



Customer Satisfaction Framework for Telecom Services: Multidimensional Constructs and Demographic Variations

Dr Uday Arun Bhale

PhD in Marketing from Lovely Professional University, IIM Indore, PGDM Welingkar Institute of Mgmt Mumbai,
MBA(IT), DMCA from CDAC Pune, BE Mechanical.

uday.bhale@gmail.com

Dr. Sudeepa Banerjee

School of Business

Dr. Vishwanath Karad MIT World Peace University

Dr Preeti Joshi

Principal & Associate Professor
Sri Balaji University, Pune

Dr. Prashant Kalshetti

HOD ,Dept. of BBA ,DYPACS, Pimpri, Pune

Dr Samrat Ray, Dean, School of Management,

Alard University,Pune,India,samratray@rocketmail.com

ABSTRACT

In the hyper-competitive post-pandemic Indian telecom landscape, traditional satisfaction models are increasingly inadequate for capturing the complexities of a diverse user base transitioning to 5G. This study proposes a multidimensional framework to investigate the key determinants of customer satisfaction and their demographic contingencies. Using a robust sample of 1,600 subscribers and a dual-stage EFA-CFA methodology, the research identifies five core dimensions: Network Performance, Perceived Value, Customer Support, Service Experience, and Customer Delight. Moving beyond standard linear models, this study employs chi-square analysis to reveal significant demographic asymmetries, proving that gender and age significantly moderate how these constructs drive satisfaction. The findings challenge the "one-size-fits-all" approach and provide a strategic roadmap for operators to personalize service delivery in the 5G era.

Keywords: Customer Satisfaction, Demographic Study, Telecom, CFA, Chi-square test

1. INTRODUCTION

Customer satisfaction is widely acknowledged as a critical determinant of organizational success and long-term sustainability in service industries, particularly in telecommunications where offerings are largely intangible and highly competitive (Grönroos, 1984; Oliver, 1980; Bloemer et al., 1999). Rapid technological advancements, aggressive pricing strategies, and increasing service commoditization have intensified competition among telecom operators, compelling firms to differentiate primarily through superior customer experiences rather than cost leadership alone (Ferguson & Brohaugh, 2008; Naik & Prabhakar, 2010). As telecom services increasingly underpin communication, digital entertainment, financial transactions, and professional productivity, customer satisfaction has emerged as a decisive factor influencing retention, loyalty, and firm performance (Alexandris et al., 2002; Angelova & Zekiri, 2011; Akroush et al., 2015).

Extant literature conceptualizes customer satisfaction as a multidimensional construct shaped by customers' cognitive and affective evaluations of service encounters (Oliver, 1980; Fornell, 1992). In the telecommunications context, satisfaction is predominantly driven by service quality attributes such as network reliability, coverage, pricing fairness, customer care, and overall service experience (Zeithaml et al., 1996; Athanassopoulos, 2000; Belwal & Amireh, 2018; Bhale & Bedi, 2021). Network performance remains a foundational determinant, as issues such as call drops, data speed, congestion, and coverage directly influence customer perceptions and provider credibility (Yang et al., 2009; Qiu & Cui, 2011; Ahmed et al., 2012; Curwen, 2018).

Alongside functional performance, customer care plays a pivotal role in shaping satisfaction by influencing customers' perceptions of responsiveness, empathy, and problem resolution (Das Gupta & Sharma, 2009; Lei & Jolibert, 2012; Ferreira et al., 2019). Effective service recovery mechanisms and proactive support interactions have been shown to mitigate dissatisfaction and reinforce trust following service failures (Kristensen et al., 2000;

Keaveney & Parthasarathy, 2001). Furthermore, customer experience represents the cumulative outcome of interactions across multiple touchpoints, integrating both tangible and emotional dimensions that influence satisfaction and loyalty (Kassim, 2006; Eggert & Ulaga, 2002; Herrmann et al., 2009; Joshi et al., 2015).

Recent studies also emphasize the role of perceived value and customer delight in extending satisfaction beyond functional adequacy. Pricing transparency, affordability, and value-added services such as OTT benefits positively influence satisfaction and retention in highly competitive telecom markets (Joshi, 2014; Briganty, 2019; Mitter, 2019). Customer delight, achieved by exceeding expectations rather than merely meeting them, has been identified as a strategic differentiator capable of enhancing post-purchase attitudes and emotional attachment (Oliver, 1980; Javalgi et al., 2005; Kim et al., 2004).

Despite substantial research on satisfaction determinants, prior studies often examine these factors in isolation or adopt unidimensional measurement approaches that inadequately capture the complexity of telecom service experiences (Beatson et al., 2006; Alam & Al-Amri, 2020). Moreover, while demographic variables such as gender, age, education, and occupation have been shown to influence satisfaction in sectors such as banking, aviation, and healthcare (Kassim, 2006; Oyewole et al., 2008; Carthy et al., 2020), empirical evidence within the Indian telecom context remains fragmented and limited. Most existing studies are grounded in Western markets, raising concerns about their generalizability to India's rapidly evolving telecom landscape characterized by digital acceleration, intense price competition, and diverse consumer profiles (Zeithaml et al., 1996; Bhale & Bedi, 2024).

Accordingly, this study addresses two key research questions: (i) What are the core multidimensional determinants of customer satisfaction in telecom services? and (ii) How do demographic variables shape these satisfaction dimensions in the Indian telecom context? By integrating multiple satisfaction constructs into a unified framework and empirically examining demographic variations, the study aims to advance satisfaction theory and provide actionable insights for telecom managers operating in emerging markets.

The Indian telecommunications sector has undergone a radical metamorphosis following the rapid rollout of 5G and the shift toward digital-first consumer behavior. As noted by **Suchanek and Bucicova (2025)**, the structural drivers of satisfaction in the post-pandemic era have shifted from basic connectivity to integrated experiential value. While the market is saturated, the challenge for operators is no longer just acquisition, but retention through nuanced understanding of user segments.

A significant gap exists in current literature regarding the 'Demographic Contingency' of satisfaction models. Most existing frameworks assume a homogenous impact of service quality across all users. However, in a diverse market like India, this assumption is flawed. This study builds upon the work of **Gupta (2024)** and **Kuey (2024)** by examining how 'Customer Delight' and 'Perceived Value' vary across age cohorts and genders, providing a more granular, multidimensional view of the modern subscriber."

2. LITERATURE REVIEW

2.1 Customer Satisfaction

Customer satisfaction in the telecommunications domain reflects the outcome of customer interactions, perceptions, and expectations concerning the services offered by telecom operators. It signifies the extent to which users evaluate their experiences with providers as adequate or superior to their anticipated needs. Within this fast-evolving sector, satisfaction is widely regarded as a benchmark of service quality (Belwal & Amireh, 2018), capturing critical aspects such as the strength of network infrastructure, responsiveness of support channels, affordability of plans, and delivery of value-added offerings. Beyond transactional outcomes, satisfaction encompasses cognitive and emotional dimensions—trust, loyalty, and a sense of overall contentment with the provider. Consequently, fostering satisfaction remains an essential priority for telecom firms aiming to build lasting customer relationships in a highly competitive, consumer-driven marketplace (Reichheld, 1990; Anderson & Sullivan, 1993; Anderson et al., 1994; 2001; Srinivasan et al., 2002; Anckar & D'incau, 2002; Anderson & Srinivasan, 2003; Anderson et al., 2004; Verhoef et al., 2009; Bhale & Bedi, 2021).

The construct of satisfaction in telecom is shaped by a range of factors influencing customer perceptions and service experiences. This section integrates findings from prior research to highlight the primary determinants affecting satisfaction.

Service quality is consistently identified as a cornerstone of satisfaction, especially in service-centric industries like telecommunications. Extant studies establish its multidimensional nature, encompassing reliability, responsiveness, empathy, assurance, and tangibility (Zeithaml et al., 1996). In telecom, service quality is often evaluated in terms of network performance, efficiency of support services (care attributes), and the holistic user experience—all of

which strongly impact consumer satisfaction (Athanasopoulos, 2000; Chandana Asif et al., 2017; Bhale & Bedi, 2021). Contemporary studies further underline its importance in an intensely competitive market where firms increasingly differentiate themselves through service excellence rather than price or technology. Understanding these dimensions enables providers to deliver experiences that surpass expectations, thereby boosting loyalty (Chandana Asif et al., 2017; Bhale & Bedi, 2021).

