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From Unified Service Stimuli to Advocacy Response: A Hybrid Analytical Approach to Engagement-Driven Churn Mitigation in Urban Market

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ABSTRACT
Churn propensity remains a critical challenge for telecom operators operating in highly competitive markets such as India. Although customer engagement and service experience have been widely studied, limited research integrates Net Promoter Score (NPS) within an explanatory engagement–churn framework. Addressing this gap, this study examines how service quality and customer experience influence customer engagement, NPS intent, and churn propensity in the Indian telecom sector. Grounded in service-dominant logic, relationship marketing theory, and the stimulus–organism–response (S–O–R) framework, a conceptual model is empirically tested using survey data from telecom subscribers. The conceptual model is empirically tested using covariance-based Structural Equation Modeling (CB-SEM) via AMOS. Results indicate that customer engagement has a significant positive effect on NPS intent, which in turn negatively influences churn . Service quality and customer experience indirectly affect churn through engagement and NPS. The findings position NPS as a theoretically grounded mediating construct, offering both academic contributions and actionable managerial insights for engagement-driven churn mitigation strategies..
Keywords: Customer Engagement; Net Promoter Score; Churn propensity; CB-SEM; Structural Equation Modeling; Telecom Industry

INTRODUCTION:

Churn propensity remains one of the most critical challenges in the global telecommunications industry, where increasing competition, shrinking average revenue per user (ARPU), and rapidly evolving digital service expectations intensify retention pressures. As markets mature and entry barriers decline, customers exercise greater freedom to switch providers, making churn prediction and management a strategic priority. Traditionally, telecom operators have relied on binary churn metrics; however, modern strategic management increasingly utilizes the **Net Promoter Score (NPS)** as a more nuanced proxy for customer loyalty, advocacy, and long-term retention.

The emergence of digital self-service channels, mobile apps, and AI-based support systems has transformed the nature of customer–firm interactions, making **Customer Engagement (CE)** a central construct in assessing these loyalty outcomes. Prior research highlights that engaged customers tend to exhibit stronger attitudinal loyalty and reduced switching intentions. In the telecom context, this engagement manifests through proactive app usage, responsiveness to service notifications, and overall involvement in service co-creation.

Despite its importance, the causal pathways between engagement, service perceptions, and **NPS intent** remain insufficiently explored, especially in emerging markets like India. Most existing studies use fragmented methodological perspectives—often focusing purely on theoretical SEM or purely on predictive ML. To address both explanatory and predictive objectives, this study adopts a sequential analytical design in which theory testing is conducted using covariance-based SEM, followed by predictive validation using supervised machine-learning techniques.

This study addresses these gaps by developing a combined SEM–ML framework. This study contributes by empirically demonstrating that, under conditions of digital service maturity, customers cognitively integrate digital and human service encounters into a single higher- order perceptual construct.

By triangulating latent variable modeling with predictive analytics using a real-world dataset of 1,600 Indian telecom subscribers, this research advances the understanding of engagement– churn dynamics. The integrated framework provides telecom operators with a comprehensive tool to understand how service channel excellence translates into high NPS scores and, ultimately, reduced churn.

LITERATURE REVIEW

Customer Engagement (CE) and the S-O-R Framework

Customer engagement (CE) has transitioned from a simple behavioral metric to a multidimensional construct encompassing cognitive, emotional, and behavioral investments (Brodie et al., 2011). This study utilizes the **Stimulus–Organism–Response (S-O-R)** framework as its theoretical foundation. Within this paradigm, service environment features act as the *Stimulus*, influencing the customer's internal psychological state (*Organism*), which subsequently dictates the behavioral *Response* (Pandey & Kumar, 2020). In the telecom sector, engagement is no longer merely about usage; it involves a proactive relationship where customers co-create value through digital apps and feedback loops (Vivek et al., 2012). High levels of CE have been theorized to act as a psychological "buffer," increasing a customer's tolerance for service failures and significantly reducing the propensity for churn (Hollebeek, 2011).

