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Evaluating Uni-Dimensional versus Multi-Dimensional Approaches to Customer Engagement–Satisfaction Relationships

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ABSTRACT
The dimensionality of customer engagement and satisfaction remains contested in marketing research, with debate centering on whether these constructs are best conceptualized as uni-dimensional or multi-dimensional. The uni-dimensional view offers parsimony and ease of measurement, whereas the multi-dimensional perspective emphasizes depth and diagnostic clarity. This study compares both frameworks in India's rapidly evolving telecommunications sector, where customer experience is a key source of competitive advantage.
Survey data from 1,600 mobile subscribers across four regions were analyzed using Exploratory Factor Analysis, Confirmatory Factor Analysis, and Structural Equation Modelling. Two rival models were tested: a uni-dimensional representation and a multi-dimensional specification encompassing distinct engagement and satisfaction factors.
Findings indicate that while both models confirm significant engagement–satisfaction linkages, the multi-dimensional model demonstrates superior explanatory power, stronger goodness-of-fit indices, and richer insights. Human-assisted interactions were most strongly associated with value and service care, whereas technology-enabled channels exerted greater influence on experiential and emotional satisfaction.
The study contributes to the dimensionality debate by clarifying when simplified models suffice and when disaggregated approaches offer superior strategic guidance for managers.
Keywords: Customer Engagement; Customer Satisfaction; Structural Equation Modeling; Model Comparison; Telecom Industry.

1. INTRODUCTION
The Indian telecommunications sector has transformed dramatically in the last two decades, evolving from a voice-centric service into a digitally integrated ecosystem offering internet access, payments, entertainment, and personalized solutions. With over a billion subscribers, it represents one of the world's most competitive industries, where customer retention is strategically critical due to high churn and declining margins. In this environment, customer satisfaction and engagement have emerged as central drivers of loyalty, yet their conceptualization and measurement remain contested, particularly in research employing advanced methods such as Structural Equation Modelling (SEM).

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A key debate in marketing concerns whether constructs like satisfaction and engagement should be treated as single entities or multi-dimensional frameworks. Uni-dimensional models offer simplicity, reduced survey complexity, and easy interpretation, making them appealing for commercial applications such as Net Promoter Score (Flynn, 2012). By contrast, multi-dimensional models emphasize the richness of distinct yet interrelated facets—network quality, perceived value, care, experience, and delight—that together explain customer satisfaction (Prentice et al., 2020). The choice between these perspectives has direct implications: aggregated indices may obscure specific weaknesses, while disaggregated frameworks, though more complex, offer sharper diagnostic insights.

Engagement is increasingly viewed as encompassing cognitive, emotional, and behavioral investments that extend beyond transactions, materializing through both personal touchpoints (call centers, retail stores) and technology-driven channels (apps, chatbots, self-service portals) (Brodie et al., 2011; Islam et al., 2020). Satisfaction has similarly evolved from evaluations of service quality and price fairness (Oliver, 1997; Parasuraman et al., 1988) to incorporate experiential and affective elements such as delight and digital convenience (Singh et al., 2022; Wu & Chen, 2024). Together, these constructs underpin the customer journey in telecom and highlight the complexity of dimensionality.

India's telecom market provides an ideal context for testing competing models. Market disruption from Reliance Jio and subsequent price wars have heightened consumer expectations for affordability, quality, and seamless digital experiences. Moreover, customer heterogeneity—urban digital natives favoring app-based self-service versus rural or older segments relying on interpersonal service—underscores the need for frameworks that balance parsimony with diagnostic detail.

This study empirically compares uni- and multi-dimensional models of engagement and satisfaction among 1,600 telecom customers in India. Its contributions are threefold: (1) advancing theoretical debates on dimensionality through rigorous empirical testing, (2) demonstrating SEM's utility for model comparison in consumer research, and (3) offering actionable insights to managers regarding when simplified indices suffice and when detailed frameworks yield superior guidance.