Research also stresses the significance of network quality, customer care, and delight in influencing satisfaction (Yang et al., 2009; Deng et al., 2010; Qiu & Cui, 2011; Ahmed et al., 2012; Joshi et al., 2015; Diegmann et al., 2017; Briganty, 2019; Kate, 2020). With the rise of high-speed mobile broadband, activities such as gaming, video streaming, and digital media consumption have become central to consumer usage. Consequently, service reliability, coverage, and data quality play decisive roles in satisfaction. Issues like call drops, network congestion, and voice clarity have been shown to directly shape customer perceptions and provider reputation (Yang et al., 2009; Qiu & Cui, 2011; Ahmed et al., 2012; Curwen, 2018). Supporting this, Ahmed et al. (2012), and Deshpande D. (2012) affirm that network coverage remains a cornerstone of satisfaction in telecom services.

Customer care represents another critical dimension, encompassing the quality of interactions between subscribers and service providers. Attributes such as empathy, responsiveness, skill, and timely resolution of complaints are central to this construct (Das Gupta & Sharma, 2009). Studies by (Lei & Jolibert, 2012), Geetha & Abitha Kumari (2012), and Ferreira et al. (2019) highlight the importance of efficient and empathetic customer support in building satisfaction.

Customer experience, as emphasized by Zeithaml et al. (1996) and Kassim (2006), reflects the cumulative journey of users across various service touchpoints—from initial awareness through purchase, usage, and post-service engagement. It integrates both tangible aspects (e.g., product features, service functionality) and intangible dimensions (e.g., ease of use, emotional connection). A positive experience generates trust, loyalty, and satisfaction, whereas poor interactions can cause dissatisfaction and disengagement (Eggert & Ulaga, 2002; Herrmann et al., 2009; Joshi et al., 2015; Briganty, 2019; Mitter, 2019).

Value perception also plays a pivotal role in telecom satisfaction. Studies demonstrate that affordability, perceived fairness of pricing, and supplementary benefits such as OTT services significantly influence satisfaction and retention (Joshi, 2014; Briganty, 2019; Mitter, 2019). Research further indicates that OTT services help reduce churn among mobile subscribers (Joshi, 2014; Barman et al., 2018; Briganty, 2019; Mitter, 2019). Earlier works by Gerpott et al. (2001), Eggert & Ulaga (2002), Ahn et al. (2006), and Herrmann et al. (2009) reinforce the connection between perceived value, fairness, and satisfaction.

The concept of customer delight, initially highlighted by Oliver (1980) and later supported by Javalgi et al. (2005), emphasizes exceeding expectations to positively influence post-purchase attitudes. Managing expectations is crucial for shaping satisfaction, as observed by Kim et al. (2004). Furthermore, service recovery efforts, such as goodwill gestures or surprise rewards, have been found to restore confidence and foster loyalty after service failures (Kristensen et al., 2000; Keaveney & Parthasarathy, 2001).

In sum, prior literature identifies multiple determinants of satisfaction in telecom, including network quality, value, customer care, experience, and delight. Together, these constructs shape customer perceptions, influence loyalty, and determine provider competitiveness in a rapidly evolving market.

2.2 Association of Customer Demographic Profile with Customer Satisfaction

Different demographic segments often carry distinct expectations, making demographic segmentation a critical strategic approach for organizations to address customer needs effectively, particularly when resources are limited (Weinstein, 2013; Zeithaml, 2000). Within the Indian telecom sector, satisfaction has become a foundational driver of business growth and competitiveness. Evidence from multiple industries highlights that customers belonging to varied demographic groups respond differently to similar service conditions. For example, Mirzagoli and Memarian (2015) investigated the role of demographics in shaping ATM satisfaction in Iran, identifying significant influences of occupation, gender, education, marital status, and residential background. Likewise, Volker et al. (2016) examined socio-demographic determinants in private banking, showing that variables such as employment, marital status, and gender moderated both satisfaction and loyalty outcomes (Martins et al., 2012; Carthy et al., 2020).

In aviation, Oyewole et al. (2008) demonstrated how demographic variables intricately shape satisfaction outcomes. While age and income did not show a direct association, gender, education, and occupational status were found to significantly influence satisfaction levels. Consistent with these findings, Zeithaml et al. (2013) argued that although income shapes willingness to pay for premium services, it does not directly determine satisfaction, which depends

more strongly on service quality and customer experience. In the telecom industry, Kassim (2006) observed that gender, education, and age were stronger predictors of satisfaction than income, whereas Zeithaml et al. (2013) noted that income may influence frequency of usage but not satisfaction itself. These perspectives echo the arguments of Zeithaml et. al (1996) and Weinstein (2013), who stressed that satisfaction is anchored in the overall service encounter rather than income.

Additional insights emerge from other service domains. Carthy et al. (2020) highlighted demographic differences in preferences for mobile health solutions versus traditional doctor consultations, while Martins et al. (2012) reported the influence of gender and education on patterns of online train ticket purchases. Similarly, research by Kassim (2006) in the Malaysian telecom industry revealed that variables such as gender, education, and age were directly associated with satisfaction, expectations, and retention. In contrast, Qayyum et al., (2013) analyzing the Pakistani telecom sector, found that age groups may not strongly affect satisfaction but gender consistently emerged as a significant determinant (Eshghi et al., 2007).

Overall, existing scholarship consistently underscores that socio-demographic variables—particularly gender, age, and education—play a meaningful role in shaping customer perceptions and satisfaction (Zeithaml et.al,1996). However, caution is advised in generalizing these findings, as much of the evidence originates from Western contexts. In the Indian telecom sector, where 4G adoption and price rationalization are transforming market dynamics, there is a pressing need to examine how demographic characteristics uniquely affect satisfaction outcomes.

2.3 Unidimensional and Multidimensional in Customer Satisfaction

The conceptualization of customer satisfaction constructs often sparks debate between two contrasting perspectives: unidimensional and multidimensional views. Proponents of the unidimensional view argue that customer satisfaction can be adequately captured as a singular construct, while advocates for the multidimensional view contend that it comprises distinct dimensions.

Those supporting the unidimensional perspective, as evidenced by studies such as Beatson et al. (2006), and Alam & Al-Amri (2020), emphasize the high degree of positive correlation among various dimensions of customer satisfaction. They interpret this correlation as indicative of the underlying unity of satisfaction, advocating for its treatment as a singular entity.

Conversely, proponents of the multidimensional viewpoint, represented by research from Kosciulek (2003), Beatson et al. (2006), Consuegra et al. (2007), Andreis & Ferrari (2014), VanScoyoc (2019), argue that different dimensions of customer satisfaction make unique contributions to overall satisfaction. They assert that disaggregating satisfaction into distinct dimensions allows for a more nuanced understanding of customer experiences and preferences.

Both perspectives are theoretically grounded and contribute valuable insights to the understanding of customer satisfaction. However, while the unidimensional perspective offers a simplified representation of customer satisfaction (Beatson et al., 2006; Alam & Al-Amri, 2020), it often masks the diverse elements that shape customer perceptions. In contrast, the multidimensional view allows for the identification of distinct drivers—such as service quality, pricing, network reliability, and customer support—that contribute uniquely to overall satisfaction (Kosciulek, 2003; Consuegra et al., 2007; Andreis & Ferrari, 2014; VanScoyoc, 2019). This disaggregation is particularly important in the telecom industry, where customer experiences are complex and highly sensitive to variations across service attributes. By adopting a multidimensional framework, the present study ensures both conceptual rigor and practical relevance, aligning with calls in the literature to recognize satisfaction as a multifaceted construct (Oliver, 1980; Fornell, 1992). This approach enables a deeper understanding of customer behavior and offers managers actionable insights for targeted improvements in service delivery. Hence for the given study multidimensional approach is considered.

2. RESEARCH GAP AND THEORETICAL MOTIVATION

Although customer satisfaction has been extensively examined in service marketing and telecommunications research, existing studies remain theoretically fragmented in their treatment of satisfaction formation. Prior research predominantly conceptualizes customer satisfaction as either a unidimensional outcome or as the additive effect of isolated service attributes such as network quality, pricing, or customer care (Oliver, 1980; Zeithaml et al., 1996; Beatson et al., 2006). Such approaches inadequately capture the complex and layered nature of telecom service experiences, where functional performance, relational interactions, and experiential evaluations jointly shape customer judgments.