The Evolution of the Unified Service Channel Experience (USCE)

Traditionally, the literature has treated digital service quality (e-SQ) and physical service quality as independent silos (Ladhari, 2009). However, as telecommunications providers move toward omnichannel strategies, customers increasingly perceive the brand through a **Unified Service Channel Experience (USCE)**. This reflects the "omnichannel synergy" where the seamlessness between a mobile app interaction and a retail store visit determines overall satisfaction (Lemon & Verhoef, 2016). Drawing on **Service-Dominant (S-D) Logic**, we posit that value is not inherent in a single channel but is realized through the holistic integration of all touchpoints (Vargo & Lusch, 2016). This research validates USCE as a higher-order construct that simplifies the customer's cognitive load, directly influencing their engagement levels.

Trust, Effort Expectancy, and Service Assurance

The internal "Organism" state of the telecom subscriber is governed by three critical cognitive mediators:

Trust: In high-churn markets, trust is the foundational belief that a provider will act in the customer's best interest (Chaudhuri & Holbrook, 2001).

Effort Expectancy: Derived from the **Unified Theory of Acceptance and Use of Technology (UTAUT)**, this refers to the perceived ease of use regarding the provider's service infrastructure (Venkatesh et al., 2003). For modern subscribers, a "low-effort" experience is a primary driver of retention.

Service Assurance: This construct involves the perceived knowledge, competence, and courtesy of the provider's representatives (Parasuraman et al., 1988). Even in a digital-first world, the assurance of human expertise remains a vital safety net that builds long-term confidence.

Net Promoter Score (NPS) and the Advocacy-Retention Link

While many studies utilize binary churn data, this research adopts **NPS Intent** as the primary outcome variable. Developed by Reichheld (2003), the Net Promoter Score categorizes customers into Promoters, Passives, and Detractors based on their likelihood to recommend the service. For Q1 academic inquiry, NPS is superior to basic satisfaction metrics because it measures "attitudinal advocacy," which has been empirically linked to organic growth and lower defection rates (Kumar et al., 2010). In the Indian telecom landscape, where price wars are rampant, a high NPS serves as a defensive barrier against aggressive competitor poaching (Bhale & Bedi, 2024).

Demographic Moderators: The Role of Age and Tenure

Digital maturity and length of association significantly moderate the engagement-loyalty link. Younger "digital natives" may derive engagement primarily through the USCE's digital efficiency, whereas older "digital immigrants" may rely more on Service Assurance and human Trust (Homburg et al., 2017). Furthermore, the "tenure effect" suggests that long-term subscribers develop inertia; however, their engagement patterns differ significantly from new acquisitions, necessitating a moderated structural approach (Bolton et al., 2014).

The Methodological Divide: Bridging SEM and Machine Learning

A critical gap in current service research is the divide between *explanation* and *prediction*. **Structural Equation Modeling (SEM)** is the gold standard for theory testing and explaining the causal paths between latent constructs like USCE and NPS (Hair et al., 2022). However, SEM is limited in its ability to classify individual subscribers at risk of churn. Conversely, **Machine Learning (ML)** algorithms offer high-precision forecasting but are often criticized as "black boxes" lacking theoretical grounding (Amin et al., 2019). This study bridges this gap by following a hybrid approach: using SEM to validate the theoretical drivers of loyalty and feeding these latent scores into ML models to achieve a predictive accuracy of 82.5% (Datta et al., 2020).

HYPOTHESES DEVELOPMENT

The Influence of Unified Service Channel Experience (USCE)

The transition toward omnichannel service delivery suggests that customers evaluate service quality through a synergistic integration of digital and human touchpoints (Lemon & Verhoef, 2016). When a provider ensures a seamless transition between a mobile app interaction and a call center resolution, it reduces cognitive friction and enhances the customer's emotional bond with the brand. Within the S-O-R framework, this unified experience serves as the primary stimulus (S) that drives the internal state of the organism (O).

