

**A STUDY ON GENAI ADOPTION FOR TELECOMMUNICATION AND GENERAL
MANAGEMENT**

by

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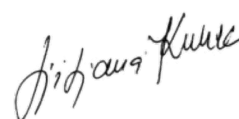
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Dedication

I dedicate this thesis to the leaders, innovators, researchers, and practitioners who are advancing the adoption of Generative Artificial Intelligence in telecommunications and general management. Their commitment to innovation, digital transformation, and organizational excellence continues to shape the future of intelligent enterprises.

I extend my sincere gratitude to my mentors, supervisors, educators, and members of professional and innovation communities whose guidance, expertise, and encouragement have been invaluable throughout this doctoral journey. Their insights have inspired and enriched this research.

Finally, I dedicate this work to my family and friends for their unwavering support, patience, and belief in my aspirations. Their encouragement has been a constant source of strength, making this achievement possible.

This thesis reflects not only my efforts but also the collective support, inspiration, and shared pursuit of knowledge that have accompanied me throughout this journey.

With deep gratitude,

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Abstract

The rapid proliferation of Generative Artificial Intelligence (GenAI) across digital industries has intensified pressure on telecommunications organizations to adopt, govern, and strategically integrate these technologies. Yet adoption in the Indian telecom sector remains fragmented and sub-optimal, constrained not solely by technical infrastructure deficits but more fundamentally by how organizational leaders and managers perceive the technology's value, reliability, governance adequacy, and strategic relevance. This study investigates the organizational perception dimensions that shape GenAI adoption in Indian telecom organizations and examines how these dimensions influence adoption behavior and practical use. A sequential explanatory mixed-method design was employed, combining Exploratory Factor Analysis (EFA) of questionnaire data from 215 Indian telecom professionals with NVivo-assisted qualitative thematic analysis of eleven semi-structured interviews. EFA identified five empirically distinct perception factors: Perceived Performance and Operational Value ($\alpha = 0.892$; $EV = 7.12$); Technological Capability and Readiness ($\alpha = 0.861$); Trust, Reliability, and Risk Perception ($\alpha = 0.834$); Governance and Regulatory Awareness ($\alpha = 0.801$); and Strategic Alignment and Innovation Orientation ($\alpha = 0.847$), collectively explaining 68.72 percent of total variance ($KMO = 0.901$; Bartlett's $p < 0.001$). NVivo analysis generated six coherent themes that confirm how these perceptual dimensions manifest as adoption behavior patterns, revealing that trust operates as a deployment scope regulator rather than merely an adoption intent predictor, governance gaps function as structural barriers requiring policy-level intervention, and strategic alignment differentiates adoption leaders from laggards across the Indian telecom sector. Integrating both phases of analysis, the study develops a six-component, ten-step adoption framework with dual applicability for Indian telecommunications policymakers and organizational practitioners. The study extends classical technology adoption models including TAM, UTAUT, and the TOE framework by empirically grounding governance awareness and strategic alignment as independent perception dimensions, and contributes the first mixed-method, sector-specific GenAI adoption study in Indian telecommunications.

Keywords - Generative AI, Technology Adoption, Organizational Perception, Indian Telecommunications, Exploratory Factor Analysis, NVivo Thematic Analysis, AI Governance, Strategic Alignment

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1.1 Background of the Study

The rapid and sustained advancement of digital technologies has fundamentally transformed how organizations design their processes, deliver services, manage knowledge assets, and formulate strategic decisions. Among these technological developments, **Generative Artificial Intelligence (GenAI)** has emerged as one of the most consequential, distinguished by its capacity to generate human-like text, images, code, analytical recommendations, and multimodal outputs. Unlike earlier generations of artificial intelligence, which were predominantly focused on prediction, classification, and structured automation, Generative AI extends the technological frontier into cognitive and creative domains. Its applications span decision-making augmentation, content generation, customer interaction management, knowledge synthesis, innovation support, and operational optimization, making it directly relevant to organizations operating in complex, data-intensive competitive environments (Brown et al., 2020; Brynjolfsson et al., 2023; Dwivedi et al., 2023).

Across industry sectors, organizations have increasingly begun exploring Generative AI as a means to improve operational productivity, reduce complexity, strengthen customer engagement, and generate new sources of competitive advantage. However, the effective adoption of Generative AI is not solely a function of technological availability. It is equally, if not more profoundly, shaped by how organizational leaders, managers, and professionals perceive the technology in terms of its usefulness, reliability, associated risks, ethical implications, and strategic relevance. This perceptual dimension is especially significant because Generative AI systems continue to evolve rapidly and generate ongoing concerns related to trust, transparency, output accuracy, algorithmic bias, data privacy, and governance accountability (Bender et al., 2021; Floridi, 2019; Jobin et al., 2019; Pathan & Shah, 2025). The adoption of Generative AI must therefore be understood as simultaneously a technological, organizational, and managerial phenomenon, one in which perception mediates the relationship between technological capability and organizational action.

The **telecommunications sector** constitutes a particularly significant context for studying Generative AI adoption. Telecom organizations operate in highly dynamic, data-driven, and customer-intensive environments where service reliability, network performance, operational efficiency, and customer experience are foundational to competitive positioning. The Indian telecommunications sector, representing one of the largest and fastest-growing telecom markets globally, provides an especially pertinent empirical setting. With over 1.2 billion subscribers, growing 5G infrastructure, and increasing regulatory attention to AI governance, Indian telecom organizations face both accelerating pressure and structural complexity in their adoption of intelligent systems (TRAI, 2024; TEC, 2024; Telecom Review Asia, 2025). The sector has already undergone substantial transformation through digitalization, cloud-based infrastructure, automation, and AI-enabled network systems; Generative AI represents the next stage of this transformation trajectory (Accenture, 2023; GSMA Intelligence, 2023; Lin et al., 2024).

Despite these opportunities, Generative AI adoption within telecom organizations remains uneven and structurally complex. Many firms continue to face challenges related to legacy infrastructure, fragmented data architectures, regulatory constraints, data governance requirements, cybersecurity vulnerabilities, and workforce capability deficits. Critically, these challenges are not purely technical. They are also mediated by managerial interpretation, organizational readiness, leadership orientation, employee acceptance, and the perceived balance between anticipated benefits and potential risks. As a result, telecom organizations frequently experiment with Generative AI at a pilot or proof-of-concept stage without successfully scaling it across functions in a structured, sustainable, and strategically aligned manner (Britto et al., 2023; Reznikov, 2024; Deloitte, 2024; Westover, 2024).

Established theoretical frameworks for technology adoption, including the **Technology Acceptance Model (TAM)** (Davis, 1989), the **Unified Theory of Acceptance and Use of Technology (UTAUT)** (Venkatesh et al., 2003), and **Diffusion of Innovation Theory (DOI)** (Rogers, 2003), offer foundational insights into how individuals and organizations evaluate and adopt new technologies. These models emphasize perceived usefulness, ease of use, social influence, facilitating conditions, compatibility, and relative advantage as central determinants of adoption behavior. However, Generative AI introduces adoption challenges that these frameworks were not originally designed to address, including probabilistic and opaque output

generation, ethical risks arising from autonomous content creation, and governance implications that extend beyond individual-level technology acceptance (Bender et al., 2021; Floridi & Chiriatti, 2020; Dwivedi et al., 2023; Seifdar & Amiri, 2025). There is, accordingly, a compelling theoretical need to extend traditional adoption models by incorporating perception-related, organizational, and governance-oriented constructs relevant to Generative AI in regulated, complex-sector settings.

The present study is grounded in the premise that **organizational perception plays a central and constitutive role in shaping Generative AI adoption**. Leaders and managers do not adopt emerging technologies solely because of their technical availability or capability. Rather, they interpret technologies through the lens of organizational priorities, strategic pressures, risk awareness, ethical expectations, and perceived readiness. When Generative AI is perceived as useful, reliable, strategically aligned, and governable, adoption is more likely to advance. Conversely, when perceived as risky, opaque, ungovernable, or strategically misaligned, adoption tends to remain hesitant, fragmented, or superficial (Davis, 1989; Venkatesh et al., 2003; Vial, 2019; Chen & Li, 2025). This study therefore examines Generative AI adoption through a perception-based analytical lens, seeking to identify latent factors that shape organizational perceptions, examine how these factors influence adoption and practical use, and develop a comprehensive framework to guide policymakers and decision-makers in enabling responsible and effective adoption within the telecom sector.

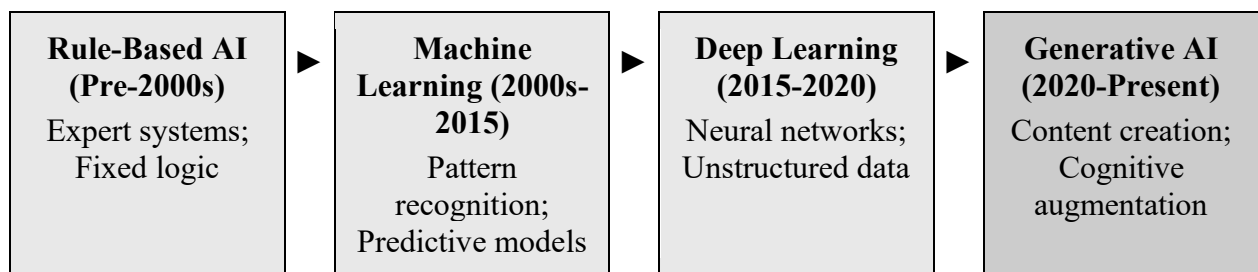


Figure 1.1: Evolution of Artificial Intelligence Toward Generative AI in Organizational Contexts (Sources: Brown et al., 2020; Brynjolfsson et al., 2023; Dwivedi et al., 2023)

1.1.1 Evolution of Generative Artificial Intelligence in Organizational Contexts

Generative Artificial Intelligence represents a decisive transition in the developmental history of AI. Earlier organizational applications of artificial intelligence were predominantly associated

with rule-based expert systems and machine learning classifiers designed for specific, bounded functions such as fraud detection, demand forecasting, customer segmentation, and process automation. While these systems delivered measurable efficiency gains, they were limited by their inability to generate novel content, adapt flexibly across domains, or support higher-order cognitive tasks (Raisch & Krakowski, 2021; Hanelt et al., 2021).

The emergence of deep learning architectures in the mid-2010s substantially extended AI capabilities by enabling the processing of unstructured data at scale, including text, images, audio, and transactional records. This phase of development significantly broadened the organizational utility of AI and reinforced its role as a foundational enabler of digital transformation (Vial, 2019; Verhoef et al., 2021; Kraus et al., 2022). The subsequent development of transformer-based large language models and generative adversarial networks from 2020 onwards has marked a qualitative shift in AI capability, enabling systems not merely to recognize patterns but to generate contextually meaningful, human-like outputs across a wide range of tasks (Brown et al., 2020; Bommasani et al., 2024; Touvron et al., 2023).

Generative AI has repositioned artificial intelligence as a general-purpose technology with systemic implications for organizational design, strategic decision-making, and competitive positioning. Unlike tools confined to operational efficiency, Generative AI extends into cognitive and strategic domains: report generation, scenario simulation, market analysis, knowledge synthesis, and innovation support (Brynjolfsson et al., 2023; Doshi et al., 2024; Vujovic, 2024). Studies conducted in the Indian context confirm that this trajectory is not confined to Western markets; Indian technology organizations and telecom providers have begun integrating Generative AI into customer operations, software development, and service intelligence at increasing scale (Kumar & George, 2024; Telecom Review Asia, 2025; TEC, 2024).

1.1.2 Generative AI in the Telecommunications Industry

The telecommunications industry offers a uniquely pertinent setting for examining Generative AI adoption. Telecom organizations are among the most data-intensive enterprises globally, continuously managing vast streams of network performance data, customer transaction records, usage analytics, and operational metrics. The ongoing expansion of 5G networks, cloud-native architectures, Internet of Things ecosystems, and edge computing infrastructure has substantially

increased the operational complexity of telecom systems and generated growing demand for intelligent, adaptive decision-support capabilities (GSMA Intelligence, 2023; Accenture, 2023; Chetty et al., 2025).

