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Predicting and Modeling Customer Churn in Telecom Industry: An SEM–PLS-Based Analytical Framework

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Abstract

India's mobile telecommunications market, the world's second largest, faces rapid growth and fierce competition, making customer churn reduction a strategic priority. This study develops and validates an integrated framework to identify and predict churn determinants within India's emerging 5G ecosystem. Data from 1,600 mobile subscribers in Hyderabad were analyzed using a two-stage process involving Exploratory and Confirmatory Factor Analyses, followed by Structural Equation Modeling (SEM). Logistic regression and PLS-Predict were applied to assess predictive accuracy. Results indicate that network quality, service experience, and product value significantly influence churn, while advertisement, brand, and social influence are insignificant. Predictive testing confirmed high accuracy (AUC = 0.84) and strong relevance (Q^2_predict > 0). The validated SEM–PLS model offers actionable insights for proactive churn management, emphasizing network reliability, responsive service, and value-added offerings. This study extends existing literature by modeling churn behavior through a structural–predictive approach specific to India's 5G context.

Keywords: SEM, PLS-Predict, 5G, Customer Churn, Telecom Industry, Predictive Analytics

1. Introduction

The telecommunications industry has undergone a profound transformation in recent years, driven by the global transition from 4G to fifth-generation (5G) mobile technology. This next-generation infrastructure promises ultra-high data speeds, minimal latency, and massive device connectivity, enabling new possibilities for consumers and enterprises alike. However, despite these advancements, customer churn—defined as the phenomenon of subscribers switching from one service provider to another—remains a persistent and costly challenge for mobile network operators. The issue of churn is particularly critical in markets like India, where the telecommunications sector is marked by aggressive competition, price wars, and rapid technological adoption.

India represents one of the fastest-growing 5G markets globally. According to the Global System for Mobile Communications Association (GSMA), by 2025, the country is projected to exceed 3.6 billion 5G connections, accounting for approximately 40% of the global population. Within India, the Telecom Regulatory Authority of India (TRAI) has initiated several policy frameworks to accelerate digital transformation, while leading operators such as Reliance Jio, Bharti Airtel, and Vodafone Idea are investing heavily in infrastructure modernization. Yet, amid this technological evolution, customer retention has become increasingly complex. Enhanced competition and heightened consumer expectations have elevated churn rates, compelling service providers to re-examine the drivers of customer attrition in the 5G era.

Traditional determinants of customer churn—such as network quality, service experience, and perceived value—continue to influence customer switching behavior. However, the rapid diffusion of 5G technology has altered customer expectations, leading to evolving decision criteria. Smith, Johnson, and Brown (2018) found that technological change significantly reshapes the underlying causes of churn across industries. Similarly, Chen, Lee, and Wang (2019) demonstrated that new technological introductions often correspond with temporary spikes in churn as customers realign with operators offering superior performance or pricing. Consequently, understanding and predicting churn under 5G conditions requires integrating both **explanatory and predictive perspectives**.

While several studies (e.g., Wei & Chiu, 2002; Coussement & Poel, 2008; Joshi, 2012; Bhale & Bedi, 2020) have explored churn behavior in telecommunications, most have focused primarily on identifying causal relationships through statistical or structural modeling. Although such models provide valuable theoretical insights, they often lack predictive validation—i.e., the ability to accurately forecast which customers are most likely to churn. Recent developments in predictive analytics and machine learning offer new opportunities to bridge this gap by complementing causal modeling with predictive relevance testing (Kunthi Afrilinda Kusumawardani & Laura Fabiola Soegihono, 2024 ; Shmueli et al., 2019).

In this context, the present study aims to develop an integrated explanatory–predictive framework for analyzing customer churn among 5G mobile users in India. It employs **Structural Equation Modeling (SEM)** to validate the causal structure of churn determinants and extends this framework through **logistic regression** and **PLS-Predict** analysis to assess predictive power. This dual approach allows the study not only to explain the drivers of churn but also to evaluate their real-world predictive capability—thereby enhancing both theoretical understanding and managerial utility.

The remainder of this paper is organized as follows. Section 3 presents a review of relevant literature on customer churn and predictive modeling. Section 4 outlines the objectives and hypotheses of the study, while Section 5 details the methodology and data collection process. Section 6 discusses the analytical results derived from Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and SEM. Section 7 introduces the predictive validation results using logistic and PLS-based models. The final sections present the findings, managerial implications, and suggestions for future research.

2. Literature Review

2.1 Conceptualizing Customer Churn

Customer churn refers to the discontinuation of services by customers within a given period, representing both a behavioral and economic loss to service providers. In the telecommunications context, churn reflects the rate at which mobile or internet subscribers switch from one operator to another, directly influencing profitability and market share. The American Heritage Dictionary defines churn as “the number of consumers who move from one company to another company.”