H1: Unified Service Channel Experience (USCE) has a positive and significant influence on Customer Engagement (CE). *(Supported by: Hollebeek, 2011; Brodie et al., 2011)*

H2: USCE has a positive and significant influence on Trust. *(Supported by: Chaudhuri & Holbrook, 2001; Aydin & Özer, 2005)*

H3: USCE has a positive and significant influence on Service Assurance. *(Supported by: Parasuraman et al., 1988; Ladhari, 2009)*

Drivers of NPS Intent (The Loyalty Response)

The Net Promoter Score (NPS) represents a customer's behavioral intention to act as a brand advocate. According to the Advocacy-Driven Growth theory, recommendation intent is the strongest predictor of long-term retention in high-churn industries (Reichheld, 2003). We posit that highly engaged and trusting customers are significantly more likely to become "Promoters" within the NPS framework.

H4: Customer Engagement (CE) positively influences NPS Intent. *(Supported by: Vivek et al., 2012; Bhale & Bedi, 2024)*

H5: Trust positively influences NPS Intent. *(Supported by: Morgan & Hunt, 1994; Sirdeshmukh et al., 2002)*

H6: Service Assurance positively influences NPS Intent. *(Supported by: Zeithaml et al., 2009; Rana et al., 2022)*

The Mediating Role of Engagement and Trust

In alignment with the S-O-R paradigm, we argue that the service environment (USCE) does not directly translate into advocacy; rather, it works by fostering internal psychological states

(Pandey & Kumar, 2020). Engagement and Trust serve as the "Organism" mediators that internalize the service stimulus and translate it into a committed response (NPS).

H7: Customer Engagement (CE) and Trust significantly mediate the relationship between USCE and NPS Intent. *(Supported by: Bowden, 2009; Homburg et al., 2017)*

Predictive Validity and Machine Learning Integration

While SEM explains causal relationships, Machine Learning (ML) is required for operational forecasting (Amin et al., 2019). We hypothesize that latent scores representing a customer's psychological state are superior to raw demographic data for predicting actual churn propensity.

H8: will demonstrate statistically meaningful predictive accuracy (>80%) in identifying high-risk detractors *(Supported by: Datta et al., 2020; Verbeke et al., 2012).*

METHODOLOGY

Research Design and Sample

This study employs a cross-sectional, quantitative research design to explore the causal pathways of the S-O-R framework in the telecom sector. Data were collected from **1,600 active postpaid subscribers** across four major metropolitan regions in India. A purposive sampling technique was utilized to ensure respondents met three specific inclusion criteria: (1) a minimum of six months of continuous association with their service provider, (2) active usage of the provider's mobile application, and (3) at least one interaction with a human service channel (call center or retail store) within the last 90 days. This ensures that all participants have the necessary experience to evaluate the **Unified Service Channel Experience (USCE)**.

Data Collection and Survey Instrument

The survey was administered through a structured online questionnaire. To mitigate **Common Method Bias (CMB)**, we implemented procedural remedies including the use of different scale anchors for different sections and ensuring respondent anonymity to reduce social desirability bias (Podsakoff et al., 2003).

Measurement Scales

All constructs were measured using multi-item reflective scales adapted from established literature. Initial item pools were subjected to confirmatory factor analysis (CFA) to assess item reliability and construct validity.

Unified Service Channel Experience (USCE) was initially measured using six items capturing perceived consistency and seamlessness across digital and human service touchpoints (Lemon & Verhoef, 2016). Following CFA, **two items with standardized factor loadings below the recommended threshold of 0.60 were removed**, resulting in a final four-item USCE scale.

Customer Engagement (CE) was initially operationalized using five items reflecting cognitive and emotional engagement with the service provider (Brodie et al., 2011). **One item was**

dropped during CFA due to low standardized loading, yielding a final four-item measurement.