Generative AI extends telecom capabilities well beyond conventional automation and predictive analytics. Earlier AI applications in telecom addressed specific, bounded functions such as network fault prediction, churn management, fraudulent activity detection, and customer tier segmentation. Generative AI enables a qualitatively richer set of applications, including conversational customer support through natural language interfaces, automated root-cause analysis and network diagnostic generation, intelligent service design and personalization, knowledge retrieval for technical support personnel, and strategic decision simulation for senior management (Lin et al., 2024; Karapantelakis et al., 2024; Britto et al., 2023; Rahman et al., 2023).

In the Indian telecom context, adoption of AI-driven solutions has gained considerable momentum. Reports indicate that a significant proportion of Indian telecom firms have moved beyond pilot stages to implement AI solutions at scale, with measurable improvements in customer satisfaction, network reliability, and operational cost management (Telecom Review Asia, 2025; TEC, 2024; Infosys, 2024). The Telecom Engineering Centre (2024) has identified Generative AI as a priority technology for next-generation network management, while the Telecom Regulatory Authority of India (TRAI, 2024) has begun formulating guidelines for responsible AI deployment within the sector. These developments reflect the growing institutional recognition of Generative AI as both a transformative opportunity and a governance challenge for Indian telecom.

Nevertheless, adoption within the sector remains uneven. Challenges related to legacy infrastructure compatibility, data governance under Indian data protection regulations, cybersecurity risk management, and workforce AI literacy continue to constrain the pace and depth of adoption (Agarwal & Nene, 2025; Reznikov, 2024; Bariah et al., 2023). Importantly, recent studies confirm that beyond these structural barriers, the perceptions of organizational leaders and managers regarding AI reliability, trustworthiness, ethical implications, and strategic alignment are critical determinants of whether adoption moves from experimentation to sustained organizational integration (Chen & Li, 2025; Gomes et al., 2025; Deloitte, 2024).

1.1.3 Generative AI in General Management and Strategic Decision-Making

Beyond telecom operations, Generative AI is increasingly reshaping the practice of general management, particularly in the domain of strategic decision-making. Senior managers and executives are leveraging Generative AI tools to synthesize large and heterogeneous information sets, generate structured strategic alternatives, and simulate potential business scenarios across competitive and regulatory environments (Doshi et al., 2024; Jarrahi et al., 2021; Bevilacqua et al., 2025). This represents a substantive shift from intuition-driven or data-limited decision processes toward augmented, computationally supported strategic reasoning.

The integration of Generative AI into management functions challenges established organizational hierarchies and decision-making structures. As AI systems demonstrate the capacity to produce high-confidence recommendations across diverse domains, organizations are developing hybrid human-AI decision models in which machine-generated outputs are treated as inputs to, rather than substitutes for, human judgment (Shrestha et al., 2019; Raisch & Krakowski, 2021; Mayer et al., 2025). This transition requires new leadership competencies, adapted governance structures, and revised organizational design principles to maintain appropriate human oversight, ensure accountability, and coordinate effectively between human and machine intelligence (Gong et al., 2024; Shatila, 2025).

1.1.4 Strategic Importance of Generative AI Adoption

The adoption of Generative AI is increasingly regarded as a strategic imperative for organizations competing in digitally disrupted environments. Academic research and global industry analyses consistently confirm that organizations successfully integrating AI into core operations achieve measurable improvements across productivity, innovation capacity, and customer engagement dimensions (Dwivedi et al., 2023; Deloitte, 2024; Brynjolfsson et al., 2023). Within the Indian telecommunications sector, this strategic imperative is amplified by the intensity of competition, rapid technological change, evolving regulatory requirements, and growing customer expectations around service personalization and reliability.

The strategic value of Generative AI extends beyond operational efficiency gains. Organizations at the frontier of AI adoption are redefining their business models, restructuring value creation processes, and establishing new sources of competitive differentiation that are difficult for laggards to replicate rapidly (Iansiti & Lakhani, 2020; Aldoseri et al., 2024; Cannavale, 2025).

Studies on AI capability and firm performance demonstrate that organizations combining strong AI infrastructure with aligned organizational practices and governance structures significantly outperform those treating AI as isolated tools (Mikalef et al., 2020; Wamba, 2022; Li et al., 2021). This reinforces the position that Generative AI adoption must be understood and managed as an organizational transformation process, not merely as a technology deployment exercise.

1.1.5 Challenges in Generative AI Adoption

Despite its transformative potential, Generative AI adoption is attended by a complex and interrelated set of challenges that span technical, organizational, behavioral, and regulatory dimensions. In the telecommunications sector, legacy infrastructure constitutes a primary structural barrier: existing operational support and business support systems are typically designed for static, rule-based processes and are poorly suited to the dynamic, context-sensitive outputs generated by AI-native architectures (Britto et al., 2023; Reznikov, 2024). The resource intensity and technical complexity of retrofitting legacy environments for AI integration creates a significant implementation burden, particularly for mid-tier and regional telecom operators.

Organizational and behavioral challenges are equally significant. Change resistance, digital skills deficits, and employee skepticism regarding AI reliability collectively constrain adoption progress within organizations (Westover, 2024; Loh et al., 2023; Muhammad, 2025). Strategic misalignment, whereby AI initiatives are implemented within isolated functional silos without integration into enterprise-wide strategy and performance management frameworks, represents a further recurring impediment identified across multiple studies (Doshi et al., 2024; Zhang et al., 2025; Najana, 2024). These dimensions collectively underscore that Generative AI adoption is a multidimensional organizational challenge demanding coordinated responses across technological, managerial, cultural, and governance fronts.

Table 1.1: Key Challenges in Generative AI Adoption in the Telecom Sector (Sources: Britto et al., 2023; Reznikov, 2024; Bender et al., 2021; Pathan & Shah, 2025; TRAI, 2024; Deloitte, 2024)

Challenge Category	Description and Organizational Implications
Legacy Infrastructure	Existing OSS/BSS systems lack flexibility for AI-native architectures, creating integration complexity (Britto et al., 2023).
Data Governance	Regulatory constraints on customer and network data limit dataset availability for GenAI training (Reznikov, 2024; TRAI, 2024).
Workforce Capability	Skills deficits in AI literacy, prompt engineering, and model governance constrain effective deployment (Westover, 2024).
Governance Gaps	Absence of sector-specific AI governance frameworks creates accountability and compliance uncertainty (Pathan & Shah, 2025; TEC, 2024).
Perceptual Barriers	Trust deficits, bias concerns, and strategic misalignment reduce managerial willingness to scale AI adoption (Bender et al., 2021; Deloitte, 2024).

1.1.6 Governance, Ethics, and Organizational Readiness

The deployment of Generative AI raises governance and ethical considerations that organizations cannot address as afterthoughts. Core concerns include algorithmic bias in model outputs, lack of transparency in generative processes, accountability gaps when AI-generated content influences consequential decisions, and privacy risks arising from the processing of sensitive customer and network data (Floridi, 2019; Jobin et al., 2019; Hagendorff, 2020; Binns, 2018). In telecom organizations, where AI applications may directly affect customer communications, network reliability decisions, and fraud management, the stakes of these concerns are particularly high.

Globally, governance frameworks for AI have proliferated but frequently remain at the level of high-level principles without adequate operational guidance for sector-specific deployment (Morley et al., 2020; Mokander et al., 2021; OECD, 2023). In the Indian context, while data protection legislation and sectoral guidelines from TRAI and TEC are evolving, gaps remain in addressing AI-specific risks such as output hallucination, systemic bias, and incident accountability (Agarwal & Nene, 2025; Pathan & Shah, 2025). Organizational readiness, encompassing leadership commitment, cultural openness to AI, workforce AI capability, and institutional governance structures, plays a correspondingly critical role in determining whether

Generative AI is adopted responsibly and sustainably (Alghamdi & Rehman, 2026; Shatila, 2025; Dacre, 2024).

1.2 Problem Context

1.2.1 Strategic Relevance and Fragmented Adoption

Generative AI has been widely recognized as a critical enabler of organizational transformation across both the telecommunications industry and general management functions. In telecom environments, growing data traffic volumes, increasing network complexity, and rising customer expectations have created sustained demand for intelligent, adaptive systems. Generative AI addresses these demands through automated customer support, predictive maintenance, anomaly detection, knowledge retrieval, and dynamic service optimization, offering substantial potential to enhance operational efficiency and service quality (Accenture, 2023; Lin et al., 2024; GSMA Intelligence, 2023).

Despite this recognized strategic relevance, Generative AI adoption remains notably fragmented across telecom organizations. Only a limited proportion of firms have successfully scaled AI initiatives beyond pilot stages to achieve enterprise-wide deployment with demonstrable business impact. Empirical evidence consistently indicates that organizations encounter difficulties in translating initial AI experiments into sustained operational value, attributable to unclear return on investment metrics, insufficient organizational capability, and weak integration with broader strategic frameworks (Simaremare & Edison, 2024; Seifdar & Amiri, 2025; Dwivedi et al., 2023). This fragmentation represents a significant strategic gap, as organizations that fail to scale AI adoption risk falling behind competitors that successfully harness its transformative potential.

1.2.2 Organizational Resistance and Leadership Readiness Gaps

Organizational and behavioral dynamics exercise profound influence over Generative AI adoption trajectories. Resistance to change remains a pervasive challenge, particularly in organizations where employees and middle managers perceive AI technologies as threats to professional autonomy, existing role definitions, or job security (Westover, 2024; Muhammad, 2025). Such perceptions tend to reduce engagement, inhibit cross-functional collaboration, and

generate institutional reluctance to invest in the organizational change processes necessary for effective AI integration.

Leadership readiness is an equally consequential factor. Global surveys indicate that a substantial proportion of senior executives express limited confidence in their organization's preparedness to manage AI-driven transformation, despite expressing strong interest in its potential benefits (Deloitte, 2024; Ransbotham et al., 2021). In the Indian telecom context, where organizations simultaneously navigate infrastructure modernization, regulatory compliance, and market competition, leadership bandwidth and AI strategic expertise are frequently constrained (TEC, 2024; TRAI, 2024). Successful Generative AI adoption therefore requires leadership capable of aligning AI investment with organizational objectives, managing the complexities of large-scale technological change, and building institutional trust in AI-generated outputs.

1.2.3 Governance, Ethical, and Regulatory Complexities

The implementation of Generative AI introduces governance and ethical complexities that extend well beyond conventional technology risk management. Generative systems produce autonomous outputs whose reliability and bias characteristics are not always transparent or controllable, creating accountability challenges when these outputs influence consequential decisions in areas such as customer communication, network management, or strategic planning (Bender et al., 2021; Floridi, 2019; Pathan & Shah, 2025).

In Indian telecom environments, governance challenges are compounded by the evolving regulatory landscape. The Telecom Engineering Centre (2024) and TRAI (2024) have begun addressing AI-related governance requirements, yet gaps persist in providing operationally specific guidance on issues such as AI output auditing, bias testing, incident reporting, and accountability allocation. The absence of structured, sector-specific governance frameworks creates compliance uncertainty and inhibits organizational confidence in scaling Generative AI deployment (Agarwal & Nene, 2025; Klein et al., 2023; OECD, 2023). At the international level, while frameworks such as the OECD AI Principles (2023) and guidelines from UNESCO and ITU provide normative direction, their translation into sector-specific operational protocols for telecom organizations remains incomplete.

1.2.4 Strategic Misalignment and the Absence of Integrated Frameworks

A critical and recurring issue in Generative AI adoption is the misalignment between AI initiatives and broader organizational strategy. Organizations frequently implement AI solutions within individual functional units without embedding these initiatives in enterprise-wide strategic frameworks, limiting their cumulative organizational impact and creating duplication and inconsistency (Doshi et al., 2024; Zhang et al., 2025). This siloed approach also undermines the development of shared AI governance norms and cross-functional learning, both of which are essential for scaling AI responsibly.

The absence of integrated, multidimensional adoption frameworks compounds this challenge. Existing research on Generative AI adoption has tended to examine individual dimensions, whether technological capability, organizational readiness, or governance requirements, in relative isolation, without offering comprehensive frameworks that integrate these dimensions with the perceptual dynamics that shape managerial decision-making (Gomes et al., 2025; Zhou et al., 2025; Ali et al., 2025). Organizations, and particularly Indian telecom organizations navigating complex regulatory and infrastructural contexts, require empirically grounded frameworks that acknowledge the interdependence of perception, capability, governance, and strategy in shaping adoption outcomes.