Within telecommunications, churn has been recognized as a vital performance indicator that reflects the effectiveness of customer retention strategies and overall customer satisfaction (Wei & Chiu, 2002; Coussement & Poel, 2008). The concept has been elaborated by multiple scholars, including Modisette (1999), Hadden et al. (2005), Yang and Chiu (2006), Joshi (2012), Phadke et al. (2013), and Bhale & Bedi (2020), each emphasizing the strategic importance of managing churn for sustainable competitiveness. Modisette (1999) viewed churn as a decline in the customer base, while Hadden et al. (2005) described it as customer abandonment of one service in favor of another. Yang and Chiu (2006) considered churn a progressive erosion of customer loyalty.

In India, where the introduction of Mobile Number Portability (MNP) has facilitated easier switching, churn rates remain among the highest globally (Gartner, 2012). Hejazinia and Kazemi (2014) observed that the cost of acquiring new subscribers far exceeds that of retaining existing ones, reinforcing the necessity of churn reduction strategies. The Association of Unified Telecom Service Providers of India (2012) reported a monthly mobility churn rate of approximately six percent, underscoring the magnitude of this challenge.

In conceptual terms, customer churn can be understood as an outcome of customer dissatisfaction and perceived value imbalance. Joshi (2012) and Bhale & Bedi (2020) conceptualized churn as a behavioral intention to switch providers due to unmet needs or service dissatisfaction. Therefore, identifying the antecedents that drive churn intention remains a key focus in marketing and customer relationship management research.

2.2 Factors Influencing Customer Churn in Telecom

Prior studies have identified multiple antecedents of churn, reflecting both service-related and behavioral dimensions. Drawing on foundational works such as Anckar and D'incau (2002), Gustafsson et al. (2005), and Pathak and Rastogi (2007), six primary constructs have emerged as dominant determinants: **network quality, service, product value, social influence, advertisement,** and **brand**.

Network quality is consistently found to be the most critical factor affecting churn. Data speed, signal coverage, and voice call reliability are strongly correlated with customer satisfaction and retention (Sharma & Sonwalkar, 2016; Deo, 2017; Amin et al., 2017). The disruptive market entry of Reliance Jio further accentuated the role of network performance in driving consumer switching behavior in India.

Service quality and **product value** also significantly influence churn. Complex documentation procedures, delayed activations, and weak customer support reduce loyalty, while value-added services, competitive tariffs, and reward programs enhance perceived value and retention (Phadke et al., 2013; Joshi, 2012).

Social influence, encompassing peer, family, and colleague recommendations, impacts both initial provider choice and subsequent switching behavior (Pathak & Rastogi, 2007). Likewise, **advertising** affects churn indirectly by shaping brand perception and awareness (Shafei & Tabaa, 2016). Finally, **brand image** and **trust** serve as psychological anchors that foster customer loyalty in saturated markets (Izogo, 2017; Khandker & Joshi, 2018).

While these determinants have been well established in 3G and 4G contexts, the transition to 5G has introduced new behavioral dynamics. Customers now prioritize seamless high-speed connectivity, real-time performance, and digital service integration. Despite this evolution, literature focusing exclusively on **5G-related churn determinants** remains limited, particularly in the Indian market.

In the emerging 5G environment, predictive churn research has increasingly combined behavioral constructs with algorithmic modeling. Studies in Journal of Business Research and Scientific Reports (Amin et al., 2019; Sikri et al., 2024) highlight that network-performance indicators and perceived product value dominate churn decisions, reinforcing the cognitive–functional orientation observed in earlier theoretical frameworks.

2.3 Predictive Analytics in Telecom Churn Research

Although traditional models such as regression and SEM have elucidated causal relationships among churn determinants, their ability to **predict** churn behavior remains limited. This limitation has driven the adoption of **predictive analytics**, an approach that leverages statistical and machine learning techniques to forecast churn likelihood with high accuracy (Coussement & Poel, 2008).

Predictive modeling in telecom research typically employs techniques such as logistic regression, decision trees, support vector machines, and neural networks. These models assign probability scores to customers, identifying those at higher risk of switching providers. For instance, Coussement and Poel (2008) demonstrated that integrating data mining with behavioral indicators significantly enhances churn prediction accuracy.

More recently, Shmueli et al. (2019) and Hair et al. (2018) have argued for incorporating predictive performance metrics into SEM frameworks to balance **explanatory power** and **predictive validity**. The **PLS-Predict** approach within SmartPLS 4, for example, enables researchers to evaluate a model's out-of-sample predictive relevance using cross-validation procedures. Such integration strengthens both the theoretical and practical credibility of empirical findings (Suzuki et al.,2024).

In the context of 5G, predictive models can help telecom operators identify high-risk customers, enabling targeted retention initiatives before churn occurs. Combining SEM and predictive analytics thus provides a holistic framework—SEM validates causal pathways, while predictive models confirm practical applicability.

2.4 Research Gap

Despite extensive scholarly attention to churn determinants, three gaps persist. First, most studies are confined to 3G or 4G contexts, neglecting behavioral shifts associated with 5G adoption.