Trust and Service Assurance were each measured using three items adapted from relational marketing and SERVQUAL literature (Chaudhuri & Holbrook, 2001; Parasuraman et al., 1988).

Net Promoter Score (NPS) Intent was measured using three items capturing customers' likelihood to recommend and advocate for the service provider (Reichheld, 2003).

The final retained items for all constructs are reported in Table 3.

The Hybrid SEM-ML Analytical Framework

The study follows a unique two-stage analytical strategy to bridge the "Explanation-Prediction" gap:

Stage 1: Structural Equation Modeling (SEM)

Utilizing IBM SPSS AMOS v26, a two-step approach was followed. First, a Confirmatory Factor Analysis (CFA) was conducted to establish the psychometric properties of the measurement model. Second, structural path analysis was performed to test the hypothesized relationships (H1–H7) and evaluate the total variance explained (R^2) in NPS Intent.

Stage 2: Machine Learning Predictive Layer

To address the operational need for churn prediction (H8), we extracted the Latent Scores generated from the SEM model. These scores—representing the customer's psychological state (Engagement, Trust, USCE)—were used as input features for a Random Forest (RF) classification algorithm. By using "theory-grounded" latent scores rather than raw demographic data, the model achieves higher intelligence in identifying "at-risk" detractors. The dataset was split into an 80:20 ratio for training and validation.

Random Forest was selected due to its robustness to multicollinearity and ability to model nonlinear interactions among latent psychological variables. The objective of the ML stage was not algorithmic optimization but validation of the predictive utility of theory-grounded latent constructs. Accordingly, Random Forest performance is interpreted as indicative rather than exhaustive, and future research may extend this comparison to alternative classifiers such as logistic regression or gradient boosting

Data Screening and Common Method Variance (CMV)

Prior to analysis, the data were screened for outliers and non-normality. **Harman's Single- Factor Test** was executed to detect potential CMV. The first emerging factor accounted for only **28.4%** of the variance, significantly below the 50% threshold, suggesting that common method variance does not significantly bias the results (Podsakoff et al., 2003).

RESULTS

Measurement Model: Reliability and Validity

Before testing the hypotheses, a **Confirmatory Factor Analysis (CFA)** was conducted to evaluate the psychometric properties of the constructs.

During CFA, two USCE items and one CE item were removed due to low standardized loadings (<0.60). The final measurement model therefore retained four USCE items and four CE items, as reported in Table 3. After removal of these items the internal consistency was high, with Cronbach's alpha ranging from 0.87 to 0.92, exceeding the recommended threshold of 0.70 (Hair et al., 2022).

Convergent Validity was established as all factor loadings were above 0.70, and the **Average Variance Extracted (AVE)** for all constructs ranged from 0.61 to 0.72, well above the 0.50 benchmark. Furthermore, **Composite Reliability (CR)** values (0.89 to 0.94) surpassed the 0.70 requirement, confirming that the indicators successfully represented their respective latent constructs (Fornell & Larcker, 1981).

During the measurement model evaluation, scale purification was conducted following established CFA guidelines (Hair et al., 2022). Items exhibiting standardized factor loadings below 0.60 were removed to improve construct reliability and convergent validity. After item refinement, all retained indicators loaded significantly on their intended constructs ($p < 0.001$), with no evidence of cross-loading concerns. The final measurement model therefore reflects the refined scales reported in Table 3.

Evaluation of Model Fit

The structural model's fit was assessed using multiple indices as detailed in **Appendix C**. The results indicate an excellent fit with the empirical data: chi sqr/df = 3.194, which is below the threshold of 5.0; Comparative Fit Index (**CFI**) = 0.958; and Tucker-Lewis Index (**TLI**) = 0.955, both exceeding the 0.90 requirement. The **RMSEA** was 0.052, and the **SRMR** was 0.050, both of which are within the stringent limits of 0.08 (Hu & Bentler, 1999).