A key theoretical insufficiency in the literature lies in the limited integration of satisfaction determinants into a unified, multidimensional framework. While individual constructs—such as service quality, perceived value, customer experience, and customer delight—have been empirically validated in prior studies, they are rarely examined collectively within a single structural model that reflects their simultaneous and interdependent influence on customer satisfaction outcomes (Athanasopoulos, 2000; Eggert & Ulaga, 2002; Herrmann et al., 2009). As a result, existing models offer partial explanations and fail to provide a holistic understanding of satisfaction formation in contemporary telecom environments.

Furthermore, demographic variables are theoretically underdeveloped in satisfaction research. Existing studies often treat demographics as control variables or rely on descriptive comparisons, implicitly assuming that satisfaction drivers operate uniformly across customer segments (Kassim, 2006; Oyewole et al., 2008). This assumption overlooks the possibility of **demographic asymmetry**, wherein the same service attribute may exert varying levels of influence on satisfaction depending on customers' age, gender, education, or occupational profiles. The absence of demographic sensitivity in dominant satisfaction frameworks limits their explanatory power and managerial relevance.

Another theoretical limitation concerns contextual generalizability. Much of the existing telecom satisfaction literature is grounded in developed market settings, where infrastructure maturity, pricing stability, and service expectations differ substantially from those in emerging markets (Zeithaml et al., 1996; Curwen, 2018). Applying these models uncritically to contexts such as India—characterized by intense price competition, rapid digital adoption, and heterogeneous consumer expectations—risks theoretical oversimplification and contextual mismatch. Accordingly, this study addresses these theoretical gaps by proposing and empirically validating a multidimensional customer satisfaction framework that integrates functional, experiential, relational, and value-based constructs within a single model. Additionally, by examining demographic variations in satisfaction perceptions, the study advances satisfaction theory beyond uniform-effect assumptions and contributes a context-sensitive understanding of satisfaction formation in the Indian telecom industry.

2.5 Motivation of the Study

The telecommunications sector represents a highly dynamic and continuously evolving environment, where ensuring customer satisfaction remains a critical priority for service providers. The motivation for this research stems from an acknowledgment of the complex, multidimensional nature of customer satisfaction and its far-reaching implications for organizational performance as well as consumer well-being.

Existing literature in this field offers extensive insights, highlighting the intricate interactions among diverse factors that influence customer perceptions and behaviors. Building on these foundations, the present study seeks to explore these dynamics in greater depth, with a particular emphasis on understanding the role of demographic variables in shaping satisfaction levels. By integrating empirical evidence with theoretical perspectives, the research aims to uncover actionable strategies that telecommunications firms can implement to strengthen satisfaction and nurture long-term customer loyalty.

This study is motivated not only by the academic need to enrich the discourse in telecommunications management but also by the practical objective of offering evidence-based recommendations that inform strategic business decisions. Ultimately, the author's intent is to address pressing challenges faced by telecom operators and to support the development of enhanced, consumer-centric experiences in today's fast-changing digital landscape.

3. HYPOTHESES DEVELOPMENT: DEMOGRAPHIC CONTINGENCY PERSPECTIVE

3.4 Analytical Approach

To assess these hypotheses, customer satisfaction scores were calculated using **summed scales** for each construct: **Network** (10 attributes), **Value** (9 attributes), **Care** (4 attributes), **Experience** (4 attributes), and **Delight** (3 attributes). The **Chi-square test of independence** was employed to evaluate the associations between demographic factors (gender, age, education, occupation) and the satisfaction dimensions. As a **non-parametric test**, it measures the degree of association between categorical variables. The decision criteria were as **Alpha level = 0.05, Fail to reject H₀ if p-value > 0.05 and Reject H₀ if p-value < 0.05**

3.1 Customer Satisfaction Construct Hypotheses

In the telecommunications sector, prior research has consistently demonstrated a strong and positive correlation between **customer satisfaction** and **network quality**. Studies by Apenes Solem (2016), Barger et al. (2016), Bhale & Bedi (2020a, 2020b, 2021), and Cavusgil et al. (2022) highlight the influential role of network quality in shaping customer satisfaction. This relationship has also been corroborated by Hwang et al. (2004), Sashi (2012), Cambra-

Fierro et al. (2015), Ilse van den Berg (2015), and Akmal (2017). These findings suggest that a robust and reliable network significantly enhances consumer perceptions and satisfaction levels.

H₁: Network quality has a positive influence on customer satisfaction.

Similarly, **value** has been widely acknowledged as a key driver of customer satisfaction in the telecommunications industry. Studies by Barger et al. (2016), Chandana Asif et al. (2017), Pansari & Kumar (2017), Breuer et al. (2020), Bhale & Bedi (2020a, 2021), and Sood & Sharma (2021) underscore the role of value in shaping consumer evaluations. The works of Sawhney et al. (2005), Apenes Solem (2016), and Chandana Asif et al. (2017) further reinforce this perspective. Hence, we propose:

H₂: Value has a positive influence on customer satisfaction.

Customer care also emerges as a critical determinant of satisfaction in the telecom sector. Inadequate customer support often results in dissatisfaction and churn (Hung et al., 2006 ; Bhale & Bedi, 2020a). Conversely, effective resolution of customer queries strengthens trust and loyalty. Therefore, we hypothesize:

H₃: Customer care has a positive influence on customer satisfaction.

A favourable **customer experience**—defined as exceeding expectations and generating confidence and commitment—is another crucial factor influencing satisfaction (Joshi et al., 2014; Briganty, 2019; Mitter, 2019). Negative experiences, on the other hand, can lead to frustration and disengagement (Brodie et al., 2011; Sashi, 2012). Thus, we propose:

H₄: Customer experience has a positive influence on customer satisfaction.

Finally, the construct of **delight** has been shown to enhance satisfaction beyond ordinary expectations. Oliver's (1980) foundational work, followed by Javalgi et al. (2005), Neslin et al. (2006), Pathak & Rastogi (2007), Joshi (2014), Fathian et al. (2016), and Banda & Tembo (2017), suggests that delight not only boosts satisfaction but also reduces churn. Accordingly, we propose:

H₅: Delight has a positive influence on customer satisfaction.**3.2 Customer Satisfaction (Multidimensional Construct) and Demographics Associations**

To examine these relationships, customer satisfaction was conceptualized as a **multidimensional construct** derived from exploratory and confirmatory factor analyses (EFA & CFA). Five dimensions—**network, value, care, experience, and delight**—were identified. The association between demographic variables (gender, age, education, and occupation) and each dimension was tested through the following hypotheses:

Prior research highlights that demographic variables exert a considerable influence on customer satisfaction across industries. Trivedi et al. (2018) identified a significant association between **gender** and satisfaction, while Apenes Solem (2016) revealed that **age** shapes consumer behaviour, with younger and older groups adopting different satisfaction approaches. In line with this, Mirzagoli & Memarian (2015) confirmed a strong linkage between age and customer satisfaction. Based on these findings, the following hypotheses were formulated to test the role of gender and age:

H₆, H₇, H₁₀, H₁₁, H₁₄, H₁₅, H₁₈, H₁₉, H₂₂, and H₂₃.

Educational attainment also plays a vital role in satisfaction levels. According to Alshari & Lokhande (2022), highly educated consumers are more adept at searching, evaluating, and enjoying information about goods and services, resulting in stronger satisfaction outcomes. Hence, the following hypotheses were established to examine education as a factor:

H₈, H₁₂, H₁₆, H₂₀, and H₂₄.

Similarly, studies reveal a link between **occupation** and satisfaction. Philip et al. (2020) demonstrated a positive relationship, while Parbat (2019) and Bhat et al. (2021) noted that the occupation–satisfaction relationship is particularly pronounced among low-income consumers. On this basis, the following hypotheses were proposed:

H₉, H₁₃, H₁₇, H₂₁, and H₂₅.**3.2.1 (a) Network dimension**

- H₆ (Null): No significant association between gender and Network score.
- H₇ (Null): No significant association between age and Network score.
- H₈ (Null): No significant association between education and Network score.
- H₉ (Null): No significant association between occupation and Network score.

3.2.1 (b) Value dimension

- H₁₀ (Null): No significant association between gender and Value score.
- H₁₁ (Null): No significant association between age and Value score.
- H₁₂ (Null): No significant association between education and Value score.

- H_{13} (Null): No significant association between occupation and Value score.

3.2.1 (c) Care dimension

- H_{14} (Null): No significant association between gender and Care score.
- H_{15} (Null): No significant association between age and Care score.
- H_{16} (Null): No significant association between education and Care score.
- H_{17} (Null): No significant association between occupation and Care score.

3.2.1 (d) Experience dimension

- H_{18} (Null): No significant association between gender and Experience score.
- H_{19} (Null): No significant association between age and Experience score.
- H_{20} (Null): No significant association between education and Experience score.
- H_{21} (Null): No significant association between occupation and Experience score.

