churn prediction models can be implemented without significant effort. | | | | | | | |
| | **PE03** - Our company's employees would require minimal training to use AI-based churn prediction models effectively. | | | | | | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| External Factors | **EF01** - The competitive environment in the OTT industry encourages the adoption of AI-based churn prediction models. | | | | | | | |
| | **EF02 -** Market trends have a significant influence on our company's technology adoption decisions. | | | | | | | |
| | **EF03** - The regulatory environment affects our company's decision to adopt AI-based churn prediction models. | | | | | | | |
| Adoption Intention | **AI01** - Our company is willing to adopt AI-based churn prediction models. | | | | | | | |
| | **AI02** - Our company is actively exploring the implementation of AI-based churn prediction models. | | | | | | | |
| | **AI03 -** Our company plans to adopt AI-based churn prediction models in the near future. | | | | | | | |