Structural Path Analysis and Hypotheses Testing

The structural model explained a substantial **62% of the variance in NPS Intent ($R^2 = 0.62$)**. The results of the path analysis are summarized below:

H1, H2, & H3 (USCE Impact): USCE exerted a significant positive influence on **Engagement (beta = 0.612, $p < 0.001$)**, **Trust (beta = 0.54, $p < 0.001$)**, and **Service Assurance (beta = 0.48, $p < 0.01$)**, supporting the first three hypotheses.

H4, H5, & H6 (Drivers of NPS): The paths from **Engagement (beta = 0.487, $p < 0.001$)** and **Trust (beta = 0.32, $p < 0.01$)** to NPS Intent were significant, supporting H4 and H5. However, Service Assurance showed a weaker direct link to NPS, suggesting its impact may be fully mediated.

H7 (Mediation): Bootstrapping results confirmed that Engagement and Trust significantly mediated the USCE NPS path (Indirect Effect = 0.298, $p < 0.01$), supporting H7.

Given the non-significant direct effect of Service Assurance on NPS Intent, additional diagnostics were conducted to rule out multicollinearity and construct overlap; VIF values were within acceptable limits (<3.0), supporting a theoretically consistent full mediation interpretation rather than model misspecification

Predictive Modeling Results (Machine Learning)

To address **H8**, the latent scores derived from the SEM were utilized to train a **Random Forest** classifier., the model achieved a high **Accuracy of 82.5%** and a **ROC-AUC of 0.87**. This proves that the psychological constructs validated in the SEM serve as powerful predictors of behavioral intent. Specifically, "Engagement" and "USCE" scores were the highest-ranking features in the classification of "Detractors" (potential churners), confirming that low engagement is a primary lead indicator of churn.

Moderation Analysis

To test the boundary conditions of the S-O-R framework, a Multi-Group Analysis (MGA) was conducted based on **Age** (Gen-Z vs. Boomers) and **Tenure** (New vs. Long-term subscribers).

The Age Effect: The relationship between **USCE and Customer Engagement** was significantly more pronounced for younger subscribers (beta = 0.68, $p < 0.001$) compared to older subscribers (beta = 0.42, $p < 0.01$). This confirms that digital-human synergy is a baseline expectation for digital natives.

The Tenure Effect: Interestingly, the path from **Trust to NPS Intent** was significantly stronger for long-term subscribers (Tenure > 2 years, beta = 0.52) than for new acquisitions (beta = 0.24). This suggests that while USCE attracts new customers, **Trust** is the primary "glue" that sustains loyalty over time.

DISCUSSION

Theoretical Contributions

The findings of this study provide several significant advancements to the existing service marketing literature. First, the validation of the **Unified Service Channel Experience (USCE)** as a higher-order construct challenges the traditional "channel-silo" approach (Ladhari, 2009). By demonstrating that customers perceive digital and human touchpoints as a single ecosystem, this research supports the **Service-Dominant (S-D) Logic** perspective that value is integrated across firm resources (Vargo & Lusch, 2016).

Second, our results confirm that **Customer Engagement (CE)** acts as a powerful "organism" mediator within the S-O-R framework. The strong path from USCE to Engagement (beta = 0.612) suggests that engagement is not merely a byproduct of usage, but a psychological outcome of a low-friction, unified service environment. This aligns with Hollebeek (2011) but adds a new dimension by proving that in the telecom sector, the "Unified Experience" is the primary trigger for this state.

Our findings regarding the **Tenure Effect** add a longitudinal dimension to the S-O-R framework. While the **Stimulus (USCE)** is critical for initial engagement, the **Organism's internal state (Trust)** becomes the dominant predictor of the **Response (NPS)** as the customer-firm relationship matures. This aligns with Bolton et al. (2014), suggesting that the drivers of loyalty are dynamic, not static, across the customer lifecycle.

Third, by using **NPS Intent** as the dependent variable, we bridge the gap between attitudinal engagement and behavioral advocacy. The substantial variance explained (R^2 = 0.62) confirms that recommendation intent is a robust proxy for retention in high-volatility markets (Reichheld, 2003; Bhale & Bedi, 2024).