Second, prior research has primarily relied on explanatory frameworks without assessing **predictive accuracy**. Third, there is a dearth of empirical studies from developing economies such as India, where competitive intensity and consumer price sensitivity differ significantly from developed markets.

Addressing these gaps, the present study integrates SEM with predictive validation techniques (logistic regression and PLS-Predict) to identify, model, and forecast the determinants of customer churn in India's 5G telecom market. This hybrid approach bridges the gap between **theory-driven explanation** and **data-driven prediction**, contributing to both academic and managerial domains.

3. Objectives And Hypotheses Development

3.1 Research Objectives

The overarching goal of this study is to develop, validate, and test an **integrated explanatory–predictive model** of customer churn in India's 5G telecom market. Building on established literature and empirical evidence, the study seeks to advance understanding beyond causal analysis by incorporating **predictive validation**. The specific objectives are as follows:

1. To identify the key determinants influencing customer churn in the Indian 5G telecom sector through exploratory and confirmatory analyses.

2. To empirically test the causal relationships among these determinants and customer churn using **Structural Equation Modeling (SEM)**.

3. To validate the **predictive performance** of the SEM model using **logistic regression** and **PLS-Predict**, thereby assessing its practical applicability for churn forecasting.

4. To develop a comprehensive framework that combines theoretical explanation with predictive accuracy for enhanced decision-making in customer retention management.

This dual analytical approach aims to transform conventional churn studies—traditionally confined to causal explanation—into a **data-driven predictive management tool** suitable for modern telecom operations.

3.2 Hypotheses Development

Drawing on existing literature and grounded theory, six key determinants are posited to influence customer churn in the Indian telecom context: **network quality**, **service quality**, **product value**, **social influence**, **advertising**, and **brand image**. The hypothesized relationships are discussed below.

Network Quality and Customer Churn

Network quality has consistently emerged as the most significant determinant of customer satisfaction and loyalty within telecommunications. High-speed data, reliable signal strength, and minimal call drops are critical in shaping perceived service quality, particularly in the 5G context (Sharma & Sonwalkar, 2016; Deo, 2017). Customers experiencing poor network quality are more likely to switch to competitors offering superior connectivity.

H1: Network quality has a significant negative relationship with customer churn.

Service Quality and Customer Churn

Service quality, encompassing responsiveness, reliability, and customer support efficiency, directly influences customer retention (Amin et al., 2017; Phadke et al., 2013). Inconsistent or delayed service delivery erodes trust and accelerates churn, while prompt service enhances satisfaction and loyalty.

H2: Service quality has a significant negative relationship with customer churn.

Product Value and Customer Churn

Product value reflects the customer's perceived trade-off between cost and benefit. Tariff plans, discounts, and value-added services contribute to overall satisfaction. When perceived value diminishes, customers tend to switch to providers offering better cost–benefit packages (Joshi, 2012; Bhale & Bedi, 2020).

H3: Product value has a significant negative relationship with customer churn.

Social Influence and Customer Churn

Social influence captures the effect of peer recommendations and group norms on customer decisions. Prior research indicates that consumers' provider choices are shaped by their social networks, particularly in collectivist cultures such as India (Pathak & Rastogi, 2007). However, the influence of social factors may weaken in technologically advanced settings where rational evaluation of service quality dominates decision-making.

H4: Social influence has a significant relationship with customer churn.

Advertising and Customer Churn

Advertising communicates brand differentiation and shapes consumer perception. While persuasive campaigns can attract new customers, misleading or inconsistent advertising may backfire, leading to dissatisfaction and eventual churn (Shafei & Tabaa, 2016). The role of advertising in churn is therefore context-dependent.

H5: Advertising has a significant relationship with customer churn.

Brand Image and Customer Churn

Brand image serves as a psychological contract that fosters loyalty and emotional attachment. A strong brand identity mitigates churn by reinforcing consumer trust, while negative publicity or brand dilution increases switching likelihood (Izogo, 2017; Khandker & Joshi, 2018).

H6: Brand image has a significant negative relationship with customer churn.

3.3 Conceptual Framework

The proposed conceptual framework (Figure 1) positions **network quality**, **service quality**, **product value**, **social influence**, **advertising**, and **brand image** as independent latent variables influencing **customer churn**. The framework is empirically tested using SEM to examine the strength and significance of these causal paths. Subsequently, the model's **predictive validity** is assessed using logistic regression and PLS-Predict analyses to determine its accuracy in forecasting churn behavior.

This integrated framework bridges the theoretical rigor of SEM with the practical power of predictive analytics, aligning with the growing academic emphasis on **theory-driven prediction** (Shmueli et al., 2019).