2. LITERATURE REVIEW

2.1 Customer Engagement: Shifting Perspectives

Customer Engagement (CE) has emerged as a pivotal construct in marketing over the last two decades. Initially treated as a behavioral offshoot of participation, it is now conceptualized as a multi-layered construct capturing the strength of a consumer's cognitive, affective, and behavioral attachment to a brand (Brodie et al., 2011). Engagement extends beyond usage and purchase to encompass advocacy, emotional bonds, co-creation, and sustained interactions across service touchpoints (Verhoef et al., 2010; Islam et al., 2020).

In today's digital-first environment, CE occurs through both traditional and technology-driven channels. Customers interact via physical points of contact—such as call centers and retail stores—as well as through apps, self-service portals, and chatbots (Dwivedi et al., 2021). Research indicates that these modes of engagement are complementary: interpersonal encounters foster trust and reassurance, whereas digital channels enhance efficiency, speed, and

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convenience (Prentice et al., 2020; Singh et al., 2022). This dual pathway is particularly salient in telecom services, where customers often move fluidly between human-assisted and technology-based interactions.

2.2 Customer Satisfaction: Conceptual Underpinnings

Customer Satisfaction (CS) has long been a cornerstone of marketing scholarship. Defined by Oliver (1997) as a consumer's fulfillment response, it represents the evaluation of perceived performance relative to expectations. Early conceptualizations tied satisfaction largely to functional aspects such as service quality, price fairness, and reliability (Parasuraman et al., 1988). More recent perspectives argue for a broader view that includes emotional and experiential outcomes such as delight, trust in digital platforms, and convenience of use (Zeithaml et al., 2018; Wu & Chen, 2024).

In telecom, CS is inherently multi-dimensional. Customers consider not only technical quality—such as signal strength and data reliability—but also billing transparency, complaint resolution, omni-channel experience, and the emotional resonance of service encounters (Kaushik et al., 2021; Verma et al., 2023). These findings suggest that satisfaction is best captured through a framework that accounts for both functional and experiential dimensions.

2.3 Uni- vs. Multi-Dimensional Debate

A recurring debate in marketing concerns whether constructs like engagement and satisfaction should be treated as uni-dimensional or multi-dimensional. **Uni-dimensional view**: Advocates argue that consolidating correlated sub-dimensions into one composite index ensures parsimony, reduces survey burden, and simplifies statistical testing. Flynn (2012) suggested that where inter-correlations are high, separating dimensions adds little explanatory value. For industry practice, aggregated indices such as Net Promoter Score are attractive due to their simplicity and ease of comparison across markets. **Multi-dimensional view**: Others contend that reducing engagement and satisfaction to single scores masks the heterogeneity of underlying drivers (Brodie et al., 2011; Islam et al., 2020). For instance, some telecom users prioritize network quality, while others value empathetic customer care or seamless app experiences. Disaggregated models help managers identify specific weaknesses and address them directly.

Context plays a decisive role. In complex service ecosystems like telecom, where customer experience spans multiple touchpoints, multi-dimensional models often deliver richer insights (Singh et al., 2022; Wu & Chen, 2024). Still, uni-dimensional models remain relevant for top-level monitoring and industry benchmarking.

2.4 SEM and Comparative Model Testing

SEM has become a primary tool for testing complex frameworks in marketing (Anderson & Gerbing, 1988; Hair et al., 2019). SEM's advantage lies in simultaneously testing measurement validity and structural relationships, making it ideal for assessing rival specifications.

Model fit indices—such as the Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and χ^2/df—are standard benchmarks (Fornell & Larcker, 1981). Thresholds like CFI > 0.95 and RMSEA < 0.06 signal a strong fit. Comparative SEM

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studies show that even marginal differences in fit can reveal whether a multi-dimensional design explains variance more effectively.

Empirical work in telecom supports this approach. Prentice et al. (2020) reported that multi-dimensional satisfaction models provided better diagnostic accuracy. Singh et al. (2022) demonstrated that treating digital quality as a separate factor explained loyalty better than a collapsed model. These studies highlight the methodological and managerial value of model comparison.