3.2.1 (e) Delight dimension

- H_{22} (Null): No significant association between gender and Delight score.
- H_{23} (Null): No significant association between age and Delight score.
- H_{24} (Null): No significant association between education and Delight score.
- H_{25} (Null): No significant association between occupation and Delight score.

3.5 Proposed Research Model and Objectives

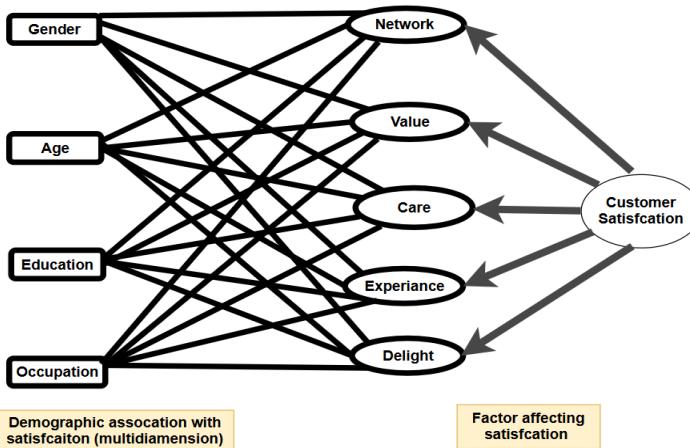


Figure no 1: Proposed Research Model: Customer Satisfaction and Demographic Association.

The objectives of this study are as follows: 1. to identify and validate the key factors that contribute to customer satisfaction. 2. To examine the relationship between customer satisfaction and demographic variables within the framework of multidimensional theory. the final research model is presented in figure no 01.

4. ANALYSIS

4.1 Data Collection

The data collection process began with the identification of key regions across India—North, South, East, and West from which the survey responses were to be obtained. An online survey was administered, and responses were recorded using a structured set of statements measured on a Likert scale. The survey was done during Jul-2022 to Jul-2023 year period. To ensure representativeness, the study considered the actual market contributions of major telecom operators in India—**Reliance Jio, Vodafone Idea Ltd., Airtel, and BSNL**—and compared them with the corresponding sample contributions. Reliance Jio, the market leader, accounted for **33.83% of actual market share**, which was closely reflected in the sample at **35%**. Airtel followed with **28.06% actual share** against **30% in the sample**, while Vodafone Idea Ltd. reported **27.37% actual share** compared to **25% in the sample**. BSNL maintained a smaller yet consistent contribution, with **10.43% actual share** mirrored by **10% in the sample**. These market shares were reported as of **31st December 2021** (Telecom Subscriptions Reports | Telecom Regulatory Authority of India, 2021). In addition to operator representation, the study also examined the geographical and gender-wise distribution of subscribers. The **North region** contributed **26.30% of actual subscribers** versus **25% in the sample**, with a balanced gender split of **50% male and 50% female**. The **East region** accounted for **20.30% actual contribution**, slightly below its **25% sample representation**, with **48.6% male and 51.3% female** subscribers. The **South region** reflected **24.30% actual contribution**, closely aligned with its **25% sample**.

representation, comprising **50.2% male** and **49.8% female** subscribers. The **West region** led with **29.20% actual contribution**, higher than its **25% sample share**, with a gender distribution of **52% male** and **48% female**.

Overall, the **total sample distribution ensured balance**, with **50.4% male** and **49.6% female respondents**, offering a representative view of the telecom subscriber base across regions and demographics. The regional and gender-based telecom subscriber contributions were also reported as of **31st December 2021** (Telecom Subscriptions Reports | Telecom Regulatory Authority of India, 2021).

4.2 EFA for Satisfaction

The analysis identified five key factors influencing customer satisfaction: **Network, Value, Care, Experience, and Delight**. Collectively, these dimensions account for **61.91% of the explained variance**, indicating strong explanatory power. All factor loadings exceeded the recommended threshold of **0.50**, signifying substantial correlations between variables and their respective constructs. Furthermore, the **Cronbach's alpha coefficients** demonstrated high internal consistency: Network (0.92), Value (0.91), Care (0.82), Experience (0.83), and Delight (0.84), mentioned in table no 01. Since all values surpass the acceptable minimum of 0.70, the results confirm the reliability of the measurement model (Bagozzi et al., 1991; Auerswald & Moshagen, 2019).

Table no. 1: Hypotheses Testing Result for Customer Satisfaction with EFA

Hypotheses	Factor Loading	Hypotheses Decision
H ₁	0.90	Accepted
H ₂	0.85	Accepted
H ₃	0.72	Accepted
H ₄	0.78	Accepted
H ₅	0.65	Accepted

4.3 Confirmatory Factor Analysis (CFA) for Satisfaction

CFA was employed to validate the adequacy of the five satisfaction constructs: **Network, Value, Care, Experience, and Delight**. Results demonstrate acceptable reliability, convergent validity, and overall model fit, supporting the use of these constructs for subsequent SEM analysis.

At the item level, **all standardized factor loadings ranged from 0.62 to 0.80**, exceeding the minimum threshold of 0.50 (Hair et al., 2019), confirming that each observed indicator contributes meaningfully to its respective construct. The **Composite Reliability (CR)** values ranged from 0.781 to 0.915, surpassing the benchmark of 0.70, while the **Average Variance Extracted (AVE)** values (0.503–0.563) exceeded the 0.50 cut-off (Fornell & Larcker, 1981). These findings establish strong internal consistency and convergent validity. At the overall model level (Table no. 2), fit indices confirm model adequacy. The **Chi-square/df ratios** (1.057–4.448) fell below the threshold of 5, with Experience (1.057) and Delight (1.97) exhibiting excellent fit (Kline, 2016). Incremental fit indices—**GFI (0.968–0.999)**, **AGFI (0.949–0.993)**, **NFI (0.965–0.999)**, and **CFI (0.973–0.999)**—all surpassed the recommended cut-off of 0.90 (Hu & Bentler, 1999). Error indices were also satisfactory: **RMR (0.021–0.084)** remained low, and **RMSEA (0.034–0.066)** fell below the 0.08 benchmark, confirming adequate approximation fit. Additionally, standardized residuals were <3.5, and all factor loadings exceeded 0.50, indicating robustness and measurement stability. Overall, the CFA results affirm that the constructs **Network, Value, Care, Experience, and Delight** demonstrate strong psychometric properties. High factor loadings, CR, and AVE values validate both reliability and convergent validity, while fit indices confirm structural adequacy. These outcomes provide a solid foundation for advancing to **structural equation modeling (SEM)** and subsequent hypothesis testing (reference table no. 3).

Table no. 2: Summary of Satisfaction Construct Model Fit Indices

Sr No	Parameter	Network	Value	Care	Experience	Delight
1	Normalised Chi-square	3.593	4.448	1.943	1.057	1.97
2	GFI	0.968	0.968	0.999	0.998	0.998
3	AGFI	0.949	0.949	0.988	0.993	0.989
4	NFI	0.969	0.965	0.998	0.997	0.997
5	CFI	0.977	0.973	0.999	0.999	0.999

Sr No	Parameter	Network	Value	Care	Experience	Delight
6	RMR	0.084	0.082	0.021	0.063	0.054
7	RMSEA	0.057	0.066	0.034	0.008	0.035
8	Standardized Residuals < 3.5	Yes	Yes	Yes	Yes	Yes
9	Standardized Factor Loadings > 0.5	Yes	Yes	Yes	Yes	Yes
10	AVE	0.52	0.508	0.56	0.504	0.563
11	CR	0.915	0.903	0.835	0.802	0.793

Table no. 3: Hypotheses Testing Result for Customer Satisfaction with CFA

Hypotheses	AVE	CR	Hypotheses Decision
H ₁	0.52	0.915	Accepted
H ₂	0.508	0.903	Accepted
H ₃	0.56	0.835	Accepted
H ₄	0.504	0.802	Accepted
H ₅	0.563	0.793	Accepted

4.4 Association of Customer Satisfaction with Customer Demographics

To test the association of customer satisfaction with the demographics of the customer (i.e., gender, age, education and occupation), the Chi-square test of independence has been applied to customer satisfaction constructs.