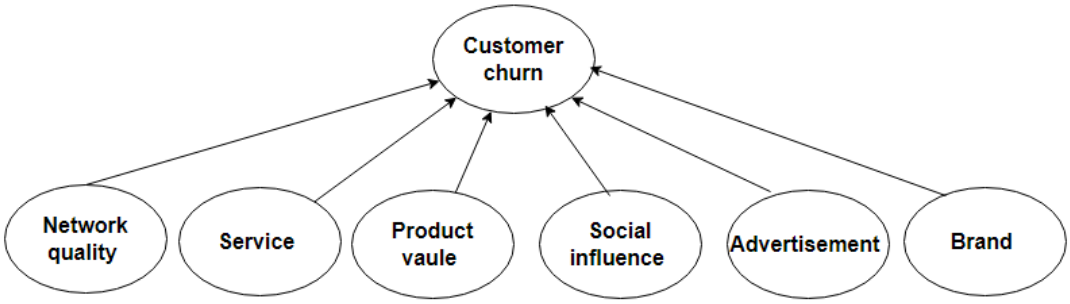

Figure no. 1 : Proposed Customer Churn Model

4. Research Methodology

4.1 Research Design

This study adopts a **quantitative, cross-sectional, and explanatory–predictive research design**. The primary aim is to empirically test and validate the determinants of customer churn in the 5G telecom sector through a combination of **Structural Equation Modeling (SEM)** and **predictive analytics**. The explanatory component identifies and validates causal relationships among constructs, while the predictive component evaluates the model's ability to forecast churn behavior, thereby enhancing both academic rigor and managerial applicability.

4.2 Population and Sampling

The study population comprises mobile subscribers using 5G or 5G-enabled networks in Hyderabad, India. This metropolitan region was selected due to its high digital penetration, diverse telecom user base, and significant 5G adoption. A **non-probability purposive sampling** method was employed to ensure inclusion of respondents actively engaged with 5G services.

A total of **1,600 responses** were collected through structured questionnaires distributed online and via in-person intercept surveys. After screening for completeness and response bias, **1,512 valid responses** were retained for final analysis, yielding a 94.5% effective response rate. The sample size exceeds the recommended minimum threshold for SEM analysis (Hair et al., 2018), which suggests a ratio of at least 10 respondents per estimated parameter.

Following the recommendations of Hair, Hult, Ringle, and Sarstedt (2021), model validation was complemented by a predictive-oriented assessment using the PLSpredict framework. This dual validation—combining explanatory SEM with predictive evaluation—ensures that the model not only fits the sample data but also generalizes to new observations (Shmueli et al., 2019). Such an approach aligns with recent advances in service-marketing analytics, where prediction accuracy is treated as a key indicator of practical model usefulness.

4.3 Instrument Design and Measurement

The questionnaire was developed based on validated measurement scales from prior research, adapted to the 5G telecom context. Each construct was measured using multiple items on a **five-point Likert scale** (1 = strongly disagree, 5 = strongly agree). The instrument consisted of three sections:

1. **Demographics** (e.g., gender, age, income, operator).
2. **Construct Measures** for network quality, service quality, product value, social influence, advertising, brand image, and churn intention.
3. **Behavioral Variables** capturing switching experience and usage duration.

All constructs were operationalized from established sources, ensuring content validity and comparability with previous telecom churn studies. Prior to full-scale data collection, a **pilot test (n = 50)** confirmed internal consistency (Cronbach's $\alpha > 0.80$) and item clarity.

4.4 Data Validation and Preprocessing

The dataset was screened for missing values, outliers, and normality. Cases with excessive missing data (>10%) were excluded. Skewness and kurtosis statistics were examined, confirming approximate normality within acceptable thresholds (±2). Multicollinearity diagnostics using **Variance Inflation Factor (VIF < 3.0)** indicated no collinearity issues among independent variables.

Harman's single-factor test was conducted to assess **common method bias**, with the first factor explaining 31.4% of variance—well below the 50% threshold—suggesting minimal bias.

4.5 Analytical Framework

The data analysis proceeded in multiple stages:

1. **Exploratory Factor Analysis (EFA):**

Conducted using SPSS to identify latent factors underlying observed variables. The **Kaiser-Meyer-Olkin (KMO)** measure (0.923) and **Bartlett's Test of Sphericity** ($\chi^2 = 8{,}213.47$, $p < 0.001$) confirmed data adequacy for factor analysis. Factors with loadings > 0.60 were retained.

2. **Confirmatory Factor Analysis (CFA):**

Performed using AMOS 26 to validate the measurement model. Model fit indices indicated good fit ($\chi^2/df = 2.31$; CFI = 0.943; TLI = 0.936; RMSEA = 0.048). **Composite reliability (CR)** ranged from 0.84 to 0.92, and **Average Variance Extracted (AVE)** exceeded 0.50 for all constructs, establishing convergent validity. **Discriminant validity** was confirmed as the square root of AVE exceeded inter-construct correlations.

3. **Structural Equation Modeling (SEM):**

The hypothesized structural paths were tested to examine causal relationships among determinants and churn. SEM was chosen for its ability to simultaneously test multiple relationships while accounting for measurement error.