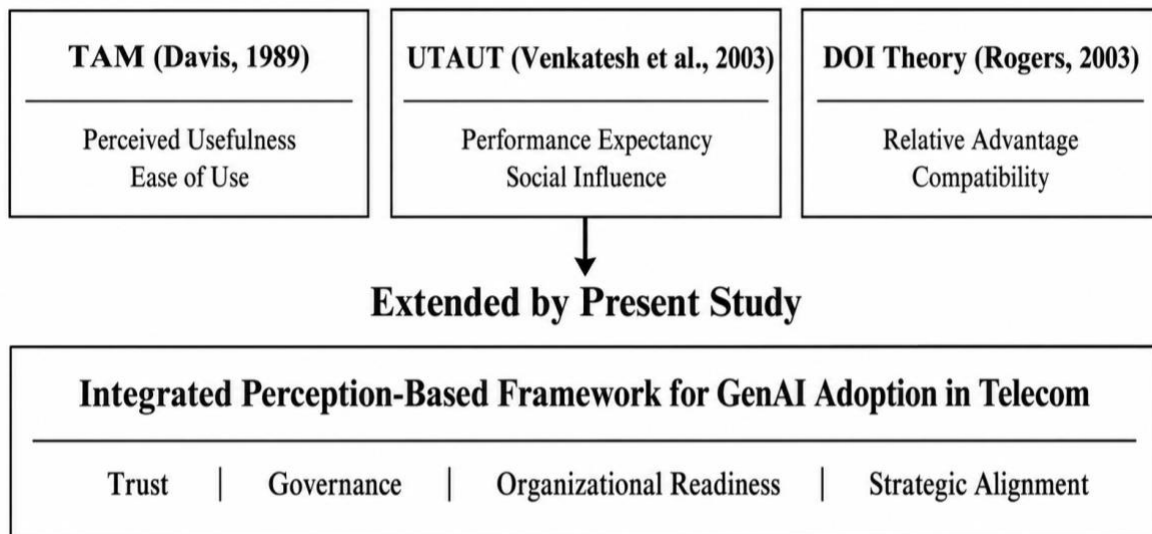


Figure 1.2: Theoretical Framework Map: From Classical Adoption Models to an Integrated GenAI Framework (Sources: Davis, 1989; Venkatesh et al., 2003; Rogers, 2003)

1.2.5 Problem Statement

The adoption of Generative Artificial Intelligence within Indian telecom organizations remains fragmented and strategically sub-optimal despite its considerable and well-documented potential. Organizations continue to encounter interconnected challenges relating to legacy infrastructure, governance gaps, leadership readiness deficits, cultural resistance, and perception-related barriers. Existing research has not provided a comprehensive, empirically grounded, and sector-specific understanding of how these factors interact to shape adoption outcomes within the telecom context. This gap constrains the capacity of both organizations and policymakers to enable, scale, and govern Generative AI adoption in a structured, responsible, and strategically coherent manner. The present study directly addresses this gap.

1.3 Research Objectives

The research objectives of the present study are formulated to examine the role of organizational perception in shaping the adoption and utilization of Generative Artificial Intelligence within the telecom sector. Prior research consistently confirms that technology adoption is determined not only by technical capability but also by managerial perception, organizational readiness, and contextual conditions (Davis, 1989; Venkatesh et al., 2003; Dwivedi et al., 2021; Gomes et al., 2025). In the Generative AI context, these perceptual and behavioral dimensions are especially critical given the centrality of trust, governance, and ethical implications (Bender et al., 2021; Pathan & Shah, 2025; Chen & Li, 2025). The study is guided by the following three objectives:

1. To identify the underlying factors that shape telecom organizational leaders' and managers' perceptions of Generative Artificial Intelligence.
2. To examine how perception-related factors influence the adoption and practical use of Generative Artificial Intelligence within telecom organizations.
3. To develop a comprehensive, policy-oriented framework to guide policymakers in supporting, regulating, and enabling the effective and responsible use of Generative Artificial Intelligence in the telecom sector.

1.4 Research Questions

The research questions are derived directly from the stated objectives and are structured to explore the perception-adoption relationship within telecom organizations systematically. Literature on digital transformation and AI adoption emphasizes the importance of understanding how managerial interpretation and organizational context mediate technology

integration (Vial, 2019; Verhoef et al., 2021; Brynjolfsson et al., 2023; Zhang et al., 2025). The following research questions guide the study:

- RQ1: What are the underlying factors that shape telecom leaders' and managers' perceptions of Generative Artificial Intelligence?
- RQ2: How do perception-related factors influence the adoption and practical use of Generative Artificial Intelligence in telecom organizations?
- RQ3: How can a comprehensive framework be developed to support policymakers in guiding the effective and responsible use of Generative Artificial Intelligence in the Indian telecom sector?

1.5 Research Hypotheses

The following hypotheses are formulated to test the existence of perception-related factors, their influence on adoption outcomes, and the efficacy of an integrated adoption framework (Hair et al., 2019; Kline, 2015; Venkatesh et al., 2013):

Hypothesis	Statement
H1	There exist significant underlying factors that explain telecom organizational perceptions of Generative Artificial Intelligence.
H2	Perception-related factors significantly influence the adoption and practical use of Generative Artificial Intelligence in telecom organizations.
H3	An integrated strategic framework combining perception, technological, and organizational factors significantly enhances the effectiveness of Generative Artificial Intelligence adoption in telecom organizations.

Table 1.2: Hypothesis Statements

1.6 Significance of the Study

The significance of the present study rests on its contributions across theoretical, empirical, practical, and policy dimensions, each directly addressing documented gaps in the existing literature.

Theoretically, the study extends classical technology adoption frameworks by incorporating constructs particularly salient to Generative AI contexts, specifically trust and reliability perception, ethical concern, governance awareness, and strategic alignment. Where TAM and UTAUT foregrounded perceived usefulness and ease of use (Davis, 1989; Venkatesh et al.,

2003), and where Diffusion of Innovation theory emphasized innovation characteristics (Rogers, 2003), the present study argues empirically that Generative AI requires an extended framework that acknowledges the governance-laden, ethically complex, and organizationally embedded nature of adoption decisions (Bender et al., 2021; Floridi & Chiriatti, 2020; Chen & Li, 2025; Gomes et al., 2025).

Empirically, the study contributes sector-specific evidence from Indian telecom organizations, a context underrepresented in the global AI adoption literature despite its structural complexity and strategic importance. The combination of Exploratory Factor Analysis for quantitative dimension identification and NVivo-assisted qualitative thematic analysis for interpretive depth provides a methodologically rigorous mixed-method foundation (Venkatesh et al., 2013; Hair et al., 2019; Saunders et al., 2019).

From a practical standpoint, the study generates actionable insights for telecom managers and organizational leaders. The identification of perception-related adoption barriers and enablers informs change management design, AI governance policy, and capability investment decisions. From a policy perspective, the framework developed in the study provides structured guidance for institutions including TRAI, TEC, and the Ministry of Communications in shaping AI governance standards, workforce readiness programs, and responsible deployment guidelines for the Indian telecom sector (TRAI, 2024; TEC, 2024; Agarwal & Nene, 2025; OECD, 2023).

1.7 Scope of the Study

The scope of the present study is defined along four dimensions: sector, geography, methodology, and analytical focus. In terms of sector, the study is confined to the telecommunications industry in India, with respondents comprising organizational leaders, managers, and professionals directly or indirectly involved in AI-related decision-making, technology implementation, or operational management within telecom organizations.

Geographically, the study is conducted within the Indian telecom sector, providing empirical grounding in one of the world's largest and most rapidly evolving telecom markets. While the conceptual insights and framework generated are expected to have broader applicability, findings reflect the institutional, regulatory, and operational characteristics of the Indian context and

should be interpreted accordingly. The Telecom Engineering Centre (2024) and TRAI (2024) frameworks provide the regulatory backdrop within which adoption is examined.

Methodologically, the study employs a sequential mixed-method design. The quantitative phase utilizes a structured Likert-scale questionnaire analyzed through Exploratory Factor Analysis (EFA) to identify underlying perception dimensions, without predefining factor structures (Hair et al., 2019; Fabrigar & Wegener, 2011; Field, 2018). The qualitative phase employs semi-structured interviews analyzed using NVivo to examine how identified factors manifest in organizational decisions, practices, and adoption experiences, providing contextual depth and interpretive richness (King et al., 2018; Bryman & Bell, 2015).

Analytically, the study focuses on perception-based factors and their relationship to adoption behavior; it does not encompass technical AI system design, network architecture specifications, or system-level implementation protocols. The policy framework developed is oriented toward strategic, governance, and organizational dimensions of adoption, rather than technical deployment guidance.

1.8 Structure of the Thesis

The thesis is organized into six chapters designed to ensure a logically coherent and methodologically integrated progression from conceptual foundation through empirical investigation to conclusion and policy recommendation. The following table provides a structured overview of each chapter and its primary content focus:

Table 1.3: Flow of the thesis

Chapter	Title	Key Content
1	Introduction	Background, problem context, objectives, research questions, hypotheses, significance, scope, and thesis structure.
2	Literature Review	Evolution of GenAI, telecom applications, TAM/UTAUT/DOI frameworks, governance, ethics, framework perspectives, and research gap.
3	Research Methodology	Research Onion framework, pragmatic philosophy, mixed-method design, EFA instrument, NVivo-assisted thematic analysis, sampling, and validity measures.

4	Data Analysis and Framework Development	EFA factor solution, NVivo thematic findings, integrated interpretation, and development of the ten-step adoption framework.
5	Discussion	Interpretation of findings against objectives, theoretical frameworks, and existing literature. Hypothesis alignment.
6	Conclusion and Recommendations	Summary of contributions, limitations, policy recommendations, and future research directions.

The organization of the thesis reflects the sequential and integrative logic underpinning the research design. Quantitative findings generated in Chapter 4 provide the empirical foundation for qualitative interpretation in the same chapter, which together inform the theoretical discussion in Chapter 5 and the policy-oriented conclusions and recommendations in Chapter 6. Each chapter builds systematically upon its predecessors to ensure internal coherence across the full thesis.

2.1 Introduction to the Literature Review

The literature review provides the conceptual, theoretical, and empirical foundation upon which the present study is built. It is structured to examine Generative Artificial Intelligence adoption systematically, progressing from the evolution of the technology through its organizational and sector-specific applications, to the theoretical models that explain how individuals and organizations adopt emerging technologies, and finally to the organizational, perceptual, and human-AI dimensions that shape adoption in complex institutional settings. This layered progression ensures that the theoretical constructs examined remain grounded in contemporary empirical evidence and are relevant to the specific context of Indian telecom organizations.

The literature reviewed in this chapter draws predominantly from peer-reviewed research published between 2020 and 2026, supplemented by foundational theoretical works that remain current in technology adoption scholarship. Indian and international sources are integrated throughout to ensure contextual relevance and scholarly breadth. The chapter is organized into two parts. Part 1, presented here, covers the evolution of GenAI, its telecom applications, established adoption theories, organizational perception dimensions, and human-AI interaction. Part 2 covers governance, ethics, organizational capabilities, digital transformation, framework development, and the identification of the research gap.

Together, the two parts establish a comprehensive scholarly foundation that justifies the research objectives, validates the methodological choices, and positions the study's contributions within the existing body of knowledge (Dwivedi et al., 2023; Vial, 2019; Gomes et al., 2025; Chen & Li, 2025).