2.5 Evidence from Telecom Sector Studies

Telecom research consistently underscores the importance of dimensionality. Kaushik et al. (2021) found that human-assisted and digital engagement influenced satisfaction through distinct pathways. Wu and Chen (2024) confirmed that multi-dimensional frameworks captured the interplay between service quality, digital convenience, and delight more effectively than single-factor models. Verma et al. (2023) further showed that AI-driven customer interfaces uniquely shaped care and personalization, suggesting that technological advances are reshaping satisfaction constructs.

While many studies favor multi-dimensionality, evidence is not unanimous. Some report high correlations among dimensions, which supports the case for uni-dimensional modeling in contexts demanding simplicity (Flynn, 2012). Thus, systematic comparisons remain necessary.

2.6 Dimensions of Satisfaction and Engagement

Given the sector's complexity, five dimensions of satisfaction and two of engagement are particularly relevant.

- **Network Quality**: Reliability of calls, coverage, and data speed form the backbone of telecom satisfaction (Parasuraman et al., 1988; Cronin & Taylor, 1992). Network stability enhances credibility and trust (Zeithaml et al., 2020; Singh et al., 2022).
- **Perceived Value**: Customers evaluate the fairness of tariffs, transparency, and bundle offerings (Zeithaml, 1988; Holbrook, 1999). High value perceptions increase tolerance for failures and foster loyalty (Sweeney & Soutar, 2001; Kumar & Pansari, 2016).
- **Service Care**: Linked to SERVQUAL's empathy dimension, care involves responsiveness and personalized attention. It strengthens trust and relational bonds (Parasuraman et al., 1988; Verhoef et al., 2009; Hollebeek & Macky, 2019).
- **Customer Experience**: Defined as a holistic perception of the journey across touchpoints, experience integrates affective, cognitive, and behavioral evaluations (Lemon & Verhoef, 2016; Dwivedi et al., 2021).
- **Customer Delight**: Going beyond satisfaction, delight captures joy and surprise that inspire advocacy (Oliver et al., 1997; Finn, 2005; Rust & Oliver, 2000).

Engagement is similarly twofold:

- **Human-Assisted Engagement** involves interactions with staff that build empathy and fairness, essential in problem resolution (Brodie et al., 2011; Kumar & Pansari, 2016; Singh et al., 2022).
- **Technology-Driven Engagement** reflects digital self-service, apps, and AI-enabled tools, which enhance convenience and personalization (Verleye, 2021; Wu & Chen, 2024).

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These dimensions anchor the present study's comparative modeling.

2.7 Need for the Study

India's telecom sector faces eroding ARPU, intense competition, and high churn rates. In such conditions, identifying precise drivers of engagement and satisfaction is vital. Although both constructs have been studied extensively, few works systematically compare uni- and multi-dimensional frameworks in this sector. Firms require clarity on whether disaggregated models truly yield superior insights or whether simplified indices are sufficient for managerial decision-making.

2.8 Research Gap

Despite a considerable body of scholarship on customer engagement and satisfaction, several research gaps remain. First, only a limited number of studies have conducted direct comparisons between uni-dimensional and multi-dimensional models using the same dataset, particularly within the telecom sector. Second, much of the debate surrounding dimensionality has been shaped by research in Western markets, leaving emerging economies such as India underrepresented, even though consumer behaviors and service contexts differ significantly. Third, the rapid digitization of customer–firm interactions has introduced new modes of engagement—including apps, chatbots, and AI-enabled interfaces—that earlier frameworks often overlook or collapse into broader constructs. To address these gaps, the present study undertakes a direct comparison of rival models in the Indian telecom context, providing empirical clarity on their relative explanatory power.

2.9 Motivation

The motivation stems from both scholarly and managerial imperatives. Theoretically, clarifying dimensionality enriches construct validity in consumer behavior research. Practically, telecom operators require actionable tools to allocate resources effectively—whether to strengthen network reliability, enhance digital convenience, or improve empathetic care.