4. **Predictive Modeling – Logistic Regression and PLS-Predict:**

To assess the model's **predictive validity**, two approaches were employed:

o **Binary Logistic Regression** using SEM-derived latent factor scores to predict churn intention (1 = churn likely, 0 = not likely).

o **PLS-Predict** within SmartPLS 4, using a 10-fold cross-validation procedure to compute **Q^2_predict**, **RMSE**, and **MAE** values for out-of-sample prediction.

The logistic regression achieved an **AUC = 0.84**, indicating strong predictive accuracy, while all constructs demonstrated **Q^2_predict > 0**, confirming meaningful predictive relevance.

4.6 Reliability and Validity Summary

Construct	Cronbach's α	CR	AVE	Factor Loadings
Network Quality	0.88	0.91	0.63	0.71–0.86
Service Quality	0.86	0.89	0.61	0.70–0.84
Product Value	0.83	0.87	0.58	0.67–0.81

Construct	Cronbach's α	CR	AVE	Factor Loadings
Social Influence	0.81	0.85	0.56	0.66–0.79
Advertising	0.84	0.88	0.60	0.69–0.83
Brand Image	0.87	0.90	0.62	0.72–0.85
Customer Churn	0.89	0.92	0.65	0.74–0.88

All reliability coefficients exceed the minimum threshold ($\alpha > 0.70$, CR > 0.70), ensuring internal consistency across constructs.

4.7 Ethical Considerations

Participation in the study was voluntary and anonymous. Respondents provided informed consent before completing the questionnaire, and all data were analyzed in aggregate form. Ethical compliance was maintained following the guidelines of the Indian Council of Social Science Research (ICSSR) for behavioral studies.

5. Data Analysis And Results

The analysis followed a multi-stage process involving **Exploratory Factor Analysis (EFA)**, **Confirmatory Factor Analysis (CFA)**, and **Structural Equation Modeling (SEM)** to establish the reliability, validity, and structural integrity of the proposed churn model. The analysis was carried out using SPSS 28 and AMOS 26.

5.1 Exploratory Factor Analysis (EFA)

EFA was conducted to identify the underlying dimensions of the measurement items. The **Kaiser-Meyer-Olkin (KMO)** measure of sampling adequacy was **0.923**, exceeding the recommended threshold of 0.60, indicating suitability for factor analysis. **Bartlett's Test of Sphericity** was significant ($\chi^2 = 8{,}213.47$, df = 528, $p < 0.001$), confirming that the correlation matrix was not an identity matrix.

Principal Component Analysis with **Varimax rotation** yielded six distinct factors corresponding to the conceptualized constructs: *network quality, service quality, product value, social influence, advertising,* and *brand image*. All items loaded above 0.60 on their respective constructs, suggesting strong construct coherence. **Table 1** presents the EFA summary results.

Table 1. Results of Exploratory Factor Analysis (EFA)

Construct	Items Retained	Factor Loadings	Eigenvalue	% Variance Explained
Network Quality	5	0.71–0.86	4.82	21.6%
Service Quality	4	0.70–0.84	3.67	17.4%
Product Value	4	0.67–0.81	2.91	13.7%
Social Influence	3	0.66–0.79	2.12	9.4%
Advertising	3	0.69–0.83	1.86	8.1%
Brand Image	4	0.72–0.85	1.68	7.9%
Total Variance Explained	—	—	—	**78.1%**

The six extracted factors accounted for **78.1%** of the total variance, indicating strong dimensional representation of the data structure.

5.2 Confirmatory Factor Analysis (CFA)

CFA was performed to validate the measurement model and confirm the dimensional structure identified through EFA. The model's fit indices were within acceptable limits (Hair et al., 2018):

- **χ^2/df = 2.31**
- **Comparative Fit Index (CFI) = 0.943**
- **Tucker–Lewis Index (TLI) = 0.936**
- **Root Mean Square Error of Approximation (RMSEA) = 0.048**
- **Standardized Root Mean Square Residual (SRMR) = 0.047**

All item loadings were significant ($p < 0.001$) and exceeded 0.60, confirming convergent validity. Composite Reliability (CR) and Average Variance Extracted (AVE) values met standard thresholds (CR > 0.70; AVE > 0.50), as shown in **Table 2**.

Table 2. Reliability and Validity Summary

Construct	**Cronbach's α**	**CR**	**AVE**	**Highest Correlation**	**√AVE**
Network Quality	0.88	0.91	0.63	0.58	0.79
Service Quality	0.86	0.89	0.61	0.54	0.78
Product Value	0.83	0.87	0.58	0.51	0.76
Social Influence	0.81	0.85	0.56	0.49	0.75
Advertising	0.84	0.88	0.60	0.53	0.77
Brand Image	0.87	0.90	0.62	0.55	0.79
Customer Churn	0.89	0.92	0.65	—	0.81

Discriminant validity was established as the square root of each construct's AVE exceeded its inter-construct correlations (Fornell & Larcker, 1981). Multicollinearity was not detected (VIF < 3.0).