Table no. 4: Association between Customer Demographics and Customer Satisfaction (Multidimensional), network

Parameter	Classification	Degree of satisfaction, (Low)	customer network	Moderate	High	Total	Chi-square	DF	P-Value	Hypotheses decision
Gender	Male	123		197	486	806	4.83	2	0.019	H ₆ =Reject
	Female	95		220	479	794				
	Total	218		417	965	1600				
Age Bracket	18-25	92		199	429	720	2.31	4	0.006	H ₇ =Reject
	26-59	96		162	397	655				
	60+	30		56	139	225				
	Total	218		417	965	1600				
Education	No formal education	11		26	32	69	45.9	6	0.100	H ₈ =Fail to Reject
	Up to schooling (10th)	97		179	467	743				
	Graduate	75		169	420	664				
	Postgraduate	35		43	46	124				
	Total	218		417	965	1600				
Occupation	Housewife	57		126	334	517	60.2	10	0.123	H ₉ =Fail to Reject
	Salary	53		111	271	435				
	Farmer	35		43	46	124				
	Business	60		93	179	332				
	Other	13		44	135	192				
	Total	218		417	965	1600				

The results of Chi-square Test Table no. 4 reveal that customer's demographics gender (Chi-square =4.83 with p-value = 0.019) and age bracket (Chi-square =2.31 with p-value =0.006) are significantly associated with network.

The demographics like education (Chi-square =45.9 with p-value =0.100) and occupation (Chi-square =60.2 with p-value = 0.123), are not significantly associated with network.

Table no.5 Association between Customer Demographics and Customer Satisfaction (Multidimensional), value

Parameter	Classification	Degree of Customer Satisfaction, Value (Low)	Moderate	High	Total	Chi-square	DF	P-Value	Hypotheses Decision
Gender	Male	107	238	461	806	0.407	2	0.008	$H_{10}=\text{Reject}$
	Female	112	225	457	794				
	Total	219	463	918	1600				
Age Bracket	18-25	403	222	403	1028	7.6	4	0.001	$H_{11}=\text{Reject}$
	26-59	381	172	381	934				
	60+	134	69	134	337				
	Total	918	463	918	2299				
Education	No formal education	21	20	28	69	47	6	0.101	$H_{12}=\text{Fail to Reject}$
	Up to schooling (10th)	99	194	450	743				
	Graduate	76	193	395	664				
	Postgraduate	23	56	45	124				
	Total	219	463	918	1600				
Occupation	Housewife	71	144	302	517	25.3	10	0.512	$H_{13}=\text{Fail to Reject}$
	Salary	49	133	253	435				
	Farmer	28	46	50	124				
	Business	44	98	190	332				
	Other	27	42	123	192				
	Total	219	463	918	1600				

The results of Chi-square Test Table no. 5 reveal that the Customer's demographics gender (Chi-square =0.407 with p-value = 0.008) and age bracket (Chi-square =7.6 with p- value =0.001) are significantly associated with value. Education (Chi-square =47 with p- value =0.101) and occupation (Chi-square =25.3 with p-value = 0.512), are not significantly associated with value.

Table no. 6 Association between Customer Demographics and Customer Satisfaction (Multidimensional), care

Parameter	Classification	Degree of Satisfaction, Care (Low)	Moderate	High	Total	Chi-square	DF	P-Value	Hypotheses Decision
Gender	Male	151	208	447	806	0.502	2	0.027	$H_{14}=\text{Reject}$
	Female	138	207	449	794				
	Total	289	415	896	1600				
Age Bracket	18-25	130	194	396	720	4.73	4	0.031	$H_{15}=\text{Reject}$
	26-59	128	164	363	655				
	60+	31	57	137	225				
	Total	289	415	896	1600				

Parameter	Classification	Degree of Satisfaction, Care (Low)	Moderate	High	Total	Chi-square	DF	P-Value	Hypotheses Decision
Education	No formal education	19	25	25	69	25.5	6	0.121	$H_{16} = \text{Fail to Reject}$
	Up to schooling (10th)	121	182	440	743				
	Graduate	116	169	379	664				
	Postgraduate	33	39	52	124				
	Total	289	415	896	1600				
Occupation	Housewife	94	138	285	517	24.7	10	0.612	$H_{17} = \text{Fail to Reject}$
	Salary	84	99	252	435				
	Farmer	29	44	51	124				
	Business	52	93	187	332				
	Other	30	41	121	192				
	Total	289	415	896	1600				

The results of the Chi-square test (Table no. 6) reveal that the Customer's demographics gender (Chi-square =0.502 with p-value = 0.027) and age bracket (Chi-square =4.73 with p- value =0.031), are significantly associated with care. Education (Chi-square =25.5 with p- value =0.121) and occupation (Chi-square =24.7 with p-value =0.612), are not significantly associated with care.

Table no.7 Association between Customer Demographics and Customer Satisfaction (Multidimensional), experience

Parameter	Classification	Degree of Customer Satisfaction, Experience (Low)	Moderate	High	Total	Chi-square	DF	P-Value	Hypotheses Decision
Gender	Male	178	214	414	806	0.962	2	0.018	$H_{18} = \text{Reject}$
	Female	176	227	391	794				
	Total	354	441	805	1600				
Age Bracket	18-25	165	190	365	720	3.43	4	0.048	$H_{19} = \text{Reject}$
	26-59	147	190	318	655				
	60+	42	61	122	225				
	Total	354	441	805	1600				
Education	No formal education	12	27	30	69	30.5	6	0.451	$H_{20} = \text{Fail to Reject}$
	Up to schooling (10th)	180	181	382	743				
	Graduate	119	196	349	664				
	Postgraduate	43	37	44	124				
	Total	354	441	805	1600				
Occupation	Housewife	114	127	276	517	51.7	10	0.511	$H_{21} = \text{Fail to Reject}$
	Salary	74	145	216	435				
	Farmer	47	43	34	124				
	Business	74	88	170	332				

Parameter	Classification	Degree of Customer Satisfaction, Experience (Low)	Moderate	High	Total	Chi-square	DF	P-Value	Hypotheses Decision
	Other	45	38	109	192				
	Total	354	441	805	1600				

The results of Chi-square Test Table no. 7 reveal that the Customer's demographics gender (Chi-square =0.962 with p-value = 0.018) and age bracket (Chi-square =3.43 with p- value =0.048), are significantly associated with experience. Education (Chi-square =30.5 with p-value= 0.451) and occupation (Chi-square =51.7 with p-value=0.511), are not significantly associated with experience.

Table no.8 Association between Customer Demographics and Customer Satisfaction (Multidimensional), delight

Parameter	Classification	Degree of Customer Satisfaction, Delight (Low)	Moderate	High	Total	Chi-square	DF	P-Value	Hypotheses Decision
Gender	Male	113	276	405	794	3.25	2	0.019	$H_{22}=\text{Reject}$
	Female	137	254	415	806				
	Total	250	530	820	1600				
Age Bracket	18-25	112	240	368	720	1.55	4	0.018	$H_{23}=\text{Reject}$
	26-59	107	219	329	655				
	60+	31	71	123	225				
	Total	250	530	820	1600				
Education	No formal education	23	23	23	69	41.7	6	0.701	$H_{24}=\text{Fail to Reject}$
	Up to schooling (10th)	89	238	416	743				
	Graduate	107	221	336	664				
	Postgraduate	31	48	45	124				
	Total	250	530	820	1600				
Occupation	Housewife	70	175	272	517	39.2	10	0.178	$H_{25}=\text{Fail to Reject}$
	Salary	63	144	228	435				
	Farmer	41	40	43	124				
	Business	55	111	166	332				
	Other	21	60	111	192				
	Total	250	530	820	1600				

The results of Chi-square test (Table no. 8) reveal that Customer's demographics gender (Chi-square = 3.2 with p-value = 0.019) and age bracket (Chi-square =1.55 with p-value=0.018) are significantly associated with delight. Education (Chi-square =41.7 with p-value= 0.701) and occupation (Chi-square =39.2 with p-value=0.178), are not significantly associated with delight.

5. FINDINGS

This study applied Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and Chi-square tests to explore the multidimensionality of customer satisfaction and its relationship with demographic attributes.

The EFA results identified five clear dimensions of customer satisfaction—**Network, Value, Care, Experience, and Delight**—which jointly explained **61.91% of the total variance**. Factor loadings for all items exceeded the recommended threshold of **0.50**, demonstrating strong construct-item alignment. Reliability tests indicated robust

internal consistency, with Cronbach's alpha values ranging from **0.82** to **0.92**. Consequently, all measurement hypotheses (H1–H5) were validated.