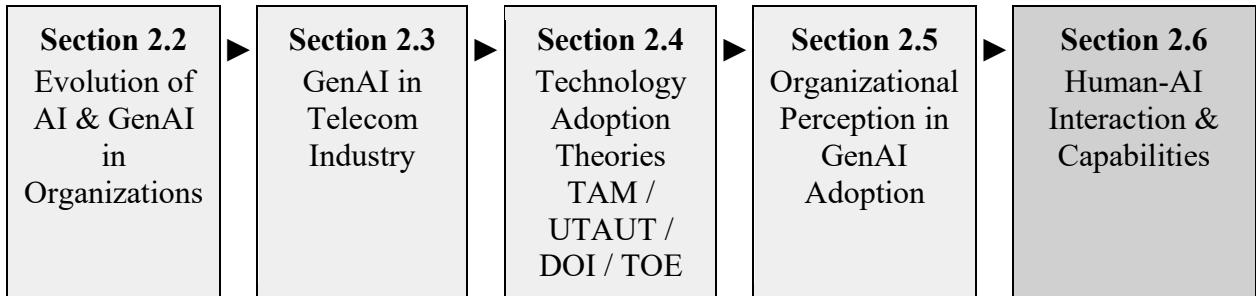


Figure 2.1: Structure of the Literature Review (Source: Author)

2.2 Evolution of Artificial Intelligence and Generative AI in Organizational Contexts

2.2.1 From Rule-Based Systems to Generative Intelligence

The organizational application of artificial intelligence has undergone several distinct and increasingly consequential phases of development over the past five decades. The earliest phase, spanning from the 1970s through the 1990s, was characterized by rule-based expert systems that encoded domain knowledge into fixed logical structures. These systems were capable of answering structured queries and supporting narrowly defined operational decisions but could not learn from experience, adapt to novel inputs, or generate outputs beyond their coded parameters. Their utility was therefore largely confined to controlled, repetitive decision environments with well-defined solution spaces (Hanelt et al., 2021; Kraus et al., 2022).

The transition to machine learning from the late 1990s onward represented a fundamental shift in AI architecture. Rather than relying on explicit human-coded rules, machine learning systems identified patterns within data and generated predictive outputs autonomously. This shift significantly expanded the organizational utility of AI, enabling applications in demand forecasting, customer churn prediction, credit scoring, image recognition, and process classification. The growing availability of digital data, improvements in computing infrastructure, and advances in statistical learning theory collectively enabled this transition, which became foundational to the wave of digital transformation that many organizations undertook in the 2010s (Vial, 2019; Verhoef et al., 2021; Kraus et al., 2022).

Deep learning, emerging as a dominant paradigm from approximately 2012 onwards, further accelerated AI capabilities by leveraging multi-layered neural network architectures to process unstructured data at unprecedented scale and complexity. Deep learning enabled substantial advances in natural language processing, speech recognition, image classification, and anomaly

detection, and became the technical foundation upon which many industry-scale AI applications were built. For organizations, this development reinforced AI's role as a strategic infrastructure asset rather than a tactical efficiency tool, driving integration into core business functions including logistics, marketing, financial risk management, and customer experience design (Li et al., 2021; Hanelt et al., 2021; Aldoseri et al., 2024).

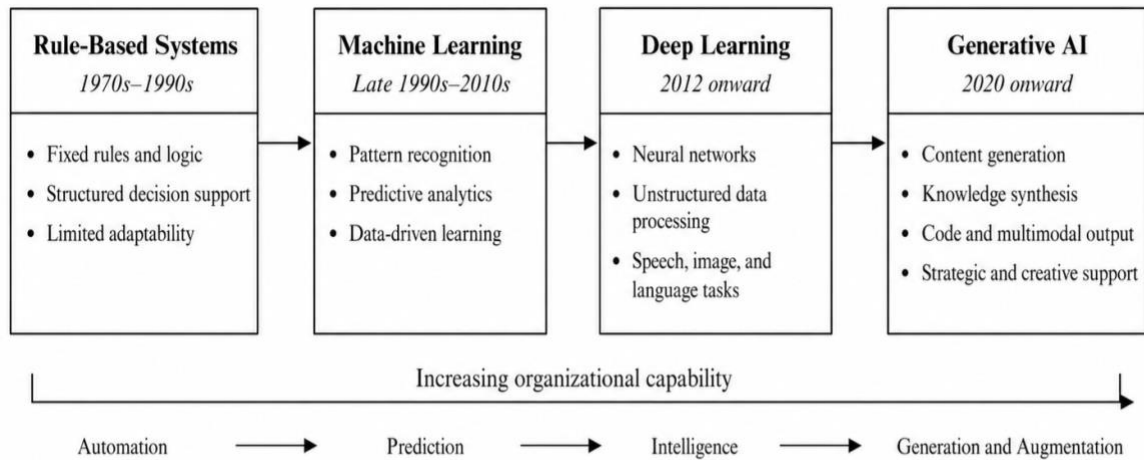


Figure 2.2: Pathway, Source: Author, based on Hanelt et al. (2021), Kraus et al. (2022), Vial (2019), Brown et al. (2020), and Dwivedi et al. (2023).

The emergence of Generative Artificial Intelligence from 2020 onwards represents the most transformative development in this evolutionary trajectory. Unlike machine learning and deep learning systems, which primarily recognized, classified, or predicted based on existing data, Generative AI systems are designed to create: generating novel text, images, code, structured data, and multimodal outputs that were not explicitly present in their training data. This generative capability is enabled by transformer architectures, large-scale pretraining on diverse corpora, and techniques including reinforcement learning from human feedback (Brown et al., 2020; OpenAI, 2023; Touvron et al., 2023; Bommasani et al., 2024). The practical consequences for organizations are substantial: Generative AI is not merely another incremental improvement in AI capability but a qualitative expansion of what machines can do in organizational settings, extending their role into domains previously considered exclusively human, including creative work, strategic reasoning, knowledge synthesis, and interpersonal communication (Dwivedi et al., 2023; Doshi et al., 2024; Vujovic, 2024).

2.2.2 Generative AI as a General-Purpose Organizational Technology

Scholars have increasingly argued that Generative AI possesses the characteristics of a general-purpose technology (GPT), analogous to previous technological revolutions such as electrification and the internet. General-purpose technologies are distinguished by their pervasive applicability across sectors, their capacity for continuous improvement, and their ability to generate complementary innovations in the domains they penetrate (Brynjolfsson et al., 2023; Vujovic, 2024). Generative AI satisfies these criteria: it can be applied across virtually every organizational function, it continues to improve rapidly as models scale and training techniques advance, and it has already begun to generate new classes of AI-native products, services, and workflows that did not exist before its emergence.

For organizations, the general-purpose nature of Generative AI means that its strategic implications are not confined to individual use cases or departments. Rather, it has the potential to reshape organizational architectures, redefine competitive dynamics, alter workforce composition and skill requirements, and transform the economics of knowledge work at a systemic level (Mariani et al., 2024; Cannavale, 2025; Raisch & Krakowski, 2021). Studies of early GenAI deployment in organizational settings confirm that productivity gains are significant: Brynjolfsson et al. (2023) report that workers using GenAI tools demonstrated measurable improvements in task completion speed and output quality, particularly in knowledge-intensive activities. Doshi et al. (2024) find that GenAI enhances individual creative output while raising questions about collective knowledge diversity, a finding with important implications for organizational innovation management.

In the Indian organizational context, adoption of Generative AI has gained significant momentum across sectors including information technology, banking, healthcare, and telecommunications. Kumar and George (2024) document measurable productivity and analytical capability improvements in Indian financial services firms that integrated GenAI into their analytics workflows. Telecom Review Asia (2025) reports accelerating GenAI deployment among Indian telecom operators. The Telecom Engineering Centre (2024) and TRAI (2024) have both acknowledged GenAI as a strategic technology priority for the Indian telecommunications sector, signaling institutional recognition of its organizational importance.

These developments indicate that the theoretical and practical literature reviewed in this chapter is directly applicable to the Indian telecom context that the present study examines.

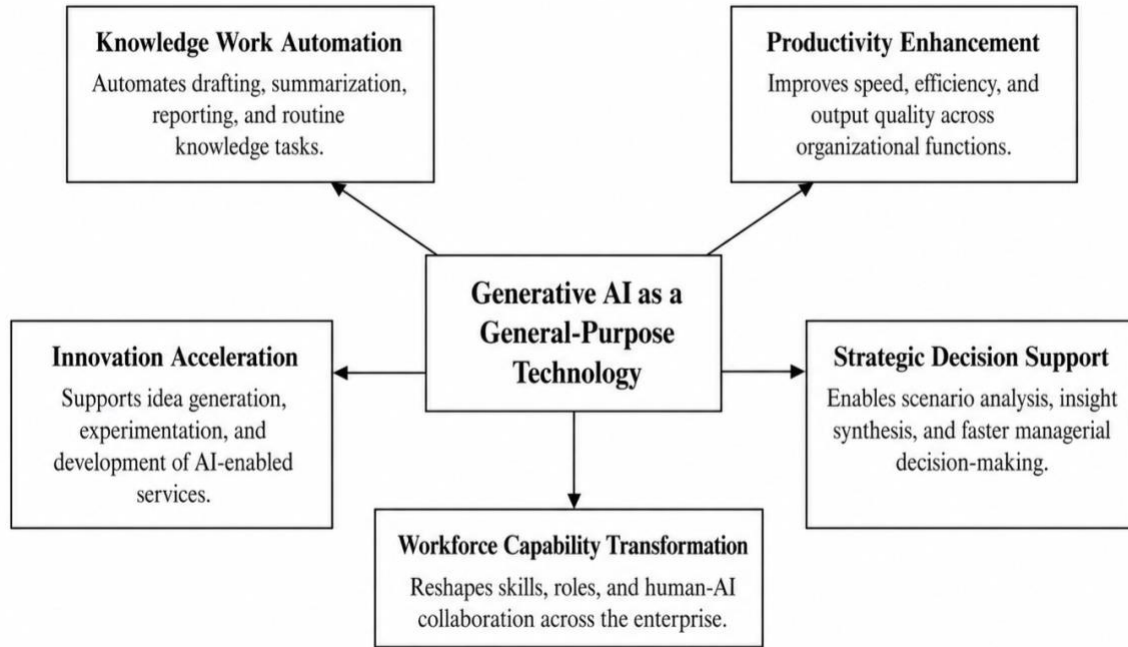


Figure 2.3: Generative AI as a General-Purpose Organizational Technology
Source: Author, based on Brynjolfsson et al. (2023), Vujovic (2024), Mariani et al. (2024), Cannavale (2025), and Raisch and Krakowski (2021).

2.2.3 Organizational Capabilities Enabled by Generative AI

Generative AI extends the organizational capability set across three interconnected domains: knowledge management, operational efficiency, and strategic decision support. In the knowledge management domain, Generative AI enables organizations to synthesize large, heterogeneous information sets into coherent summaries, recommendations, and structured analyses, substantially reducing the time and cognitive load associated with information-intensive tasks (Mariani et al., 2024; Davenport et al., 2020). This has particular relevance for organizations managing complex regulatory, technical, and market intelligence environments, including large telecom operators.

In the operational efficiency domain, Generative AI automates the creation of structured outputs including technical reports, customer communications, compliance documentation, code, and testing artifacts, reducing cycle times and enabling scale without proportionate increases in

headcount (Li et al., 2024; Brynjolfsson et al., 2023; Kanakadandi, 2025). Studies of software development contexts confirm that GenAI-assisted teams complete coding tasks significantly faster than unassisted teams, though quality assurance and ethical review requirements persist (Li et al., 2024).

In the strategic decision support domain, Generative AI enables scenario simulation, competitive intelligence synthesis, and strategic option generation at speeds and scales that were previously impractical for human analysts. Research on management applications documents that executives and strategy teams are increasingly using GenAI tools to augment strategic planning processes, improve the comprehensiveness of environmental scanning, and accelerate the preparation of decision materials (Shrestha et al., 2019; Bevilacqua et al., 2025; Talaei-Khoei et al., 2024). At the same time, scholars caution that the value of GenAI in strategic contexts depends critically on the quality of human oversight, the reliability of model outputs, and the governance mechanisms through which AI-generated recommendations are evaluated and acted upon (Glikson & Woolley, 2020; Najana, 2024).