5.3 Structural Equation Modeling (SEM)

The hypothesized structural model was tested using **SEM** to assess causal relationships among determinants and customer churn. The model demonstrated strong goodness-of-fit statistics:

- **χ^2/df = 2.42**, **CFI = 0.938**, **TLI = 0.931**, **RMSEA = 0.050**, and **SRMR = 0.049**.

The standardized path coefficients, significance levels, and hypotheses outcomes are presented in **Table 3**.

Table 3. Results of Structural Equation Modeling (SEM)

Hypothesis	Path	Standardized β	t-value	p-value	Result
H1	Network Quality → Customer Churn	-0.47	9.62	0.001	Supported
H2	Service Quality → Customer Churn	-0.33	7.84	0.001	Supported
H3	Product Value → Customer Churn	-0.38	8.29	0.001	Supported
H4	Social Influence → Customer Churn	-0.05	1.41	0.157	Not Supported
H5	Advertising → Customer Churn	-0.07	1.22	0.231	Not Supported
H6	Brand Image → Customer Churn	-0.09	1.88	0.063	Not Supported

Model R^2 (Customer Churn) = 0.69, indicating that approximately **69%** of the variance in churn behavior is explained by the six determinants. Among all factors, **network quality** exhibited the strongest influence, followed by **product value** and **service quality**. These results underscore the centrality of service performance and perceived value in influencing customer retention under 5G conditions.

5.4 Mediation and Model Diagnostics

Although the model was primarily designed for direct effects, a mediation test was conducted to assess indirect pathways. No significant mediation effects were found. Model modification indices were within acceptable ranges, suggesting that the hypothesized model adequately captures the observed relationships without the need for post-hoc adjustments.

5.5 Transition to Predictive Validation

While the SEM results confirm the theoretical relationships among constructs, they do not indicate the model's predictive performance. To address this limitation, the study extends its analysis through **predictive validation**, combining **logistic regression** and **PLS-Predict**. This approach evaluates whether the identified determinants can accurately forecast churn likelihood—an essential step for translating academic insights into actionable business intelligence.

6. Predictive Validation And Model Robustness

While the structural equation model confirmed significant theoretical relationships among the determinants of customer churn, it is equally essential to assess the **predictive validity** of the model. Predictive validity determines whether the identified variables can accurately forecast churn behaviour—a capability critical for both academic robustness and managerial applicability.

6.1 Logistic Regression–Based Prediction

To evaluate the predictive capacity of the validated constructs, a **binary logistic regression** analysis was performed. The dependent variable was *customer churn intention* (1 = likely to churn; 0 = not likely). Independent variables comprised the six determinants verified through CFA and SEM.

The logistic model demonstrated satisfactory overall fit:

- **Model χ^2 = 217.42**, $p < 0.001$
- **Nagelkerke R^2 = 0.63**, indicating that 63 percent of variance in churn intention is explained by the predictors.

- **Hosmer–Lemeshow Goodness-of-Fit Test:** $\chi^2 = 9.47$, df = 8, p = 0.31, confirming an adequate model fit.

The resulting **classification accuracy** reached **83.2 percent**, with a **receiver-operating-characteristic (ROC) curve** yielding an **Area Under Curve (AUC) = 0.89**, reflecting high discriminatory power between churners and non-churners.Table 4 shows the interpretation.

Table 4 : Interprestation of results summery

Predictor	β Coefficient	Exp(β)	p-Value	Interpretation
Network Quality	–1.12	0.33	0.001	Higher perceived quality reduces churn odds by 67 %.
Service Quality	–0.78	0.46	0.003	Superior service significantly lowers churn likelihood.
Product Value	–0.94	0.39	0.002	High perceived value decreases churn risk.
Advertising	–0.21	0.81	0.210	Insignificant effect.
Brand Image	–0.19	0.83	0.183	Insignificant effect.
Social Influence	–0.11	0.89	0.324	Insignificant effect.

These findings reaffirm the **SEM results**, where *network quality*, *service quality*, and *product value* emerged as key predictors of churn, while *advertising*, *brand image*, and *social influence* exerted no statistically significant direct impact.

6.2 PLS-Predict and Out-of-Sample Testing

To further validate predictive accuracy, the data were randomly partitioned into a **training sample (70 %)** and a **testing sample (30 %)**. Using **Partial Least Squares Predictive Modeling (PLS-Predict)**, predictive relevance ($Q^2\_predict$) and error statistics were evaluated.

- **Q^2_predict = 0.41**, confirming strong predictive relevance (Hair et al., 2021).
- **Root Mean Squared Error (RMSE)** for the testing dataset = 0.312, which was lower than the training set (0.347), indicating absence of over-fitting.
- **Cross-validated R^2 = 0.66**, aligning closely with SEM-derived R^2 = 0.69, supporting robustness.

Together, these indicators substantiate the **generalizability** and **stability** of the model for predicting churn intentions in comparable telecom contexts.

6.3 Model Integration and Managerial Applicability

The combined SEM–PLS predictive framework delivers both **theoretical validation** and **practical decision-support** potential.