CFA confirmed the dimensional structure suggested by EFA. Standardized factor loadings fell between **0.62** and **0.80**, surpassing the cut-off of 0.50. Reliability and validity indicators were satisfactory, with **Composite Reliability (CR) ranging from 0.781 to 0.915** and **Average Variance Extracted (AVE) between 0.503 and 0.563**, confirming convergent validity. Model fit indices supported the adequacy of the measurement model, with values meeting established thresholds: **Chi-square/df < 5**; **GFI, AGFI, NFI, and CFI > 0.90**; **RMSEA = 0.034–0.066 (< 0.08)**; **RMR = 0.021–0.084**.

The Chi-square analysis demonstrated that **gender and age** had a significant association with all five satisfaction constructs, whereas **education and occupation** did not exhibit any statistically significant impact. This highlights the stronger role of demographic characteristics such as gender and age in shaping satisfaction compared to socio-economic background.

6. DISCUSSION

The findings reaffirm that customer satisfaction is inherently **multidimensional**, represented by the five constructs of Network, Value, Care, Experience, and Delight. This perspective aligns with earlier service management studies which argued that satisfaction cannot be fully explained through a unidimensional lens (Oliver, 1999; Cronin & Taylor, 1992). The five-factor model not only accounted for a substantial proportion of variance but also exhibited high internal reliability, confirming its robustness in service contexts.

The CFA outcomes further strengthened the validity of the measurement model. High factor loadings, AVE values above 0.50 (Fornell & Larcker, 1981), and composite reliability above 0.70 demonstrated both convergent validity and internal consistency. Fit indices also confirmed model adequacy, consistent with Hu & Bentler (1999).

Demographic analysis uncovered meaningful patterns: **gender and age significantly influenced satisfaction**, supporting prior research that emphasized demographic predictors in service perceptions (Mittal & Kamakura, 2001; Tam, 2012). Younger consumers were more likely to prioritize digital experiences and network reliability, while older groups placed greater emphasis on reliability and care. Gender differences reflected varied expectations in communication styles and service interaction. By contrast, **education and occupation did not significantly influence satisfaction**, corroborating earlier findings that socio-economic variables are often less impactful than psychographic and demographic attributes.

Collectively, these insights reinforce the importance of adopting a **demographically nuanced and multidimensional framework** to capture the dynamics of customer satisfaction.

7. CONCLUSION

This study enhances the understanding of customer satisfaction by confirming it as a **five-dimensional construct**, comprising Network, Value, Care, Experience, and Delight. Both EFA and CFA established the **reliability, validity, and structural soundness** of the model, providing a solid foundation for future structural modeling.

The demographic analysis revealed that **gender and age** significantly shape satisfaction outcomes, whereas **education and occupation** do not. These insights call for service providers to design **customer-centric strategies tailored to demographic expectations**, such as differentiated communication styles, age-specific service customization, and personalized experiences.

Although education and occupation are often employed as demographic bases for market segmentation, the present analysis found no significant association with customer satisfaction in the Indian telecom sector. This outcome aligns with prior studies which demonstrated that satisfaction in telecom is primarily shaped by **service quality, network reliability, pricing transparency, and customer support**, while demographic characteristics like education or profession play only a marginal role (Kale, 2024). Similar findings were reported in other service contexts where **demographics such as education, occupation, gender, and age did not significantly influence customer choice or satisfaction**, underscoring that telecom services are largely standardized and functional in nature (Seejph, 2022). In addition, scholars argue that **psychographic and behavioral variables**, such as perceived service value, trust, and loyalty, are stronger predictors of satisfaction than socio-economic demographics (Richtmann, 2015). Collectively, these insights confirm that telecom operators should prioritize **enhancing service quality, reliability, and customer experience**, rather than differentiating strategies solely based on educational or occupational segments. Theoretically, the study contributes by validating a multidimensional construct of satisfaction in a competitive telecom context. Practically, it provides actionable recommendations for managers

aiming to **strengthen customer engagement and loyalty** through targeted, segment-specific strategies. Figure no 2 shows the final research multidimensional model of customer satisfaction and demographic.

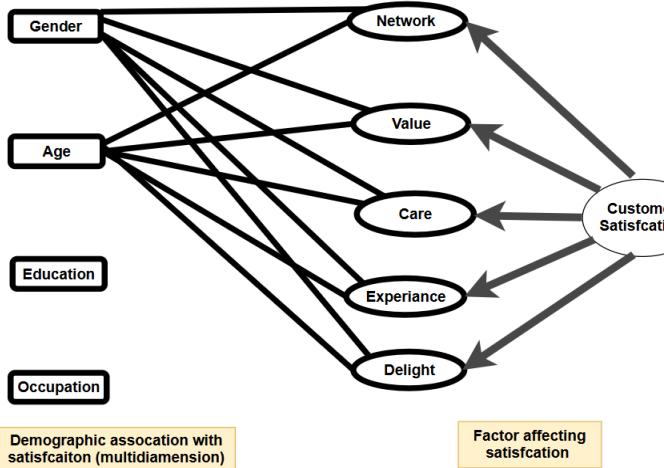


Figure no 2: Final Research Model of Customer Satisfaction (Multidimensional View) and Customer Demographic

8. IMPLICATIONS

For industry practitioners, the results suggest that improving satisfaction requires more than functional excellence. While **network quality and value** are essential, providers must also foster **experiences and delight** that create emotional connections. Proactive service care, personalization, and experience-driven innovation can enhance loyalty and reduce churn. The proposed multidimensional framework offers managers a **diagnostic lens** to prioritize interventions across both functional and emotional aspects of service delivery, ultimately enhancing long-term customer value.

9. LIMITATIONS AND FUTURE SCOPE

Despite its contributions, the study acknowledges several limitations. The analysis was confined to a **single sector (telecom)**, which may limit its applicability to industries with distinct service characteristics. In this research The **cross-sectional design** restricts the ability to capture temporal variations in customer satisfaction. On survey The reliance on **self-reported survey data** introduces potential response biases and External factors such as **digital adoption, cultural influences, and market competition** were not considered, though they may play a role in shaping satisfaction outcomes.

Future research can extend this framework across diverse service industries such as **banking, healthcare, and e-commerce**, to test its generalizability. Employing **longitudinal designs** could provide insights into how satisfaction evolves with service innovations and digital transformation. Integrating **behavioral data** (e.g., **churn rates, usage patterns**) with perceptual measures could yield a more comprehensive understanding of the satisfaction–loyalty relationship. Additionally, examining moderators such as **technology adoption, cultural context, and demographic differences** would enrich theoretical and practical implications. Expanding the framework to investigate **satisfaction–engagement–advocacy linkages** could also reveal new avenues for strengthening customer relationships.

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 availability : data is available basis on the request