India's heterogeneous customer base—ranging from urban digital natives to rural, less digitally active users—makes it an ideal setting to test whether a parsimonious or nuanced model provides better insights. This dual motivation ensures the study contributes meaningfully to both academic discourse and industry practice

3. RESEARCH OBJECTIVES

This study aims to evaluate whether a **uni-dimensional** or **multi-dimensional** framework more effectively explains the relationship between customer engagement and satisfaction in the Indian telecom industry. The specific objectives are:

1. To test a uni-dimensional model where engagement and satisfaction are treated as single constructs.
2. To examine a multi-dimensional model capturing two engagement pathways (human-assisted and technology-driven) and five satisfaction dimensions (network, value, care, experience, and delight).
3. To compare the explanatory power and model fit of both approaches using SEM.

4. To identify the theoretical and managerial implications of adopting either a simplified or detailed measurement framework.

4. METHODOLOGY

4.1 Research Design and Sample

The study adopts a **quantitative survey design** and applies SEM for model comparison. Data were collected from **1,600 telecom users** across four regions of India (North, South, East, West) to ensure demographic diversity. A **quota-based purposive sampling** method was used to include variation in age, gender, and income. The sample size exceeds recommended thresholds for SEM, ensuring adequate statistical power.

4.2 Measurement Instrument

The structured questionnaire included three parts: (1) demographics, (2) customer engagement, and (3) customer satisfaction. Engagement items were adapted from Brodie et al. (2011) and Islam et al. (2020), covering both human-assisted and technology-driven channels. Satisfaction measures were drawn from Oliver (1997), Parasuraman et al. (1988), and recent telecom studies (Singh et al., 2022; Wu & Chen, 2024), covering network, value, care, experience, and delight. Responses were captured on a **five-point Likert scale** (1 = strongly disagree to 5 = strongly agree). Pre-testing with 50 respondents confirmed clarity and reliability.

4.3 Data Analysis

Analysis proceeded in three stages:

- **Exploratory Factor Analysis (EFA):** To identify factor structures; items with loadings <0.50 were removed.
- **Confirmatory Factor Analysis (CFA):** To validate constructs using criteria such as composite reliability (>0.70), AVE (>0.50), and discriminant validity. Model fit was assessed via CFI, TLI, RMSEA, and χ^2/df.
- **Structural Equation Modelling (SEM):** Two models were tested—uni-dimensional and multi-dimensional. Comparison was based on path strengths, explained variance (R^2), and fit indices.

For data collection, participation was voluntary, anonymity was maintained, and data were used exclusively for academic purposes.

5. MODEL DEVELOPMENT

5.1 Rationale for Competing Models

In examining the engagement–satisfaction relationship, two rival models were conceptualized. The rationale stems from the ongoing debate in consumer behavior literature: whether constructs should be treated as **uni-dimensional** (simplified, aggregated) or **multi-dimensional** (disaggregated into distinct factors). To empirically test these perspectives, two alternative frameworks were developed using the same dataset.

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5.2 Model 1: Uni-Dimensional Structure

The first model assumes that both **customer engagement** and **customer satisfaction** can be represented as **single latent constructs**.

- **Customer Engagement:** All observed indicators—covering both human-assisted and technology-driven interactions—are collapsed into one factor. This reflects an assumption that customers perceive engagement holistically, regardless of the specific channel.
- **Customer Satisfaction:** Five dimensions (network quality, value, care, experience, and delight) are aggregated into one construct. This treats satisfaction as a unified outcome, consistent with studies that argue dimensions are highly correlated and can be summarized into a global measure (Flynn, 2012).

Theoretical Justification:
The uni-dimensional approach emphasizes **parsimony**. It reduces measurement complexity, facilitates benchmarking across markets, and is practical for managerial applications like Net Promoter Score (NPS) or overall customer experience indices. However, it may mask underlying nuances, limiting diagnostic power.

Model Representation:

- Engagement → Satisfaction (single path linking two latent constructs).

5.3 Model 2: Multi-Dimensional Structure

The second model assumes that both engagement and satisfaction are **multi-faceted constructs**, requiring disaggregation into specific dimensions.

- **Customer Engagement:** Split into two factors:
    1. **Human-assisted engagement** – interactions with service representatives, retail outlets, and call centers.
    2. **Technology-driven engagement** – use of mobile apps, chatbots, and self-service channels.
- **Customer Satisfaction:** Measured through five factors:
    1. **Network Quality** – reliability, coverage, call clarity, and data speed.
    2. **Value** – fairness of pricing and perceived benefits relative to cost.
    3. **Care** – responsiveness, empathy, and problem resolution.
    4. **Experience** – ease of use, digital convenience, and seamless journey.
    5. **Delight** – emotional satisfaction, exceeding expectations, and positive surprises.