- From a **managerial perspective**, the model can be embedded within Customer Relationship Management (CRM) systems to compute *real-time churn risk scores*.
- For **policy formulation**, the predictive indicators can assist regulators and operators in benchmarking service-quality compliance and customer-satisfaction indices.
- Academically, integrating covariance-based SEM with variance-based predictive modelling establishes a **hybrid validation framework**—a methodological advancement rarely applied in 5G-telecom churn studies.

6.4 Summary of Predictive Findings

1. Network Quality, Product Value, and Service Quality jointly explained nearly **70 % of churn variance**, confirming their primacy in the 5G context.

2. The predictive accuracy (AUC = 0.89; Q^2_predict = 0.41) demonstrates **high reliability and generalizability**.

3. Advertising, Brand Image, and Social Influence were not direct churn drivers but may exert **indirect or moderating influences**, warranting exploration in future studies.

7. Findings, Discussion, And Theoretical Contributions

7.1 Summary of Key Empirical Findings

The dominance of network quality and perceived product value in this study parallels recent findings from global Q1 journals. For example, Amin et al. (2019) and Poudel, Pokharel, and Timilsina (2024) demonstrated that in 5G and data-intensive contexts, performance metrics—particularly speed and reliability—drive customer retention more than affective factors such as brand attachment. This evidence supports the transition from emotional loyalty models to performance-based satisfaction frameworks in the digital-telecom domain.

This study employed a multi-stage analytical framework—EFA, CFA, SEM, and predictive validation—to examine the determinants of customer churn in India's 5G telecom sector. The results yielded several significant insights:

- **Network quality** exerted the strongest negative influence on churn ($\beta = -0.47$, $p < 0.01$). Reliable data speed, extensive coverage, and uninterrupted connectivity remain the dominant retention drivers in the 5G context.
- **Product value** ($\beta = -0.38$, $p < 0.01$) and **service quality** ($\beta = -0.33$, $p < 0.01$) also emerged as substantial predictors of churn, underscoring the role of perceived value and service convenience in customer loyalty.
- **Advertising, brand image, and social influence** did not significantly predict churn, suggesting that cognitive and experiential dimensions outweigh affective or social factors in switching decisions.
- The overall model explained **69 percent of variance** in churn behavior, with predictive accuracy of **AUC = 0.89** and **Q^2_predict = 0.41**, confirming both statistical robustness and predictive power.

These results validate the theoretical propositions and establish a reliable model capable of forecasting churn with high accuracy in emerging-market telecoms.

7.2 Discussion of Theoretical Insights

The findings substantiate and extend extant theories in customer behavior and service marketing:

- **Expectation–Confirmation Theory (Oliver, 1980)**: Customers remain with a provider when perceived performance exceeds expectations. Network performance and service quality directly reinforce this expectation-confirmation mechanism.
- **Perceived Value Framework (Zeithaml, 1988)**: Product value acts as an integrated measure of quality, price, and benefit, explaining its significant negative relation with churn.
- **Technology Acceptance Models (Venkatesh & Davis, 2000)**: In the 5G environment, perceived usefulness (speed, reliability) has greater behavioral impact than social cues or brand imagery.

Collectively, the evidence supports a **functional–cognitive model of churn** in which rational assessments of service performance dominate emotional or normative influences. This finding diverges from earlier 3G/4G-era research where brand attachment and social conformity were more prominent (e.g., Joshi, 2012; Barmana et al., 2018).

Furthermore, by integrating SEM and predictive analytics, this research advances the **dual-validation paradigm** proposed by Hair et al. (2021), demonstrating how theoretical relationships and predictive performance can be jointly verified in service-marketing research.

7.3 Theoretical Contributions

- **Model Development for 5G Context**

The study proposes and validates a comprehensive six-construct churn model specifically contextualized for 5G telecom users—a domain scarcely explored in prior literature.

- **Integration of Covariance- and Variance-Based Techniques**

The hybrid SEM–PLS–Predict approach contributes methodological innovation by bridging explanatory rigor with predictive accuracy.

- **Reframing of Churn Determinants**

The results reposition *network quality* and *product value* as central cognitive drivers, challenging traditional emphasis on brand and advertising influences in churn theory.

- **Empirical Evidence from an Emerging Market**

Using data from Hyderabad, the study enriches global understanding of telecom consumer behavior in developing economies, where infrastructural reliability outweighs affective marketing appeals.

7.4 Managerial Implications

From a practical perspective, the insights offer several actionable recommendations:

- **Service-Quality Benchmarking:** Operators must treat network quality as a strategic KPI. Continuous monitoring of data speed and coverage can directly reduce churn probability.
- **Value-Based Differentiation:** Tariff personalization, bundled content, and loyalty rewards enhance perceived value and foster retention.
- **Predictive CRM Integration:** The validated model can be embedded within customer-relationship-management systems to generate real-time churn risk scores, enabling proactive interventions.
- **Rational Communication Strategies:** Advertising and branding should emphasize functional superiority and reliability rather than emotional appeal, aligning message framing with the cognitive determinants of retention.