10. REFERENCES

- [1] Thommandru, A., Espinoza-Maguiña, M., Ramirez-Asis, E., Ray, S., Naved, M., & Guzman-Avalos, M. (2023). Role of tourism and hospitality business in economic development. *Materials Today: Proceedings*, 80, 2901-2904.
- [2] Voumik, L. C., Islam, M. A., Ray, S., Mohamed Yusop, N. Y., & Ridzuan, A. R. (2023). CO2 emissions from renewable and non-renewable electricity generation sources in the G7 countries: static and dynamic panel assessment. *Energies*, 16(3), 1044.
- [3] Bhargava, A., Bhargava, D., Kumar, P. N., Sajja, G. S., & Ray, S. (2022). Industrial IoT and AI implementation in vehicular logistics and supply chain management for vehicle mediated transportation systems. *International Journal of System Assurance Engineering and Management*, 13(Suppl 1), 673-680.
- [4] Rakhra, M., Sanober, S., Quadri, N. N., Verma, N., Ray, S., & Asenso, E. (2022). Implementing machine learning for smart farming to forecast farmers' interest in hiring equipment. *Journal of Food Quality*, 2022.
- [5] Al Ayub Ahmed, A., Rajesh, S., Lohana, S., Ray, S., Maroor, J. P., & Naved, M. (2022, June). Using Machine Learning and Data Mining to Evaluate Modern Financial Management Techniques. In *Proceedings of Second International Conference in Mechanical and Energy Technology: ICMET 2021*, India (pp. 249-257). Singapore: Springer Nature Singapore.
- [6] Pallathadka, H., Leela, V. H., Patil, S., Rashmi, B. H., Jain, V., & Ray, S. (2022). Attrition in software companies: Reason and measures. *Materials Today: Proceedings*, 51, 528-531.
- [7] Sharma, A., Kaur, S., Memon, N., Fathima, A. J., Ray, S., & Bhatt, M. W. (2021). Alzheimer's patients detection using support vector machine (SVM) with quantitative analysis. *Neuroscience Informatics*, 1(3), 100012.
- [8] Mehbodniya, A., Neware, R., Vyas, S., Kumar, M. R., Ngulube, P., & Ray, S. (2021). Blockchain and IPFS integrated framework in bilevel fog-cloud network for security and privacy of IoMT devices. *Computational and Mathematical Methods in Medicine*, 2021.
- [9] Ray, S. (2020). How COVID-19 changed dimensions of human suffering and poverty alleviation: economic analysis of humanitarian logistics. *Вестник Астраханского государственного технического университета. Серия: Экономика*, (4), 98-104.
- [10] Akbar, A., Akbar, M., Nazir, M., Poulova, P., & Ray, S. (2021). Does working capital management influence operating and market risk of firms?. *Risks*, 9(11), 201.
- [11] Dutta, A., Voumik, L. C., Ramamoorthy, A., Ray, S., & Raihan, A. (2023). Predicting Cryptocurrency Fraud Using ChaosNet: The Ethereum Manifestation. *Journal of Risk and Financial Management*, 16(4), 216.
- [12] Polcyn, J., Voumik, L. C., Ridwan, M., Ray, S., & Vovk, V. (2023). Evaluating the influences of health expenditure, energy consumption, and environmental pollution on life expectancy in Asia. *International Journal of Environmental Research and Public Health*, 20(5), 4000.
- [13] Sajja, G. S., Jha, S. S., Mhamdi, H., Naved, M., Ray, S., & Phasinam, K. (2021, September). An investigation on crop yield prediction using machine learning. In *2021 Third International Conference on Inventive Research in Computing Applications (ICIRCA)* (pp. 916-921). IEEE.
- [14] Ali, N. G., Abed, S. D., Shaban, F. A. J., Tongkachok, K., Ray, S., & Jaleel, R. A. (2021). Hybrid of K-Means and partitioning around medoids for predicting COVID-19 cases: Iraq case study. *Periodicals of Engineering and Natural Sciences*, 9(4), 569-579.
- [15] Gupta, S., Geetha, A., Sankaran, K. S., Zamani, A. S., Ritonga, M., Raj, R., ... & Mohammed, H. S. (2022). Machine learning-and feature selection-enabled framework for accurate crop yield prediction. *Journal of Food Quality*, 2022, 1-7.
- [16] Gupta, S., Geetha, A., Sankaran, K. S., Zamani, A. S., Ritonga, M., Raj, R., ... & Mohammed, H. S. (2022). Machine learning-and feature selection-enabled framework for accurate crop yield prediction. *Journal of Food Quality*, 2022, 1-7.
- [17] Ma, W., Nasriddinov, F., Haseeb, M., Ray, S., Kamal, M., Khalid, N., & Ur Rehman, M. (2022). Revisiting the impact of energy consumption, foreign direct investment, and geopolitical risk on CO2 emissions: comparing developed and developing countries. *Frontiers in Environmental Science*, 1615.
- [18] Shukla, S. (2017). Innovation and economic growth: A case of India. *Humanities & Social Sciences Reviews*, 5(2), 64-70

[19] Soham, S., & Samrat, R. (2021). Poverty and financial dearth as etiopathogen of psychotic and neurotic diseases. *Заметки ученого*, (4-1), 568-578.

[20] Park, J. Y., Perumal, S. V., Sanyal, S., Ah Nguyen, B., Ray, S., Krishnan, R., ... & Thangam, D. (2022). Sustainable marketing strategies as an essential tool of business. *American Journal of Economics and Sociology*, 81(2), 359- 379.

[21] Роков, А. И., Дубаневич, Л. Э., & Рэй, С. (2021). Повышение экономической эффективности труда за счет изменения системы оплаты. *E-Scio*, (9 (60)), 53-62.

[22] Ray, S. (2021). How Emotional Marketing can help better understand the Behavioral Economic patterns of Covid19 pandemic: Economic Judgments and Falsifications from India Samrat Ray-Alagappa University, Tamil Nadu, India. *samratray@ rocketmail. com*. *Вестник МИРБИС*, (2), 26-34.

[23] Ravi, S., Kulkarni, G. R., Ray, S., Ravisankar, M., krishnan, V. G., & Chakravarthy, D. S. K. (2023). Analysis of user pairing non-orthogonal multiple access network using deep Q-network algorithm for defense applications. *The Journal of Defense Modeling and Simulation*, 20(3), 303-316.

[24] Priya, P. S., Malik, P., Mehbodniya, A., Chaudhary, V., Sharma, A., & Ray, S. (2022, February). The relationship between cloud computing and deep learning towards organizational commitment. In 2022 2nd International Conference on Innovative Practices in Technology and Management (ICIPTM) (Vol. 2, pp. 21-26). IEEE.

[25] Ray, S., & Leandre, D. Y. (2021). How entrepreneurial university model is changing the Indian COVID-19 Fight?. *Путеводитель предпринимателя*, 14(3), 153-162.

[26] Inthavong, P., Rehman, K. U., Masood, K., Shaukat, Z., Hnydiuk-Stefan, A., & Ray, S. (2023). Impact of organizational learning on sustainable firm performance: Intervening effect of organizational networking and innovation. *Heliyon*, 9(5).

[27] Rajendran, R., Sharma, P., Saran, N. K., Ray, S., Alanya-Beltran, J., & Tongkachok, K. (2022, February). An exploratory analysis of machine learning adaptability in big data analytics environments: A data aggregation in the age of big data and the internet of things. In 2022 2nd International Conference on Innovative Practices in Technology and Management (ICIPTM) (Vol. 2, pp. 32-36). IEEE.

[28] Elkady, G., & Samrat, R. (2021). An analysis of Blockchain in Supply Chain Management: System Perspective in Current and Future Research. *International Business Logistics*, 1(2).

[29] Korchagina, E., Desfontaines, L., Ray, S., & Strekalova, N. (2021, October). Digitalization of Transport Communications as a Tool for Improving the Quality of Life. In International Scientific Conference on Innovations in Digital Economy (pp. 22-34). Cham: Springer International Publishing.

[30] Kumar, A., Nayak, N. R., Ray, S., & Tamrakar, A. K. (2022). Blockchain-based Cloud Resource Allocation Mechanisms for Privacy Preservation. In *The Data-Driven Blockchain Ecosystem* (pp. 227-245). CRC Press.

[31] Wawale, S. G., Bisht, A., Vyas, S., Narawish, C., & Ray, S. (2022). An overview: Modeling and forecasting of time series data using different techniques in reference to human stress. *Neuroscience Informatics*, 2(3), 100052.

[32] Batool, A., Ganguli, S., Almashaqbeh, H. A., Shafiq, M., Vallikannu, A. L., Sankaran, K. S., ... & Sammy, F. (2022). An IoT and Machine Learning-Based Model to Monitor Perishable Food towards Improving Food Safety and Quality. *Journal of Food Quality*, 2022.

[33] Verma, K., Sundararajan, M., Mangal, A., Ray, S., & Kumar, A. (2022, April). The Impact of COVID-19 to the Trade in India Using Digital, IOT and AI Techniques. In 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE) (pp. 01-05). IEEE.

[34] Bangare, J. L., Kapila, D., Nehete, P. U., Malwade, S. S., Sankar, K., & Ray, S. (2022, February). Comparative Study on Various Storage Optimisation Techniques in Machine Learning based Cloud Computing System. In 2022 2nd International Conference on Innovative Practices in Technology and Management (ICIPTM) (Vol. 2, pp. 53-57). IEEE.

[35] Kiziloglu, M., & Ray, S. (2021). Do we need a second engine for Entrepreneurship? How well defined isintrapreneurship to handle challenges during COVID-19?. In *SHS Web of Conferences* (Vol. 120, p. 02022). EDP Sciences.

[36] Samajpaty, S., & Ray, S. (2020). Innovation strategies in health economics: a force that makes blood move and game of gravity in it-futuristic economic plans. *Московский экономический журнал*, (9), 397-409.

[37] Nikam, R. U., Lahoti, Y., & Ray, S. (2023). A Study of Need and Challenges of Human Resource Management in

Start-up Companies. Mathematical Statistician and Engineering Applications, 72(1), 314-320.

[38] Yanbin, X., Jianhua, Z., Wang, X., Shabaz, M., Ahmad, M. W., & Ray, S. (2023). Research on optimization of crane fault predictive control system based on data mining. Nonlinear Engineering, 12(1), 20220202.