Table 2.1: Generative AI Capability Matrix and Telecom Applications (Sources: Brown et al., 2020; Lin et al., 2024; Karapantelakis et al., 2024; Britto et al., 2023; Bommasani et al., 2024)

Capability Domain	Description	Telecom Application	Key Sources
Natural Language Generation	Produces human-like text, summaries, and structured reports from unstructured inputs.	Automated customer communications, network incident reports, service advisories.	Brown et al., 2020; Lin et al., 2024
Conversational AI	Engages users in multi-turn dialogue with contextual memory and intent recognition.	AI-powered customer service agents, technical helpdesk automation.	Karapantelakis et al., 2024; Accenture, 2023
Code and Script Generation	Generates, reviews, and optimizes software code across programming languages.	Network automation scripts, OSS/BSS integration, testing pipelines.	Li et al., 2024; Kanakadandi, 2025

Knowledge Retrieval (RAG)	Combines generation with retrieval from domain-specific document corpora.	Technical knowledge bases, policy retrieval, compliance question answering.	Lin et al., 2024; Bariah et al., 2023
Predictive and Diagnostic Output	Generates scenario-based predictions and fault diagnostics from sensor and log data.	Predictive network maintenance, anomaly detection, fault root-cause analysis.	Rahman et al., 2023; Britto et al., 2023
Multimodal Content Creation	Generates outputs combining text, image, and structured data representations.	Service design documentation, training content, executive dashboards.	Bommasani et al., 2024; Dwivedi et al., 2023

2.3 Generative Artificial Intelligence in the Telecommunications Industry

2.3.1 Digital Transformation Trajectory of the Telecom Sector

The telecommunications sector has undergone one of the most sustained and consequential digital transformations of any industry over the past two decades. Originally structured around voice services and fixed-line infrastructure, the sector has evolved into a complex digital ecosystem spanning mobile broadband, cloud services, Internet of Things platforms, over-the-top applications, enterprise connectivity, and increasingly, AI-native network intelligence. This transformation has been driven by the convergence of rapidly growing data traffic, shrinking hardware costs, expanding software-defined networking capabilities, and intensifying competitive dynamics (GSMA Intelligence, 2023; WEF, 2025; Verhoef et al., 2021).

In India, this transformation has proceeded at exceptional scale and pace. The Indian telecommunications market is among the largest globally, with over 1.2 billion subscribers, three major national operators, and one of the world's highest rates of mobile data consumption per subscriber (TRAI, 2024). The rollout of 5G infrastructure across major Indian metropolitan and tier-2 markets from 2022 onwards has significantly expanded the technical complexity of network management and created new imperatives for AI-assisted operational intelligence (TEC, 2024; Chetty et al., 2025). At the same time, intense competitive pressure, thin operating margins, and legacy infrastructure inherited from previous technology generations create structural constraints on the pace of AI adoption, making the Indian telecom context both opportunity-rich and challenge-intensive for Generative AI deployment (Reznikov, 2024; Agarwal & Nene, 2025).

2.3.2 Applications of Generative AI Across Telecom Functions

Generative AI is being applied across a broadening range of telecom functions, and the literature documents a progression from experimental use cases toward increasingly mission-critical deployments. The most extensively documented application domain is customer service and experience management. Telecom organizations manage exceptionally high volumes of customer interactions across billing queries, service disruptions, plan changes, device troubleshooting, and connectivity issues. Generative AI-powered conversational systems, including large language model-based chatbots and virtual agents, enable more contextually accurate, personalized, and scalable responses than rule-based predecessors (Accenture, 2023; Lin et al., 2024; Karapantelakis et al., 2024).

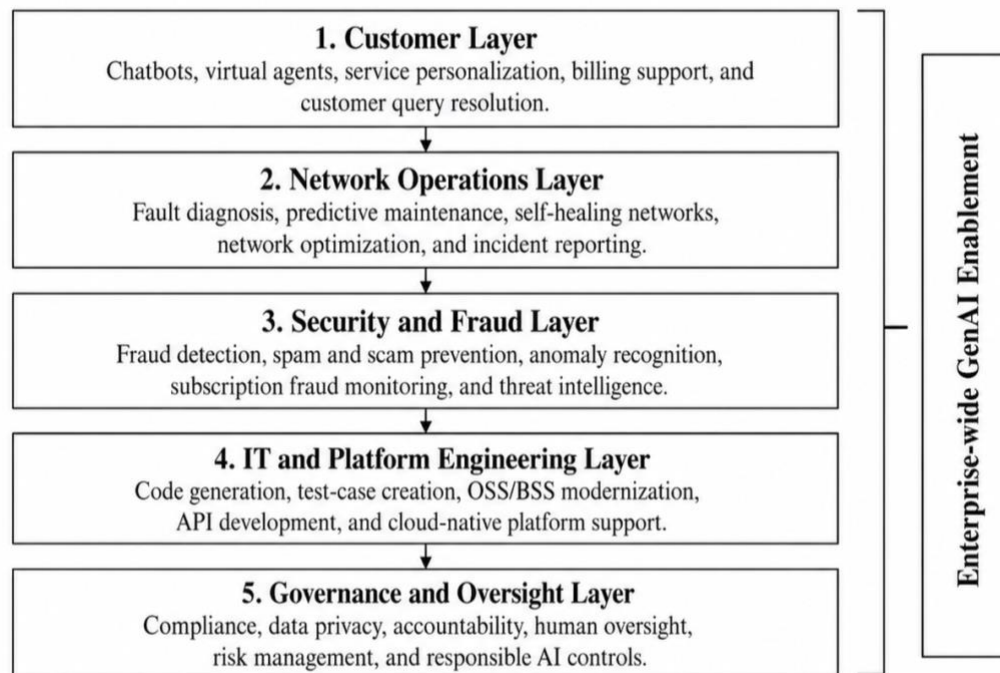


Figure 2.4: Generative AI Application Architecture in Telecom Organizations

Source: Author, based on Accenture (2023), Lin et al. (2024), Karapantelakis et al. (2024), Rahman et al. (2023), Britto et al. (2023), Pietri et al. (2024), Kanakadandi (2025), Infosys (2024), and PwC (2024).

Lin et al. (2024), in their comprehensive technical primer on GenAI for telecom, document how retrieval-augmented generation (RAG) architectures are being deployed to build telecom-domain-specific knowledge systems that enable virtual agents to access and synthesize operator-

specific technical and policy information in real time. This approach substantially improves response accuracy over generic large language models while maintaining the conversational fluency that customers expect. Karapantelakis et al. (2024) extend this analysis to mobile network contexts, demonstrating that GenAI systems with domain-specific fine-tuning show significantly improved performance on network management reasoning tasks compared to general-purpose models.

Network operations and intelligent maintenance represent a second major application domain. Telecom networks involve thousands of distributed hardware and software components that require continuous monitoring, capacity planning, fault diagnosis, and optimization. Generative AI enables technical operations teams to process large volumes of network log data, generate diagnostic narratives, recommend fault resolution paths, and support predictive maintenance decision-making at a speed and scale that exceeds human analytical capacity (Rahman et al., 2023; Britto et al., 2023). Rahman et al. (2023) specifically demonstrate the application of GenAI to self-healing 5G networks, where AI-generated diagnostic outputs are used to initiate automated network reconfiguration processes without human intervention, reducing mean time to repair and improving network availability metrics.

Fraud detection and network security constitute a third application domain of growing importance. Telecom fraud, including subscription fraud, SIM swap attacks, and roaming fraud, costs the industry billions of dollars annually. GenAI models trained on historical fraud patterns can generate synthetic fraudulent transaction profiles to augment training data scarcity and improve classification model performance (Liu et al., 2025; Pietri et al., 2024). Pietri et al. (2024) evaluate the effectiveness of GenAI-based countermeasures against telecom spam and scam campaigns in an AI-augmented threat environment, finding that GenAI-assisted detection substantially outperforms rule-based approaches for novel attack patterns.

Software development, testing, and telecom platform engineering represent a fourth and increasingly significant application domain. Kanakadandi (2025) documents a structured framework for applying GenAI to telecom e-commerce development and testing optimization, reporting significant reductions in testing cycle time and defect escape rates when GenAI-assisted code review and test case generation are integrated into development pipelines. More broadly, the application of GenAI to OSS/BSS modernization, API development, and cloud-

native architecture migration is emerging as a major productivity lever for telecom IT organizations managing complex system integration programs (Britto et al., 2023; Infosys, 2024; PwC, 2024).

Table 2.2: Generative AI in the Indian Telecommunications Ecosystem (Sources: TRAI, 2024; TEC, 2024; Telecom Review Asia, 2025; Agarwal & Nene, 2025; Reznikov, 2024; Infosys, 2024)

Dimension	Description and Evidence
Market Scale	India is the world's second-largest telecom market with over 1.2 billion subscribers and three dominant operators: Jio, Airtel, and BSNL (TRAI, 2024).
5G Expansion	Rapid 5G rollout across 100+ Indian cities as of 2024 is driving demand for AI-native network management and intelligent operations (TEC, 2024; Chetty et al., 2025).
AI Adoption Rate	Indian telecom firms report accelerating AI deployment with measurable ROI in customer operations and network efficiency (Telecom Review Asia, 2025; Infosys, 2024).
Regulatory Context	TRAI (2024) and TEC (2024) have issued guidelines and consultations on responsible AI use in Indian telecommunications.
Governance Gaps	Despite regulatory activity, gaps persist in AI-specific incident reporting, bias auditing, and accountability frameworks for Indian telecom (Agarwal & Nene, 2025).
Perceptual Barriers	Trust in AI outputs, legacy system integration challenges, and workforce AI literacy remain primary barriers to scaling adoption in Indian telecom firms (Reznikov, 2024; Bariah et al., 2023).

2.3.3 Constraints and Challenges in Telecom GenAI Adoption

Despite its substantial documented potential, the adoption of Generative AI in telecom organizations faces a set of structural, technical, and organizational constraints that the literature consistently identifies. Legacy infrastructure incompatibility is the most frequently cited structural barrier. Telecom network management systems, billing platforms, and customer care infrastructures in many operators, including Indian ones, were designed and deployed over multiple technology generations with different data models, protocols, and interface standards. Integrating GenAI tools with these heterogeneous, often siloed systems requires substantial data engineering investment, API development, and governance restructuring that many organizations are unprepared or unable to undertake rapidly (Britto et al., 2023; Reznikov, 2024).

Data governance constraints present a second category of challenge. GenAI training, fine-tuning, and deployment in telecom contexts requires access to large, high-quality datasets encompassing network performance records, customer interaction logs, and service usage histories. In India, evolving data protection legislation and TRAI guidelines on data usage and privacy impose regulatory constraints on how this data can be collected, stored, and utilized for AI training purposes (TRAI, 2024; Agarwal & Nene, 2025). Organizations must develop robust data governance frameworks that satisfy regulatory requirements while enabling the data access necessary for effective GenAI development, a balance that many are still working to achieve.

Workforce capability deficits represent a third structural constraint. Effective GenAI deployment requires personnel with expertise spanning AI engineering, prompt design, model evaluation, output quality management, and AI governance. These skills remain scarce relative to demand in the Indian telecom labor market, creating a capability bottleneck that slows adoption timelines and reduces the quality of initial deployments (Westover, 2024; TEC, 2024; Muhammad, 2025). Building internal capability through recruitment, training, and organizational learning represents a significant and ongoing investment requirement for telecom organizations pursuing GenAI at scale (Ransbotham et al., 2021; Dacre, 2024).

2.4 Theoretical Foundations of Technology Adoption

2.4.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model, originally proposed by Davis (1989) and among the most extensively validated frameworks in information systems research, provides the foundational theoretical basis for understanding how individual users and organizational actors evaluate and adopt new technologies. TAM posits that two primary perceptual constructs, **perceived usefulness** and **perceived ease of use**, determine user attitudes toward a technology, which in turn influence behavioral intention to use and, ultimately, actual system use. Perceived usefulness reflects the individual's belief that using the technology will enhance their job performance or organizational outcomes, while perceived ease of use reflects the degree to which the technology is considered free of cognitive or operational effort (Davis, 1989; Gefen et al., 2003).

TAM's relevance to Generative AI adoption in telecom organizations is direct and well-supported. When telecom managers perceive GenAI tools as genuinely improving their ability to serve customers, manage networks, or make strategic decisions, they are more likely to engage with and advocate for broader adoption. Similarly, when GenAI interfaces are designed for accessibility and contextual relevance, the cognitive barrier to adoption is reduced. Chen and Li (2025), in their empirical study of AI adoption among IT professionals, confirm that perceived usefulness remains one of the strongest predictors of GenAI adoption intention, consistent with the original TAM formulation. Simaremare and Edison (2024), in a systematic literature review, confirm that TAM constructs appear across the majority of empirical AI adoption studies, validating their continued explanatory relevance.

However, TAM faces important limitations in the GenAI context. As scholars have consistently noted, the original model's focus on individual-level cognitive evaluation does not capture the organizational, social, ethical, and governance dimensions that shape adoption in complex enterprise settings (Dwivedi et al., 2023; Gomes et al., 2025). In the specific context of Generative AI, where outputs are probabilistic, potentially biased, and ethically consequential, the dimensions of trust, governance awareness, and risk perception are central to adoption decisions in ways that TAM does not address. The present study accordingly treats TAM constructs as foundational while building beyond them to incorporate these additional dimensions.