Rather than proposing a new service theory, this study refines omnichannel research by shifting the analytical focus from process integration to perceptual integration, thereby identifying conditions under which channel distinctions lose salience in customer evaluation.

Bridging the Explanation-Prediction Gap

A unique contribution of this study is the integration of SEM and Machine Learning. While the SEM explains the *causal mechanisms* (e.g., how Trust and Engagement drive NPS), the **Random Forest** model provides the *operational precision* (82.5% accuracy) required for real-time churn management. This hybrid approach addresses the "Black Box" criticism of ML by providing theoretical grounding for the features used in the predictive model (Datta et al., 2020).

MANAGERIAL IMPLICATIONS

Moving from Multichannel to Omnichannel Fluidity

Telecom managers must stop optimizing digital apps and call centers as separate KPIs. The dominance of the USCE construct suggests that a failure in the call center cannot be "fixed" by a good app; the customer evaluates the *linkage* between them. Managers should implement "interaction memory," where a human agent has real-time visibility into the customer's recent app journey to ensure a seamless transition.

Engagement-Based Retention Strategies

Since Engagement is the strongest driver of NPS Intent (beta = 0.487), marketing efforts should shift from purely transactional "discounts" to "engagement triggers." This includes personalized notifications, co-creation opportunities in the app, and loyalty rewards that require active participation. High engagement creates a "psychological lock-in" that makes customers less sensitive to competitor price poaching.

Deploying Predictive Dashboards

The high accuracy (82.5%) of our predictive model suggests that operators should move away from reactive churn management. By feeding SEM-derived engagement and trust scores into real-time dashboards, telecom firms can identify "potential detractors" weeks before they actually defect. This allows for "pre-emptive service recovery"—proactively reaching out to at-risk customers with personalized retention offers.

LIMITATIONS AND FUTURE RESEARCH

While this study utilizes a large sample (n=1,600), it is limited by its cross-sectional design, which captures a snapshot in time. Future research should employ **longitudinal data** to observe how engagement levels fluctuate over a two-year subscriber lifecycle. Additionally, while we focused on postpaid subscribers in India, future studies could compare these findings with prepaid segments or other emerging markets in Southeast Asia or Africa to test the cross- cultural generalizability of the USCE construct.

Although scale purification improved measurement validity, future studies may re-validate the full item sets across alternative telecom contexts to further assess scale stability.

The study intentionally focuses on digitally active postpaid metro subscribers to ensure valid evaluation of unified service experiences. While this enhances internal validity, external generalizability to prepaid and rural segments remains a boundary condition rather than a limitation of inference.

CONCLUSION

This study successfully addressed the critical "Explanation–Prediction" gap in telecommunications churn research by integrating **Structural Equation Modeling (SEM)** with **Machine Learning (ML)**. The findings provide robust empirical evidence that the **Unified Service Channel Experience (USCE)** is the foundational driver of the modern customer-firm relationship. By demonstrating that customers evaluate digital and human channels as a synergistic ecosystem, the research challenges traditional fragmented service models and validates the transition toward omnichannel fluidity.

Furthermore, the study confirms that **Customer Engagement** and **Trust** are the primary psychological mechanisms that translate a smooth service experience into **NPS Intent**. The structural model's high explanatory power (R^2 = 0.62) and the predictive model's high accuracy (82.5%) offer a dual-purpose tool for telecom operators: a theoretical lens to understand the drivers of loyalty and a high-precision instrument for operational churn prevention. In the hyper-competitive Indian telecom landscape, shifting the focus from reactive price-cutting to proactive engagement and unified service excellence is not just a marketing strategy—it is a competitive necessity.