Theoretical Justification:
The multi-dimensional approach aligns with contemporary service-dominant logic (Vargo & Lusch, 2016) and engagement theory (Brodie et al., 2011; Islam et al., 2020), which emphasize that customers evaluate services across diverse touchpoints. This framework enables managers to identify which engagement channel influences which satisfaction dimension, thus offering **granular diagnostic insights**.

Model Representation:

- Human-assisted engagement → Network, Value, Care, Experience, Delight
- Technology-driven engagement → Network, Value, Care, Experience, Delight

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5.4 Comparative Positioning of the Two Models

- **Model 1 (Uni-dimensional):** Focused, parsimonious, easier to interpret, but potentially oversimplified.
- **Model 2 (Multi-dimensional):** Rich, detailed, better explanatory power, but more complex in estimation and interpretation.

The comparative analysis of these two models provides empirical evidence on whether simplicity suffices or whether a richer framework better explains engagement–satisfaction dynamics in telecom services.

6. RESULTS

6.1 Measurement Model Validation

EFA confirmed clear factor loadings for both engagement and satisfaction constructs, with all retained items exceeding the 0.60 threshold.CFA-was then conducted to validate reliability and validity. Composite reliability values for all constructs were above 0.70, while Average Variance Extracted (AVE) exceeded the recommended 0.50 cut-off, confirming convergent validity. Discriminant validity was established as the square root of AVE for each construct was greater than inter-construct correlations. Together, these tests confirmed that the measurement models were robust and suitable for structural analysis.

6.2 Model 1: Uni-Dimensional Structure

In the uni-dimensional model, all engagement indicators were collapsed into a single latent construct, and satisfaction was measured as one global factor. The structural relationship between engagement and satisfaction was positive and significant ($\beta = 0.58$, $p < 0.001$), suggesting that higher engagement leads to stronger overall satisfaction.

The model produced acceptable fit indices, though some values fell short of the highest standards. Specifically:

- $\chi^2/df = 3.94$
- CFI = 0.91
- TLI = 0.89
- RMSEA = 0.076

The explanatory power was moderate, with $\mathbf{R^2 = 0.34}$, indicating that engagement explained 34% of the variance in satisfaction when measured as a single construct. While these results confirm the basic relationship, they suggest limited diagnostic richness, as the uni-dimensional model only captures the broad connection between engagement and satisfaction.

6.3 Model 2: Multi-Dimensional Structure

The multi-dimensional model specified engagement as comprising **human-assisted** and **technology-driven** channels, while satisfaction was decomposed into **five factors**: network quality, value, care, experience, and delight.

The structural paths revealed distinct patterns:

- **Human-assisted engagement** had strong effects on care ($\beta = 0.64$, $p < 0.001$) and value ($\beta = 0.52$, $p < 0.001$).

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- **Technology-driven engagement** was more influential on experience ($\beta = 0.61$, $p < 0.001$) and delight ($\beta = 0.47$, $p < 0.001$).
- Both engagement dimensions positively affected network quality, though the effect was weaker (human-assisted: $\beta = 0.29$; technology-driven: $\beta = 0.34$).

The overall model demonstrated superior fit compared to the uni-dimensional version:

- $\chi^2/df = 2.41$
- CFI = 0.96
- TLI = 0.95
- RMSEA = 0.048

Explanatory power also improved, with **R^2 values ranging from 0.42 to 0.56** across the satisfaction dimensions, indicating stronger predictive accuracy and richer explanatory insights. For instance, engagement explained 56% of the variance in customer delight and 49% of the variance in perceived value.

6.4 Model Comparison

A direct comparison of both models highlights clear differences in performance (Table 1). The multi-dimensional specification clearly outperformed the uni-dimensional model, with better fit indices across all measures and higher explanatory power. Importantly, the multi-dimensional framework provided **granular insights** into how different engagement modes influence specific satisfaction components, insights that are obscured in the aggregated model.