2.4.2 Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT2)

The Unified Theory of Acceptance and Use of Technology, developed by Venkatesh et al. (2003) through synthesis of eight prior technology adoption models, provides a more comprehensive account of adoption determinants by incorporating social and organizational contextual factors alongside individual perception. The original UTAUT model identifies four primary constructs: **performance expectancy** (the degree to which using the technology improves job performance), **effort expectancy** (the perceived ease of using the technology), **social influence** (the extent to which significant others believe the individual should use the technology), and **facilitating conditions** (the degree to which organizational and technical infrastructure supports use). Moderating variables including gender, age, experience, and voluntariness of use were also incorporated, providing a richer contextual specification than TAM (Venkatesh et al., 2003).

UTAUT2, proposed by Venkatesh et al. (2012), extended the original model for consumer contexts by adding hedonic motivation, price value, and habit as additional predictors. While UTAUT2's consumer orientation limits its direct applicability to enterprise telecom settings, its incorporation of motivational and habitual dimensions has relevance for understanding how individual telecom professionals internalize and routinize GenAI tool use over time. Seifdar and Amiri (2025) draw on UTAUT-derived constructs in their game-theoretic model of GenAI adoption, confirming that social influence and organizational facilitating conditions are among the most significant determinants of adoption momentum at organizational scale.

For the present study, UTAUT constructs inform the design of the quantitative instrument by highlighting the importance of social influence, organizational support, and infrastructure facilitation alongside individual performance and effort perceptions. These constructs are particularly salient in Indian telecom organizations, where hierarchical management cultures and centralized decision-making structures mean that leadership advocacy and peer adoption patterns significantly shape individual employee adoption behavior (Gong et al., 2024; Alghamdi & Rehman, 2026; Westover, 2024).

2.4.3 Diffusion of Innovation Theory (DOI)

Rogers' (2003) Diffusion of Innovation Theory provides a complementary temporal and systemic perspective on technology adoption, conceptualizing adoption as a process of social diffusion that unfolds across distinct stages and adopter categories within and across organizations. The theory identifies five innovation characteristics that shape adoption rates: **relative advantage** (the degree to which the innovation is perceived as better than its predecessor), **compatibility** (alignment with existing values and practices), **complexity** (difficulty of understanding and using the innovation), **trialability** (the degree to which the innovation can be experimented with on a limited basis), and **observability** (the visibility of adoption outcomes to others). The theory also delineates adopter categories from innovators and early adopters through the late majority and laggards, explaining variation in adoption timing across organizational populations (Rogers, 2003).

DOI theory's relevance to GenAI adoption in telecom is particularly evident in its explanation of fragmented and uneven adoption patterns. The literature consistently documents that GenAI adoption in telecom organizations proceeds through early-adopter pilot stages before diffusing

across functional units and organizational levels, with the pace of diffusion shaped by the perceived complexity of integration, the compatibility of GenAI outputs with existing workflows, and the observability of business benefits from early deployments (Britto et al., 2023; Infosys, 2024; Deloitte, 2024). Zhou et al. (2025) apply a DOI-informed analytical lens to government GenAI adoption, finding that compatibility and relative advantage are the most significant innovation characteristics predicting adoption decisions among public sector organizations, a finding with transferable implications for regulated private-sector contexts such as Indian telecom.

2.4.4 Technology-Organization-Environment (TOE) Framework

The Technology-Organization-Environment (TOE) framework, proposed by Tornatzky and Fleischer (1990), provides an organizational-level complement to the individual-level orientation of TAM and UTAUT. TOE posits that technology adoption is shaped by three contextual factors. The **technological context** encompasses both existing and emerging technologies relevant to the organization's operations. The **organizational context** captures internal characteristics including size, structure, culture, management, and resource availability. The **environmental context** includes industry characteristics, competitive dynamics, regulatory requirements, and relationships with external stakeholders. Together, these three dimensions provide a comprehensive account of the conditions that enable or constrain organizational-level technology adoption.

TOE has been widely applied in AI and digital technology adoption research, particularly in organizational and industry-level studies. Na and Zheng (2024) apply the TOE framework to examine GenAI adoption in China's marine industry, finding that organizational readiness and environmental regulatory conditions are the most significant predictors of adoption depth. Zhou et al. (2025) extend TOE by connecting GenAI adoption to ambidextrous innovation outcomes in government organizations, demonstrating that technology and environmental factors interact to shape both adoption and post-adoption performance. Ali et al. (2025), in their cross-national study of GenAI adoption enabling conditions, identify organizational infrastructure, workforce capability (organizational factors), and national AI policy development (environmental factors) as critical determinants of large-scale adoption, findings with direct relevance to the Indian telecom context where TRAI and TEC policy frameworks are evolving rapidly.

For the present study, the TOE framework complements TAM and UTAUT by ensuring that organizational infrastructure, leadership readiness, regulatory environment, and sectoral dynamics are incorporated into the analytical model alongside individual-level perception constructs. This integration reflects the multidimensional nature of GenAI adoption as documented in the most recent empirical literature (Gomes et al., 2025; Seifdar & Amiri, 2025; Zhang et al., 2025).

2.4.5 Technology Readiness and Perception Measurement

Beyond formal adoption theories, the concept of technology readiness, as operationalized by Parasuraman (2000), provides important insights into the attitudinal predispositions that shape how individuals and organizations respond to new technologies. The Technology Readiness Index (TRI) identifies four dimensions: **optimism** (a positive view of technology and its benefits), **innovativeness** (a tendency to be a technology pioneer), **discomfort** (a perceived lack of control over technology), and **insecurity** (distrust of technology and skepticism about its capabilities). These dimensions collectively capture the attitudinal complexity that underlies technology adoption decisions in ways that behavioral intention measures alone cannot.

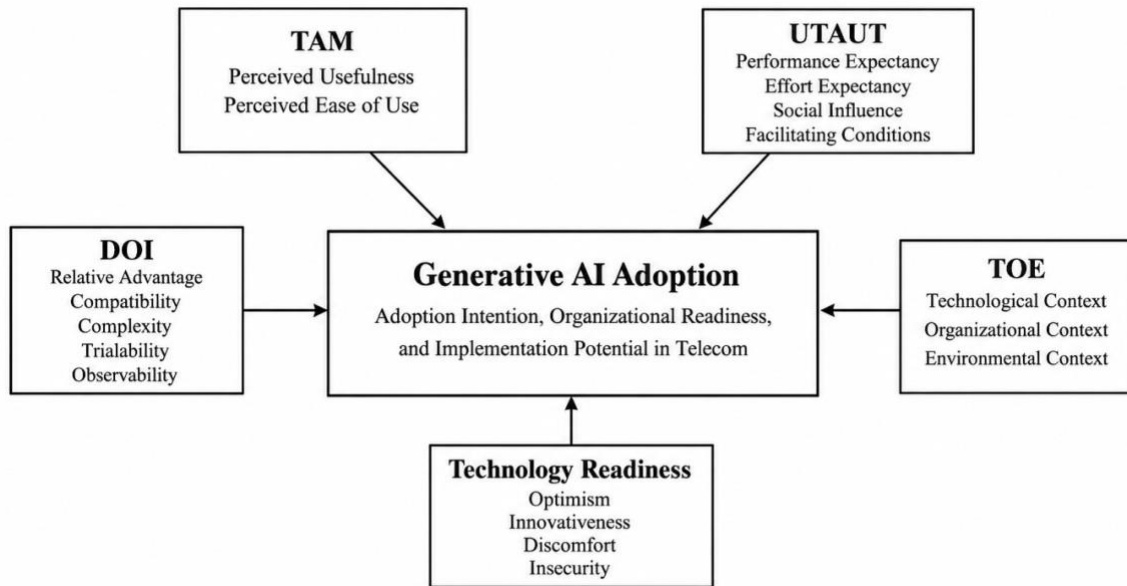


Figure 2.5: Integrated Theoretical Foundation for Generative AI Adoption

Source: Author, based on Davis (1989), Venkatesh et al. (2003), Rogers (2003), Tornatzky and Fleischer (1990), and Parasuraman (2000).

In the GenAI context, technology readiness is particularly relevant because it captures the ambivalence that many organizational actors experience when confronted with a technology whose outputs are powerful but not always predictable or explainable. Research on AI readiness in organizational settings confirms that leaders' optimism about AI's potential is frequently tempered by discomfort arising from concerns about job displacement, loss of control, and ethical risk, a tension that shapes both individual adoption behavior and organizational AI strategy (Deloitte, 2024; Alghamdi & Rehman, 2026; Westover, 2024; Muhammad, 2025). Moore and Benbasat (1991) provide the foundational measurement framework for innovation perception constructs, and their instrument design principles inform the questionnaire development approach employed in the present study (see Chapter 3).

Table 2.3: Comparative Analysis of Technology Adoption Theories and Their Relevance to GenAI Adoption in Telecom (Sources: Davis, 1989; Venkatesh et al., 2003, 2012; Rogers, 2003; Tornatzky & Fleischer, 1990)

Theory	Origin	Core Constructs	Relevance to GenAI in Telecom	Limitation for GenAI
TAM	Davis, 1989	Perceived Usefulness; Perceived Ease of Use; Attitude; Behavioral Intention	Explains how telecom managers evaluate GenAI utility and usability before adoption.	Does not address trust, ethics, governance, or organizational context.
UTAUT	Venkatesh et al., 2003	Performance Expectancy; Effort Expectancy; Social Influence; Facilitating Conditions	Captures social and infrastructural influences on GenAI adoption in telecom teams.	Originally designed for individual-level adoption; limited organizational scope.
UTAUT2	Venkatesh et al., 2012	Hedonic Motivation; Price Value; Habit; above UTAUT constructs	Relevant for consumer-facing GenAI tools in telecom customer service.	Consumer orientation limits applicability to enterprise and B2B telecom contexts.
DOI Theory	Rogers, 2003	Relative Advantage; Compatibility; Complexity; Trialability; Observability	Explains staged adoption patterns and internal diffusion of GenAI within telecom firms.	Temporal focus; limited attention to risk, governance, or ethical considerations.

TOE Framework	Tornatzky & Fleischer, 1990	Technological Factors; Organizational Factors; Environmental Factors	Captures infrastructure, readiness, and regulatory conditions affecting telecom adoption.	Does not explicitly address perception-based or trust-related adoption dimensions.
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2.5 Organizational Perception in Generative AI Adoption

2.5.1 Conceptual Role of Perception in Technology Adoption

Organizational perception occupies a central and constitutive role in determining how emerging technologies are interpreted, evaluated, and adopted within firms. This observation is well established in the technology adoption literature and has been reinforced in numerous empirical studies of AI-specific adoption dynamics (Davis, 1989; Venkatesh et al., 2003; Dwivedi et al., 2021). In the Generative AI context, however, the role of perception is particularly salient because GenAI's capabilities are simultaneously impressive and opaque, its outputs powerful and potentially unreliable, and its organizational implications both transformative and ethically complex. These characteristics create a perceptual environment in which organizational actors must make adoption decisions under substantial uncertainty, drawing on interpretive frameworks that integrate prior technological experience, organizational values, risk tolerance, and strategic priorities (Chen & Li, 2025; Gomes et al., 2025; Najana, 2024).

Managerial cognition research establishes that decision-makers do not evaluate technologies purely on the basis of objective technical specifications. Rather, they interpret technologies through cognitive schemas, organizational heuristics, and social sense-making processes that reflect their accumulated experience and institutional context (Hanelt et al., 2021; Shrestha et al., 2019). In the specific context of Generative AI, this means that a technology with equivalent technical capability may be perceived very differently by telecom leaders in organizations with strong AI governance cultures versus those with limited prior AI exposure, with strong versus weak leadership advocacy for digital transformation, or with high versus low levels of workforce digital literacy. Perception, in this sense, is not merely a precursor to adoption but a fundamentally organizational phenomenon that reflects and reproduces institutional patterns of interpretation and action.