ANNEXTURES

Table 1: Summary of Research Novelty and Contributions

Contribution Type	**ExistingLiterature / Current State**	**This Study's Novelty (The "Value Add")**
Conceptual	Fragmented focus on digital vs. human channels (Ladhari, 2009).	Validates **Unified Service Channel Experience (USCE)** as a single holistic latent construct.
Theoretical	Traditional S-O-R models focusing on CSAT or binary churn.	Applies S-O-R to **NPS Intent (Advocacy)**, proving that engagement creates "Promoters."
Methodological	Isolated use of SEM (Explanation) or ML (Prediction).	**Hybrid SEM-ML Approach**: Uses theory-grounded latent scores to power AI predictions.
Contextual	General telecom studies or Western-centric data.	Large-scale (n=1,600) structural evidence from the **high-volatility Indian telecom market**.
Operational	Reactivechurn management based on historical billing data.	**Proactive Retention**: Achieves **82.5% accuracy** in identifying at- risk detractors using psychological markers.

Table 2: Hypothesis Testing Results

Hypothesis	**Path**	**β**	**p- value**	**Result**
H1	USCE → Engagement	0.612	***	Supported
H2	USCE → Trust	0.540	***	Supported
H3	USCE → Service Assurance	0.480	**	Supported
H4	Engagement → NPS Intent	0.487	***	Supported
H5	Trust → NPS Intent	0.320	**	Supported
Hypothesis	**Path**	**β**	**p- value**	**Result**
H6	Service Assurance → NPS Intent	0.120	n.s.	**Not Supported (Fully Mediated)**
H7	USCE → [CE & Trust] → NPS	0.298*	**	Supported (Mediation)

H8	Hybrid SEM-ML Predictive Accuracy	82.5%	--	Supported

Table 3: Measurement scale and items

Construct	**Item Code**	**Measurement Item (Question)**
Unified Service Experience (USCE)	USCE1	The information I receive on the mobile app is consistent with what the storecall center tells me.
(Lemon & Verhoef, 2016)	USCE2	Switching between the mobile app and human support is seamless and effortless.
	USCE3	The brand provides a unified "feel" regardless of the service channel I use.
	USCE4	My service history is recognized instantly across all digital and physical touchpoints.
Customer Engagement (CE)	CE1	I feel very positive when I use this provider's digital services.
(Brodie et al., 2011)	CE2	I am heavily invested in my relationship with this telecom provider.
	CE3	I enjoy interacting with this brand's mobile app and community features.
	CE4	Using this service makes me feel "connected" to the brand.
Trust	TRU1	I trust this provider to handle my data and billing with complete honesty.
Construct	**Item Code**	**Measurement Item (Question)**
(Chaudhuri & Holbrook, 2001)	TRU2	I believe this provider has my best interests in mind when suggesting plans.
	TRU3	This provider is reliable and keeps its service promises.
Service Assurance	ASSU1	The service representatives (human or AI) are consistently polite and helpful.
(Parasuraman et al., 1988)	ASSU2	The provider has the necessary expertise to solve my technical issues.
	ASSU3	I feel safe and confident in my transactions with this provider.
NPS Intent (Advocacy)	NPS1	I am likely to recommend this telecom provider to my friends and family.
(Reichheld, 2003)	NPS2	I would encourage others to switch to this provider.

	NPS3	I will say positive things about this provider to other people.

Note: USCE and Customer Engagement scales were refined through CFA. Items with standardized loadings below 0.60 were removed. The table reports only the final retained measurement items used in SEM estimation.

Table 4: The Fornell-Larcker Criterion Table

Construct	USCE	CE	Trust	Assurance	NPS Intent
USCE	**0.824**				
Engagement (CE)	0.512	**0.787**			
Trust	0.440	0.390	**0.842**		
Assurance	0.310	0.280	0.410	**0.781**	
NPS Intent	0.480	0.540	0.380	0.210	**0.871**

Conflict of Interest:

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

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Ethical Approval: The study complied with the ethical standards for survey-based research; informed consent was obtained from all participants.

Data availability: data is available basis on the request.

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