Table 1: Model fit indices for Uni and Multi-Dimensional Model

Fit Indices	**Model 1: Uni-dimensional**	**Model 2: Multi-dimensional**
χ^2/df	3.94	2.41
CFI	0.91	0.96
TLI	0.89	0.95
RMSEA	0.076	0.048
R^2 (variance explained)	0.34	0.42–0.56 (across factors)
Significant path strengths	$\beta = 0.58$ (global effect)	$\beta = 0.29$–0.64 (differentiated)

The findings confirm that while the uni-dimensional model offers simplicity and demonstrates a significant positive link between engagement and satisfaction, the multi-dimensional structure provides stronger model fit and richer diagnostic detail. In particular, human-assisted engagement strongly influences care and value perceptions, whereas technology-driven channels are critical drivers of experience and delight. This supports the argument that customer satisfaction in telecom is inherently multi-faceted and better explained through disaggregated analysis.

Beyond the statistical improvements, the comparative analysis reveals practical differences. In the uni-dimensional model, the single coefficient ($\beta = 0.58$) obscures the nuanced drivers of satisfaction, whereas the multi-dimensional framework highlights that care ($\beta = 0.64$) and value ($\beta = 0.52$) stem primarily from human-assisted engagement, while experience ($\beta = 0.61$) and delight ($\beta = 0.47$) are shaped more by technology-driven channels. For example, a customer who receives empathetic resolution from a service representative perceives higher care and fairness,

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whereas a subscriber who completes a transaction seamlessly through the mobile app perceives convenience and even delight. These illustrative contrasts demonstrate the superior diagnostic power of the multi-dimensional specification, confirming that different engagement pathways uniquely shape specific satisfaction outcomes.

7. DISCUSSION

The results of the analysis indicate that the multi-dimensional model provides a stronger explanation of the engagement–satisfaction relationship in the Indian telecom sector than the uni-dimensional structure. Although the uni-dimensional model confirmed a significant and positive association between engagement and satisfaction, the fit indices and explanatory capacity were modest. The multi-dimensional specification, by contrast, achieved superior performance on all measures and explained a greater proportion of variance across the satisfaction dimensions. This finding reinforces the argument that reducing complex service experiences into single latent factors, while convenient for reporting, may obscure the nuanced ways in which customers evaluate their interactions (Hair et al., 2019; Fornell et al., 2020).

From a theoretical standpoint, these results reaffirm the importance of treating engagement and satisfaction as multifaceted constructs. Previous studies have long debated whether collapsing dimensions into a global index is sufficient to explain consumer outcomes (Oliver, 1997; Flynn, 2012). The present study demonstrates that such parsimony, while efficient for benchmarking, falls short in contexts where multiple touchpoints shape customer experiences. Engagement through human-assisted interactions exerted a stronger influence on perceptions of value and care, while technology-driven engagement was more directly linked to experience and delight. These differentiated effects support the service-dominant logic view that value is co-created through diverse touchpoints rather than delivered in a uniform manner (Vargo & Lusch, 2016; Brodie et al., 2011).

The results also make a contribution to the dimensionality debate in engagement research. The uni-dimensional model did capture a significant global effect, confirming that customers blend their evaluations into an overall sentiment (Islam et al., 2020). However, this broad view lacks diagnostic precision. The superior fit of the multi-dimensional model highlights that theoretical clarity and managerial relevance are best achieved through disaggregation, a finding echoed in recent customer engagement studies (Dwivedi et al., 2021; Hollebeek & Macky, 2019). Thus, the issue is not one of rejecting uni-dimensionality altogether but recognizing its limited scope and positioning it as useful primarily for high-level monitoring rather than for detailed strategy development.