The multidimensional nature of organizational perception in GenAI adoption is increasingly recognized in the empirical literature. Chen and Li (2025), in their large-scale study of AI adoption among IT professionals, identify distinct perception dimensions including perceived usefulness, trust, contextual understanding, and ethical concern, all of which independently predict adoption intention. Gomes et al. (2025) confirm through multi-criteria empirical analysis that organizational dimensions of GenAI adoption, including leadership perception, governance readiness, and strategic alignment perception, carry greater explanatory weight than purely technological factors. These findings validate the present study's focus on organizational perception as the primary analytical lens for examining GenAI adoption in Indian telecom organizations.

2.5.2 Perceived Value and Usefulness Dimensions

Perceived value represents the most consistently documented driver of Generative AI adoption across organizational contexts. When organizational actors perceive that GenAI tools will produce measurable improvements in their ability to complete tasks, deliver services, or achieve strategic objectives, their motivation to adopt and invest in these tools increases substantially. This construct is directly related to TAM's perceived usefulness but extends beyond task-level performance to encompass strategic and innovation-related value perceptions (Aldoseri et al., 2024; Fuwen & Jin, 2025; Wamba, 2022).

In telecom organizational contexts, perceived value manifests across multiple dimensions. At the operational level, GenAI is perceived as valuable to the extent that it reduces the time and effort required to manage customer interactions, generate technical reports, analyze network performance data, and support compliance documentation (Lin et al., 2024; PwC, 2024; Infosys, 2024). At the strategic level, perceived value encompasses GenAI's potential to enable new service offerings, improve competitive positioning, enhance customer experience quality, and support evidence-based strategic decision-making (Karapantelakis et al., 2024; WEF, 2025). Research indicates that organizations where senior leaders clearly articulate and communicate the strategic value of GenAI achieve significantly higher levels of adoption engagement across employee populations than those where value articulation remains vague or fragmented (Gong et al., 2024; Ransbotham et al., 2021; Bevilacqua et al., 2025).

2.5.3 Trust, Risk Perception, and Output Reliability

Trust represents one of the most critical and distinctive perception dimensions in the Generative AI adoption literature, reflecting the inherent challenges posed by AI systems that produce autonomous, probabilistic, and not always verifiable outputs. Glikson and Woolley (2020), in their comprehensive review of human trust in artificial intelligence, identify three primary dimensions of AI trust: **cognitive trust** (belief in the AI's technical reliability and competence), **affective trust** (emotional confidence and comfort with the AI's behavior), and **dispositional trust** (general tendency to trust AI systems based on prior experience). All three dimensions influence whether organizational actors rely on GenAI outputs in practice, and all three can be undermined by experiences of output error, bias, or unexplained behavior (Glikson & Woolley, 2020; Bender et al., 2021).

Risk perception constitutes the counterpart to trust and value perception in the adoption decision calculus. Organizational actors weigh the anticipated benefits of GenAI adoption against perceived risks including output inaccuracy and hallucination (Bender et al., 2021), algorithmic bias in customer-facing decisions (Binns, 2018; Hagendorff, 2020 – discussed in Part 2), data security vulnerabilities arising from model deployment, regulatory compliance risks associated with AI-generated content, and reputational risks from publicly visible GenAI failures. In Indian telecom organizations, where customer trust and regulatory compliance are commercial and legal imperatives, risk perception carries particular weight in adoption decisions (Agarwal & Nene, 2025; TRAI, 2024).

Empirical studies consistently confirm that trust and risk perception are among the strongest moderators of the relationship between perceived usefulness and actual adoption behavior. Simaremare and Edison (2024) find that trust in AI outputs is a stronger predictor of sustained adoption than initial perceived usefulness, particularly in high-stakes operational contexts. Chen and Li (2025) similarly report that concerns about AI bias and output reliability significantly reduce adoption depth even among users who find GenAI useful in principle. These findings have direct methodological implications for the present study, supporting the inclusion of trust-related items within the quantitative perception instrument analyzed through EFA.

2.5.4 Governance Awareness and Regulatory Perception

Governance awareness, defined as organizational actors' knowledge of and orientation toward the policies, regulations, and ethical frameworks governing GenAI deployment, has emerged as a significant and increasingly researched perception dimension in the recent literature. Zhang et al. (2025), examining GenAI adoption in enterprise digital platforms, find that institutional pressures from regulatory bodies and industry associations significantly shape organizational adoption decisions, with organizations in more intensively regulated environments demonstrating more structured and cautious approaches to GenAI scaling. Ali et al. (2025), in their cross-national study, confirm that the maturity of national AI policy frameworks is one of the strongest environmental predictors of organizational GenAI adoption at scale.

In Indian telecom, the regulatory dimension is particularly salient. Telecom organizations operate under TRAI oversight and TEC technical guidance, both of which are evolving to incorporate AI-specific requirements (TRAI, 2024; TEC, 2024; Agarwal & Nene, 2025). Organizational awareness of and orientation toward these evolving requirements shapes adoption strategies: firms with proactive governance cultures are more likely to develop structured AI policies, invest in compliance capability, and design deployment approaches that anticipate regulatory expectations, while firms with reactive governance orientations may delay adoption or deploy GenAI in ways that create subsequent compliance risks. Pathan and Shah (2025) document the governance dimensions most relevant to GenAI adoption, confirming that transparency, accountability, and bias management are the governance dimensions most frequently cited by organizational actors as adoption considerations.

2.5.5 Strategic Alignment as a Perception Dimension

Strategic alignment perception, defined as the degree to which organizational actors perceive GenAI as aligned with their organization's long-term strategic objectives and competitive positioning, represents the most organizationally proximal dimension of adoption perception. Research on AI strategy consistently finds that organizations achieving the highest levels of AI adoption and value realization are those where AI initiatives are embedded within, rather than isolated from, broader corporate strategy (Mikalef et al., 2020; Wamba, 2022; Kane et al., 2015; Orero-Blat et al., 2025).

In telecom organizations, strategic alignment perception encompasses the degree to which GenAI is perceived as supporting core competitive priorities such as network excellence, customer experience leadership, cost efficiency, and service innovation. Deloitte (2024) reports that organizations where senior leaders articulate a clear GenAI strategy aligned with business objectives achieve adoption rates and business impact metrics significantly higher than those where GenAI is deployed opportunistically. Ransbotham et al. (2021) confirm that organizational learning culture and leadership commitment to AI strategy are the strongest cultural predictors of sustained AI value realization, reinforcing the strategic alignment dimension of perception as central to adoption outcomes.

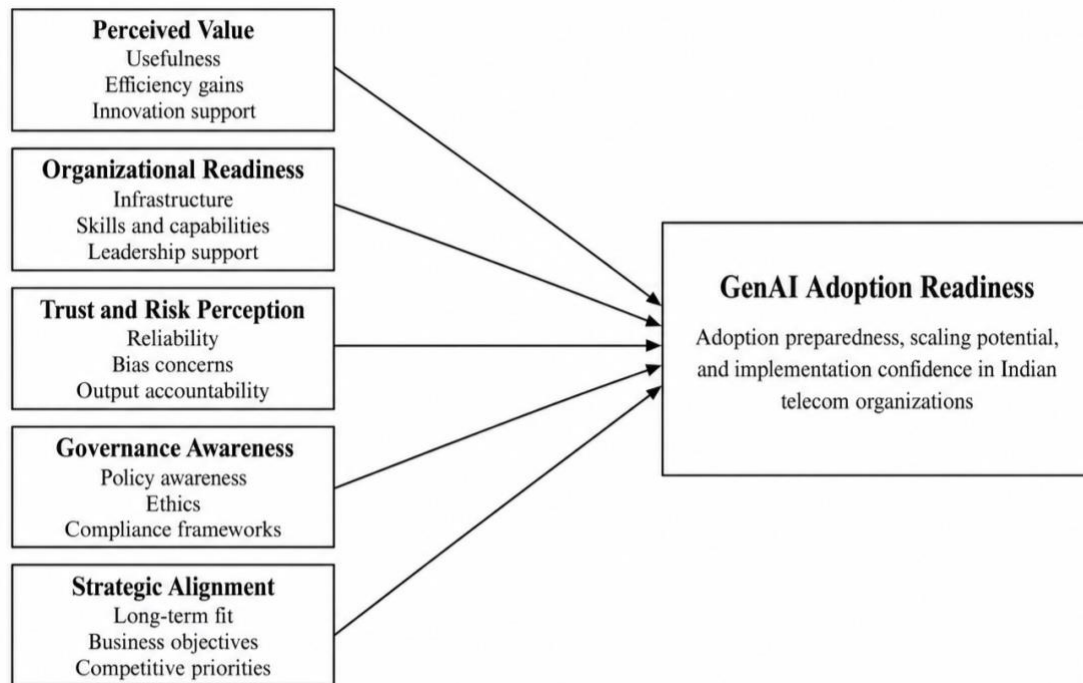


Figure 2.6: Five Dimensions of Organizational Perception in Generative AI Adoption
(Sources: Chen & Li, 2025; Gomes et al., 2025; Glikson & Woolley, 2020; Zhang et al., 2025; Deloitte, 2024)

2.6 Human-AI Interaction and Organizational Capability

2.6.1 The Augmentation Paradigm

The relationship between human organizational actors and AI systems has been conceptualized along a spectrum from full automation, where AI replaces human labor, to full augmentation,

where AI enhances human capability without displacing human judgment. The preponderance of contemporary organizational research supports an augmentation paradigm for the most valuable and strategically relevant applications of Generative AI (Raisch & Krakowski, 2021; Wilson & Daugherty, 2018; Mayer et al., 2025). This paradigm posits that the greatest organizational value from GenAI emerges when AI systems handle high-volume, data-intensive, and time-consuming cognitive tasks, while human actors focus on judgment, contextual interpretation, ethical oversight, relationship management, and strategic synthesis.

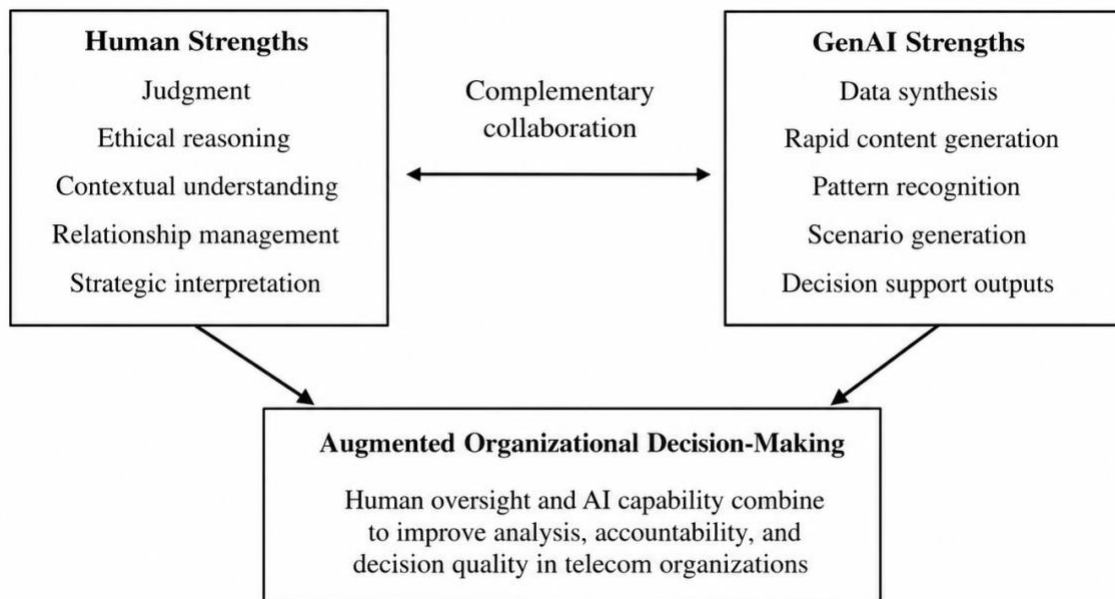


Figure 2.7: Human-AI Augmentation Model in Organizational Decision-Making

Source: Author, based on Jarrahi et al. (2021), Raisch and Krakowski (2021), Lukyanenko et al. (2022), and Mayer et al. (2025).

Jarrahi et al. (2021) provide one of the most influential theoretical accounts of human-AI collaboration in organizational work, distinguishing between AI's comparative advantage in pattern recognition, data synthesis, and rapid generation of structured outputs, and human comparative advantage in contextual judgment, ethical reasoning, social intelligence, and creative problem framing. Their framework implies that organizational AI strategies should be designed to exploit these complementary strengths rather than pursuing wholesale automation of knowledge work. Lukyanenko et al. (2022) extend this analysis to innovation contexts, demonstrating that human-AI collaborative teams in design and problem-solving tasks

consistently outperform either humans or AI working independently when appropriate interaction structures are established.