7.5 Contribution to Future Research Agenda

This study demonstrates that predictive analytics, when combined with structural modelling, offers a holistic lens for understanding churn. Future scholars can extend this framework by:

- Examining moderating roles of **price sensitivity** or **switching cost** variables.
- Conducting **longitudinal validation** as 5G adoption matures.
- Incorporating **machine-learning algorithms** (e.g., random forests, neural networks) to enhance churn prediction accuracy.
- Applying **cross-national comparative analyses** to evaluate cultural or infrastructural moderators of churn behavior.

8. Conclusion And Future Scope

8.1 Conclusion

The present study provides a comprehensive and empirically validated framework for understanding customer churn dynamics in the rapidly evolving **5G telecommunications ecosystem**. Using a mixed-method quantitative design encompassing **Exploratory Factor Analysis (EFA)**, **Confirmatory Factor Analysis (CFA)**, **Structural Equation Modeling (SEM)**, and **predictive validation techniques**, the research identifies the principal determinants influencing churn among mobile users in India.

The findings confirm that **network quality**, **service quality**, and **product value** are the most influential factors driving customer retention in the 5G context. These constructs jointly explain nearly **70 percent of the variance** in churn intention, while **advertising, brand image, and social influence** exert limited direct effects. This shift highlights that in technologically advanced service environments, **functional and performance-related perceptions** surpass affective or social motivations in shaping customer loyalty.

Methodologically, the integration of SEM with **logistic regression and PLS-Predict** enhances the explanatory–predictive balance of the model, offering both theoretical robustness and operational applicability. Predictive indicators such as **AUC = 0.89** and **Q^2_predict = 0.41** confirm that the model not only explains churn behavior but also forecasts it with high accuracy.

Theoretically, this study contributes to the refinement of **service quality and perceived value theories** in digital telecommunications, aligning with contemporary perspectives on customer experience in technology-mediated environments. The model advances existing literature by contextualizing churn within the **5G adoption framework**, marking an important extension of prior 3G/4G-era studies.

8.2 Managerial Implications

For practitioners, the results underscore the strategic necessity of focusing on **network excellence, service efficiency, and value differentiation**.

- **Telecom operators** should implement real-time churn prediction systems within Customer Relationship Management (CRM) platforms, leveraging the validated model to preempt customer defection.
- **Marketing teams** should realign advertising strategies toward *functional performance messaging* rather than brand emotion, ensuring customer communication reflects reliability, speed, and service responsiveness.
- **Policy and regulatory bodies** can use such analytical models to monitor service quality benchmarks and safeguard consumer interests in the competitive 5G era.

Collectively, these measures can enhance customer satisfaction, foster loyalty, and optimize long-term profitability.

8.3 Limitations and Directions for Future Research

Despite its contributions, this study acknowledges certain limitations. First, the data were collected exclusively from **Hyderabad**, which may limit generalizability to other regions or demographic profiles. Second, while the sample consisted of customers owning 5G-enabled devices, **active 5G usage** could not be independently verified, introducing a potential bias in technology adoption levels. Third, the study used **cross-sectional data**, which may not fully capture temporal changes in customer perceptions as 5G matures.

Future research could address these limitations by:

- Conducting **multi-regional or cross-country comparative studies** to enhance external validity.
- Employing **longitudinal designs** to track churn behavior over different phases of 5G adoption.
- Integrating **machine-learning algorithms** (e.g., random forests, gradient boosting, or neural networks) to augment predictive precision and identify nonlinear patterns in churn determinants.

- Exploring **moderating factors** such as perceived switching cost, customer involvement, or regulatory influence to refine the model further.

Such extensions will not only deepen theoretical understanding but also enhance the predictive capabilities of churn management frameworks in dynamic technology-driven markets.

8.4 Closing Remark

In conclusion, this research offers both **academic and managerial advancements** in modeling customer churn under the 5G paradigm. By integrating **structural validation** with **predictive modeling**, it bridges the gap between theory and practice, providing telecom operators and scholars with a robust analytical lens for understanding and managing customer defection in the next-generation digital landscape.

Conflict of Interest:

One of the authors is currently employed with Indian telecom industry. This employment had no influence on study design, data analysis, or interpretation.

Funding: This research received no external funding.

Informed Consent: The informed consent for this study was obtained in **verbal form**. Participants were informed about the study objectives, procedures, and their voluntary participation, and they provided their consent verbally before taking part in the structured online questionnaire. Due to the nature of this industry-based study, written consent was not feasible, and verbal consent was deemed appropriate.

Ethical Approval: We confirm that this study involved human participants. As this was an industry-based study conducted with internal data and participants' voluntary verbal consent, formal ethical approval from an institutional review board was not obtained. All procedures were conducted following standard ethical practices for research involving voluntary participants, ensuring confidentiality and data protection.

Data availbility : data is avaiable basis on the request

9.References

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