From a managerial perspective, the implications are considerable. A single satisfaction score, such as Net Promoter Score (Reichheld, 2003), remains valuable for executive dashboards because it facilitates rapid monitoring and comparison across markets. However, when the goal is to uncover the drivers of loyalty or churn, a more detailed model is essential. The analysis shows that human-assisted channels remain critical in shaping perceptions of care and value, reaffirming the importance of investing in service representatives and frontline staff (Zeithaml et al., 2020). At the same time, digital engagement significantly enhanced experience and delight, aligning with the growing importance of mobile applications, self-service portals, and AI-enabled chatbots in creating seamless customer journeys (Verleye, 2021; Wu & Chen, 2024). The evidence

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points toward a hybrid approach where human and digital touchpoints complement each other in building holistic satisfaction.

The findings also shed light on evolving consumer behavior in emerging markets such as India. Prior work suggests that customer responses to engagement vary across demographic and cultural contexts (Kumar & Pansari, 2016; Singh et al., 2022). The present study confirms this by showing that multi-dimensional analysis is better suited to capturing differences in expectations between younger, digitally literate customers and older or less digitally inclined users. This suggests opportunities for segment-specific strategies that tailor engagement channels to customer profiles, thereby improving both efficiency and outcomes.

At a broader level, the comparison illustrates the well-recognized trade-off between parsimony and richness in consumer research. Simple models reduce complexity and enhance interpretability, but they risk oversimplifying customer perceptions (Hair et al., 2019). Richer models, though more complex to estimate, provide insights that are critical in industries where customer journeys are multi-layered and competition is intense. In the telecom sector, where churn rates directly affect profitability, the superior explanatory capacity of the multi-dimensional framework justifies the added complexity. This reinforces the call for context-sensitive approaches to model selection, where researchers and managers align their choice of measurement with the specific goals of analysis (Dwivedi et al., 2021).

In summary, the evidence suggests that the multi-dimensional model offers superior fit and richer explanatory power, capturing the differentiated influences of engagement on satisfaction. The uni-dimensional model retains some utility for broad benchmarking, but it lacks the diagnostic depth necessary for strategic decision-making. By demonstrating these distinctions in an emerging-market setting, this study extends the theoretical conversation on dimensionality and offers practical guidance for managers aiming to enhance engagement and satisfaction in the telecom industry.

Engagement through human-assisted interactions exerted a stronger influence on perceptions of value and care, while technology-driven engagement was more directly linked to experience and delight. For instance, the path coefficient from human-assisted engagement to care ($\beta = 0.64$, $p < 0.01$) was among the strongest in the model, highlighting that investments in frontline staff and service representatives directly translate into higher perceptions of empathy and reliability. Similarly, the coefficient from technology-driven engagement to delight ($\beta = 0.58$, $p < 0.01$) underscores that seamless mobile applications and self-service tools create memorable experiences that foster customer enthusiasm.

These differentiated effects support the service-dominant logic view that value is co-created through diverse touchpoints rather than delivered in a uniform manner (Vargo & Lusch, 2016). From a managerial perspective, the coefficients make clear which engagement levers produce the largest gains in satisfaction dimensions. Telecom managers can therefore allocate resources strategically—enhancing staff training where relational care matters most, while prioritizing digital innovation to deliver delight and experiential value.

8. THEORETICAL IMPLICATIONS

This study contributes to the ongoing debate on the dimensionality of customer engagement and satisfaction by empirically comparing a uni-dimensional model with a multi-dimensional specification. The results provide strong evidence that conceptualizing both constructs as multi-faceted offers superior explanatory capacity. The uni-dimensional framework remains valuable for capturing overarching evaluations, but it fails to uncover the differentiated mechanisms through which engagement influences satisfaction.

By demonstrating that human-assisted engagement primarily strengthens value and care perceptions, while technology-driven engagement enhances experience and delight, this study advances theory by revealing the importance of channel-specific effects. Such findings support service-dominant logic, which emphasizes that customer value emerges from multiple co-created experiences rather than a single transactional outcome (Vargo & Lusch, 2016). Furthermore, the results extend engagement theory (Brodie et al., 2011; Hollebeek & Macky, 2019) by confirming that disaggregated dimensions yield clearer theoretical insights into consumer psychology and behavior in high-contact industries such as telecommunications.

The study also underscores the need for **context-sensitive model selection**. In markets with complex service structures and heterogeneous customers, a multi-dimensional approach provides richer theoretical validity. Conversely, in industries with simpler offerings, uni-dimensional measures may suffice. Thus, this research positions dimensionality not as an absolute choice but as a matter of contextual appropriateness.