[39] Ray, S., Abinaya, M., Rao, A. K., Shukla, S. K., Gupta, S., & Rawat, P. (2022, October). Cosmetics Suggestion System using Deep Learning. In 2022 2nd International Conference on Technological Advancements in Computational Sciences (ICTACS) (pp. 680-684). IEEE.

[40] Bhaskar, T., Shiney, S. A., Rani, S. B., Maheswari, K., Ray, S., & Mohanavel, V. (2022, September). Usage of Ensemble Regression Technique for Product Price Prediction. In 2022 4th International Conference on Inventive Research in Computing Applications (ICIRCA) (pp. 1439-1445). IEEE.

[41] Kanade, S., Surya, S., Kanade, A., Sreenivasulu, K., Ajitha, E., & Ray, S. (2022, April). A Critical analysis on Neural Networks and Deep Learning Based Techniques for the Cloud Computing System and its Impact on Industrial Management. In 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE) (pp. 325-331). IEEE.

[42] Pallathadka, H., Tongkachok, K., Arbune, P. S., & Ray, S. (2022). Cryptocurrency and Bitcoin: Future Works, Opportunities, and Challenges. ECS Transactions, 107(1), 16313.

[43] Li, Y. Z., Yu, Y. H., Gao, W. S., Ray, S., & Dong, W. T. (2022). The Impact of COVID-19 on UK and World Financial Markets. Jundishapur Journal of Microbiology, 373-399.

[44] Samrat, R., Elkadyghada, E. G., Rashmi, N., & Elena, K. (2022). UPSKILLING AND RESKILLING FOR A GREENER GLOBAL BUSINESS ECOSYSTEM: WEB 4.0 PERSPECTIVE. Журнал прикладных исследований, 1(11), 49-60.

[45] Ray, S. (2022). Fraud detection in e-Commerce using machine learning. BOHR International Journal of Advances in Management Research, 1(1).

[46] Samrat, R. (2021). WHY ENTREPREUNERAL UNIVERSITY FAILS TO SOLVE POVERTY ERADICATION?. Вестник Тувинского государственного университета. № 1 Социальные и гуманитарные науки, (1), 35-43.

[47] Ray, S. (2021). Are Global Migrants At Risk? A Covid Referral Study of National Identity. In Трансформация идентичностей: опыт Европы и России (pp. 26-33).

[48] Saravanan, A., Venkatasubramanian, R., Khare, R., Surakasi, R., Boopathi, S., Ray, S., & Sudhakar, M. POLICY TRENDS OF RENEWABLE ENERGY AND NON RENEWABLE ENERGY.

[49] Varma, A., & Ray, S. (2023). The case of amazons E-commerce digital strategy in India.

[50] Ray, S. (2023). Can Change Management Be Disrupted Through Leadership Stategies?: Evidence From Start-Up Firms in Asia. In Change Management During Unprecedented Times (pp. 100-127). IGI Global.

[51] Al Noman, M. A., Zhai, L., Almukhtar, F. H., Rahaman, M. F., Omarov, B., Ray, S., ... & Wang, C. (2023). A computer vision-based lane detection technique using gradient threshold and hue-lightness-saturation value for an autonomous vehicle. International Journal of Electrical and Computer Engineering, 13(1), 347.

[52] Nayak, N. R., Kumar, A., Ray, S., & Tamrakar, A. K. (2023). Blockchain-Based Cloud Resource Allocation Mechanism for Privacy Preservation (No. 9700). EasyChair.

[53] Ray, S. (2023). XA-GANOMALY: AN EXPLAINABLE ADAPTIVE SEMI-SUPERVISED LEARNING METHOD FOR INTRUSION DETECTION USING GANOMALY IN GLOBAL ECONOMIC DYNAMIC SHIFTS. ЭКОНОМИЧЕСКАЯ СРЕДА, 4.

[54] Zamani, A. S., Rajput, S. H., Bangare, S. L., & Ray, S. (2022). Towards Applicability of Information Communication Technologies in Automated Disease Detection. International Journal of Next-Generation Computing, 13(3).

[55] Korchagina, E. V., Barykin, S. E., Desfontaines, L. G., Ray, S., Shapovalova, I. M., & Repnikova, V. (2022). Digitalisation of Ecosystem-Based Management and the Logistics Potential of the Arctic Region. Journal of Environmental Assessment Policy and Management, 24(03), 2250034.

[56] Zamani, A. S., Rajput, S. H., Bangare, S. L., & Ray, S. (2022). Towards Applicability of Information Communication Technologies in Automated Disease Detection. International Journal of Next-Generation Computing, 13(3).

[57] Ray, S., Korchagina, E. V., Druzhinin, A. E., Sokolovskiy, V. V., & Kornev, P. M. (2022, April). Emergence of the New Start Up Ecosystem: How Digital Transformation Is Changing Fintech and Payment System in Emerging Markets?.

[58] Wagh, S., Nikam, R., & Ray, S. (2022). Exploration of the Higher Education System's Mechanism and Impact on More Than Just the Effective Growth of the Indian Economy. *Globsyn Management Journal*, 16(1/2), 85-91.

[59] Ray, S., Korchagina, E. V., Druzhinin, A. E., Sokolovskiy, V. V., & Kornev, P. M. (2022, April). Emergence of the New Start Up Ecosystem: How Digital Transformation Is Changing Fintech and Payment System in Emerging Markets?. In International Scientific Conference "Digital Transformation on Manufacturing, Infrastructure & Service" (pp.621-638). Cham: Springer Nature Switzerland.

[60] Chakraborty, T., & Ray, S. (2022). STRATEGIES OF CYBERLOAFING AND PHUBBING WHICH AFFECT WORKPLACE DIGITAL TRANSFORMATION. *Московский экономический журнал*, (10), 430-446.

[61] Ray, S., & Pal, R. P. (2022). IMPORTANCE OF ENTREPRENEURSHIP AND INNOVATION IN THE HEALTHCARE INDUSTRY DURING THE COVID-19 PANDEMIC. *Beneficium*, (2 (43)), 85-93.

[62] Samrat, R., Pratap, P. R., & Korchagina, E. V. (2022). WORLD ECONOMY AND INTERNATIONAL COOPERATION· МИРОВАЯ ЭКОНОМИКА И МЕЖДУНАРОДНОЕ СОТРУДНИЧЕСТВО.

[63] Ray, S., & Pal, R. P. (2021). ARE WE TRANSFORMING OUR PAYMENT THROUGH INNOVATION IN FINTECH AND THE DIGITAL ECONOMY? PERSPECTIVES FROM ASIAN DRAMA IN FINTECH INNOVATION©.

[64] Samrat, R. (2021). NEUROMARKETING EVIDENCES FROM THE ECONOMICS OF BOOKSELLERS ON THE STREETS: COVID-19 PERSPECTIVES AND IMPLICATIONS ON LUXURY BRANDS GLOBALLY. *Экономика и управление инновациями*, (2), 83-90.

[65] Korchagina, E. V., & Ray, S. (2021). TRIPLE HELIX CONCEPT IN INNOVATIVE UNIVERSITY DEVELOPMENT MODEL.

[66] Ray, S., & Pal, R. P. (2021). ARE WE TRANSFORMING OUR PAYMENT THROUGH INNOVATION IN FINTECH ANDTHE DIGITAL ECONOMY? PERSPECTIVES FROM ASIAN DRAMA IN FINTECH INNOVATION©.

[67] Самрат, Р. (2021). НЕЙРОМАРКЕТИНГ В ЭКОНОМИКЕ КНИЖНЫХ МАГАЗИНОВ НА УЛИЦАХ: ПЕРСПЕКТИВЫ ГЛОБАЛЬНОГО ВЛИЯНИЯ COVID-19 НА ЛЮКСОВЫЕ БРЕНДЫ. *Экономика и управление*, (2), 83-90.

[68] Ray, S., Muhammad, G., & Adnan, M. The administrative role of principals: Insights and implication in secondary schools of.

[69] Pradhan, D., Ray, S., & Dash, A. A Critical Review on Sustainable Development of Green Smart Cities (GSCs) for Urbanization. *communities* (Fig. 1), 13, 15.

[70] Van Minh, N., Huu, N. N., & Ray, S. Responses of varied quinoa (*Chenopodium quinoa* Willd.) genotypes grown in Central Highlands, Vietnam.

[71] Ray, S., Nikam, R., Vanjare, C., & Khedkar, A. M. Comparative Analysis Of Conventional And Machine Learning Based Forecasting Of Sales In Selected Industries.