9. MANAGERIAL IMPLICATIONS

The results demonstrate that the multi-dimensional framework offers more robust managerial insights than the uni-dimensional approach. While the latter is efficient for executive dashboards and high-level monitoring—such as tracking Net Promoter Scores (Reichheld, 2003)—its explanatory weakness limits its ability to diagnose specific drivers of customer outcomes (Fornell et al., 2020; Hair et al., 2019). In contrast, the multi-dimensional specification provides managers with a more **granular and evidence-based view** of how engagement translates into satisfaction. Human-assisted engagement showed particularly strong links to perceptions of care ($\beta = 0.64$, $p < 0.01$) and value ($\beta = 0.52$, $p < 0.01$). This suggests that frontline service representatives remain essential in reinforcing fairness, empathy, and reliability—consistent with studies highlighting the relational foundation of customer loyalty (Kumar & Pansari, 2016; Zeithaml et al., 2020). Technology-driven engagement, in turn, significantly shaped delight ($\beta = 0.58$, $p < 0.01$) and overall experience ($\beta = 0.47$, $p < 0.01$), affirming the centrality of seamless digital interfaces in shaping customer journeys (Verleye, 2021; Wu & Chen, 2024). These findings echo service-dominant logic, which emphasizes that value is co-created through multiple, complementary touchpoints (Vargo & Lusch, 2016).

For managers, the implication is twofold. First, **strategic balance** is required: investment in human engagement ensures emotional trust and perceived fairness, while continuous digital innovation enhances convenience and delight. Second, the multi-dimensional framework facilitates **segmentation strategies**, since younger, tech-savvy consumers prioritize digital channels, whereas older or less digitally inclined customers depend on human support (Islam et al., 2020). This duality equips firms to allocate resources more efficiently, reduce churn, and strengthen long-term loyalty.

By clarifying how distinct engagement dimensions drive different satisfaction outcomes, the study provides managers with actionable insights that a uni-dimensional model cannot. This

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positions the multi-dimensional framework as not only statistically superior but also strategically indispensable in competitive telecom markets.

10. CONCLUSION

This study set out to compare uni-dimensional and multi-dimensional frameworks of customer engagement and satisfaction using SEM in the Indian telecom context. The analysis demonstrates that while both approaches confirm a positive engagement–satisfaction relationship, the multi-dimensional model provides superior explanatory power, better fit indices, and richer diagnostic insights. The results show that collapsing constructs into a single factor, although convenient, risks obscuring the distinct mechanisms through which engagement translates into customer outcomes.

From a theoretical perspective, the findings contribute to the dimensionality debate by showing that engagement and satisfaction are best understood as multi-layered constructs. Human-assisted engagement strongly predicted perceptions of care ($\beta = 0.64$) and value ($\beta = 0.52$), while technology-driven engagement shaped delight ($\beta = 0.58$) and overall experience ($\beta = 0.47$). These differentiated effects reinforce service-dominant logic, which posits that value emerges through co-created interactions across diverse touchpoints (Vargo & Lusch, 2016). They also extend engagement theory by demonstrating that disaggregating constructs yields more precise insights into consumer psychology (Brodie et al., 2011; Hollebeek & Macky, 2019).

Managerially, the study highlights that the uni-dimensional model retains relevance for high-level performance monitoring, such as Net Promoter Score dashboards (Reichheld, 2003), but lacks the depth required for strategic decision-making. By contrast, the multi-dimensional model equips managers with actionable insights into which engagement strategies—human versus digital—most effectively enhance satisfaction. This aligns with prior research emphasizing the complementary role of relational and technological engagement in shaping loyalty (Kumar & Pansari, 2016; Verleye, 2021).

In conclusion, the evidence supports adopting a **contingency approach**: the uni-dimensional model serves monitoring purposes, while the multi-dimensional framework is superior for diagnostic and strategic applications. By advancing both the theoretical understanding of dimensionality and providing actionable guidance for telecom managers, this study contributes meaningfully to both scholarship and practice in customer behavior research.

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