In Indian telecom organizations, the augmentation paradigm has particular cultural resonance. Organizational cultures in Indian telecoms are characterized by high respect for managerial expertise and hierarchical decision authority, which creates institutional resistance to the idea of AI as an autonomous decision-maker but significant openness to AI as a sophisticated analytical assistant that supports and enhances human decisions (Gong et al., 2024; Alghamdi & Rehman, 2026; Shatila, 2025). This cultural orientation aligns well with augmentation-oriented GenAI deployment strategies and provides a favorable institutional context for building trust in AI-assisted workflows progressively over time.

2.6.2 Leadership and Digital Readiness for AI

Leadership orientation and digital readiness are among the most consistently documented organizational factors shaping GenAI adoption trajectories. Gong et al. (2024) demonstrate empirically that digital leadership, defined as leadership that integrates AI literacy, digital vision, and change management capability, significantly predicts the depth and pace of AI integration across organizational functions. Leaders who actively champion GenAI initiatives, invest in workforce upskilling, and establish clear governance expectations create conditions in which broader organizational adoption is more likely to succeed.

Bevilacqua et al. (2025), in their systematic literature review of leadership in the AI era, identify several leadership competencies that are specifically associated with successful AI adoption: AI literacy (understanding the capabilities and limitations of AI systems), ambidextrous thinking (balancing AI-driven efficiency with innovation), distributed governance design (building accountability structures for AI use across organizational levels), and adaptive sensemaking (helping organizational members interpret and trust AI outputs in novel situations). These competency demands are particularly challenging for telecom organizations whose senior leadership cohorts have typically developed expertise in network engineering, regulatory affairs, and traditional customer management rather than AI and data science.

Shatila (2025) documents the mediating role of digital leadership in the relationship between AI capability investment and organizational resilience outcomes, finding that leadership quality

substantially amplifies or attenuates the performance returns from AI investment. Mayer et al. (2025), in McKinsey's global workforce study, identify "superagency," the capacity of leaders and employees to act with AI-augmented capability and confidence, as a critical organizational capability that distinguishes AI leaders from laggards. These findings collectively reinforce the importance of leadership development as a prerequisite for GenAI adoption success, particularly in complex, regulated sectors such as Indian telecommunications.

2.6.3 Organizational Culture and Change Readiness

Organizational culture shapes the degree to which employees embrace or resist Generative AI adoption in their daily work. Cultures characterized by innovation orientation, psychological safety, learning agility, and collaborative problem-solving tend to facilitate GenAI adoption by creating environments where experimentation with new tools is encouraged and where failures are treated as learning opportunities rather than career risks (Ransbotham et al., 2021; Alghamdi & Rehman, 2026; Talaei-Khoei et al., 2024).

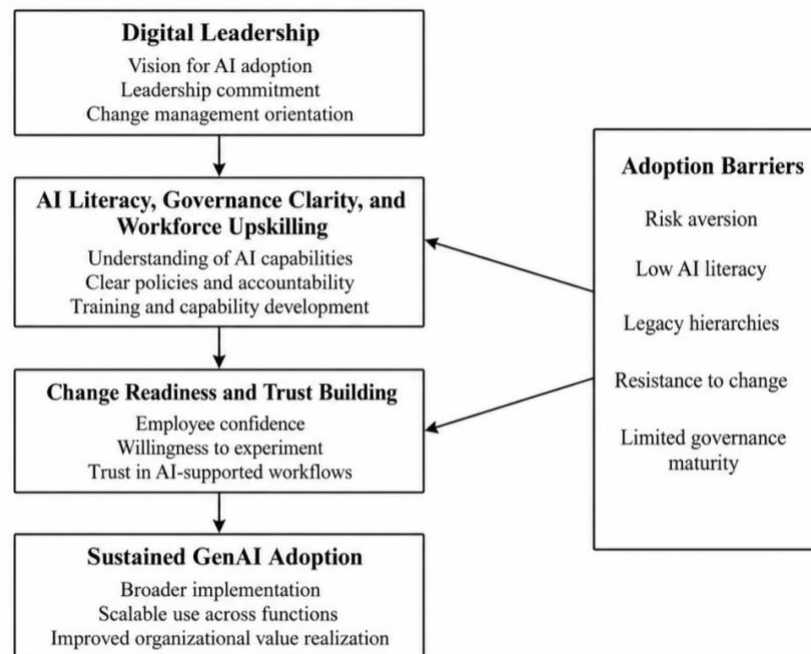


Figure 2.8: Leadership and Change Readiness Pathway for Generative AI Adoption

Source: Author, based on Gong et al. (2024), Bevilacqua et al. (2025), Shatila (2025), Mayer et al. (2025), Ransbotham et al. (2021), and Dacre (2024).

Conversely, cultures characterized by risk aversion, hierarchical information control, and low tolerance for ambiguity create significant barriers to GenAI adoption, particularly at the middle management and frontline employee levels where adoption decisions are most consequential for operational impact (Westover, 2024; Muhammad, 2025; Loh et al., 2023). In large Indian telecom organizations, where workforce demographics, educational backgrounds, and organizational hierarchies are highly diverse, managing cultural change for GenAI adoption requires differentiated strategies that address the specific concerns and capability gaps of different employee segments (TEC, 2024; Deloitte, 2024).

Adarkwah (2025) examines GenAI integration in adult learning and professional development contexts, finding that change readiness interventions that combine technical training with reflective practice and organizational narrative-building are most effective in shifting cultural orientations toward AI acceptance. Dacre (2024) similarly identifies organizational learning investment and governance clarity as the two strongest cultural enablers of AI-driven transformation in both public and private sector organizations, a finding with direct applicability to Indian telecom organizations managing large-scale GenAI adoption programs.

2.7 Ethical, Governance, and Risk Considerations in Generative AI

2.7.1 Ethical Concerns and Algorithmic Bias

The rapid organizational adoption of Generative AI has intensified scrutiny of its ethical implications, particularly concerning the reliability of outputs, the fairness of algorithmic processes, and the adequacy of human oversight over consequential AI-assisted decisions. Unlike conventional software systems whose behavior is fully determined by explicit rules, Generative AI models produce probabilistic outputs that may appear coherent and authoritative while being factually inaccurate, contextually inappropriate, or structurally biased. This creates a distinctive ethical challenge for organizations: the apparent fluency of GenAI outputs can mask underlying uncertainty, reinforce existing inequities, or generate organizational risk without clearly visible warning signs (Bender et al., 2021; Floridi & Chiriatti, 2020; Hagendorff, 2020).

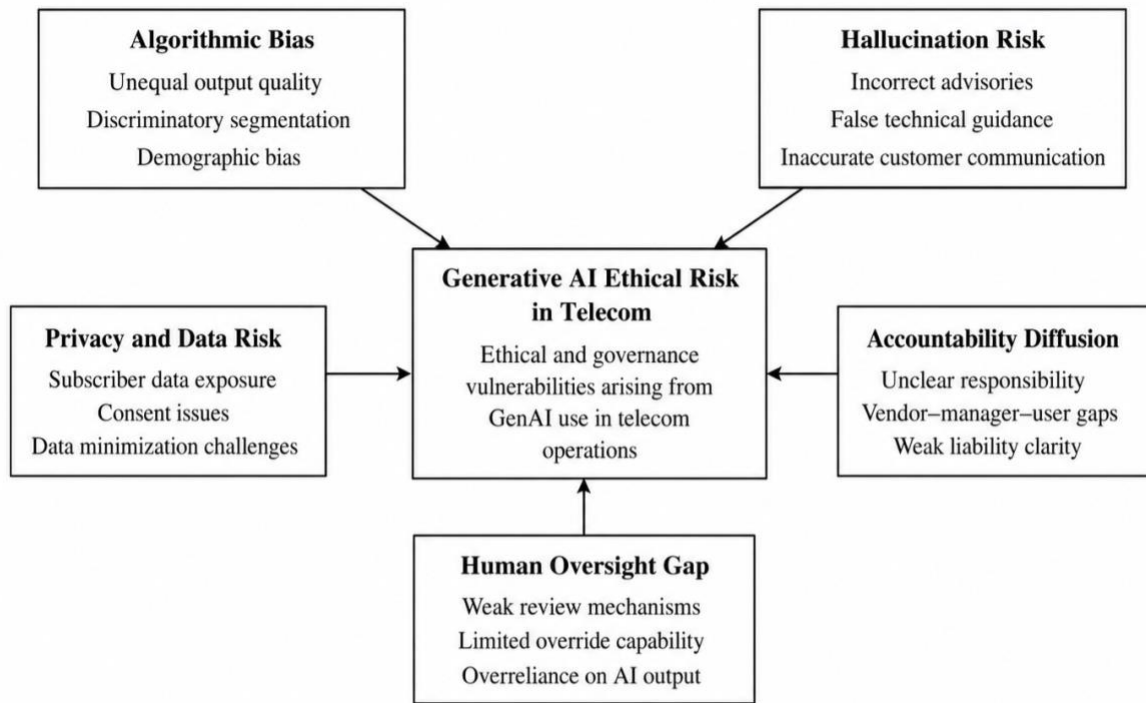


Figure 2.9: Ethical Risk Map for Generative AI Deployment in Indian Telecom

Source: Author, based on Bender et al. (2021), Floridi and Chiriatti (2020), Hagendorff (2020), Binns (2018), Jobin et al. (2019), Mokander et al. (2021), TRAI (2024), and Agarwal and Nene (2025).

Algorithmic bias is among the most extensively documented ethical concerns in the AI literature, and its relevance to Generative AI deployment is direct and significant. GenAI models trained on large corpora of text and data inherit the distributional properties and representational biases present in their training sets. When deployed in organizational contexts such as customer communication, employee evaluation, or credit and service tier assessment, these inherited biases may produce discriminatory or inequitable outputs that reflect and amplify historical patterns of disadvantage (Binns, 2018; Jobin et al., 2019; Pathan & Shah, 2025). In Indian telecom organizations, where customer populations are extraordinarily diverse across language, geography, digital literacy, and socioeconomic status, the risk of demographically differentiated AI output quality is a governance concern that extends from ethical principle to commercial and regulatory obligation (TRAI, 2024; Agarwal & Nene, 2025).

Hallucination, defined as the generation of factually incorrect or fabricated content presented with apparent confidence, represents a second major ethical concern with direct operational implications for telecom organizations. When GenAI systems are used to generate technical advisories, customer communications, compliance documentation, or network management recommendations, hallucinated content can produce customer harm, regulatory violation, or operational disruption (Bender et al., 2021; Bommasani et al., 2024; OpenAI, 2023). Mokander et al. (2021), in their foundational work on ethics-based auditing of automated decision systems, emphasize that organizations cannot manage hallucination risk through post-deployment monitoring alone; it must be addressed through systematic pre-deployment testing, output validation procedures, and human-in-the-loop oversight structures integrated into AI workflows from the outset.

Accountability diffusion constitutes a third ethical challenge unique to AI-assisted organizational decision-making. When an AI system contributes to a harmful or legally consequential outcome, responsibility may be distributed across AI developers, technology vendors, deployment engineers, organizational managers, and end users in ways that make accountability difficult to assign clearly. Floridi (2019) argues that establishing trustworthy AI requires organizations to move beyond general ethical principles toward operational accountability structures that specify who is responsible for AI outputs in specific decision contexts. Morley et al. (2020) extend this argument by documenting the practical gap between high-level AI ethics frameworks and their operational implementation, a gap that is particularly evident in organizations that have adopted GenAI tools rapidly without establishing corresponding governance maturity.

Table 2.4: Ethical Principles for Generative AI Deployment and Their Relevance to Indian Telecom (Sources: Floridi, 2019; Jobin et al., 2019; Binns, 2018; TRAI, 2024; Pathan & Shah, 2025; OECD, 2023)

Ethical Principle	Description	Relevance to Telecom GenAI	Key Sources
Transparency	AI systems must be explainable; outputs traceable to inputs; decision logic auditable.	Telecom customers and regulators require explainability for AI-driven billing, service, and network decisions.	Floridi, 2019; Jobin et al., 2019; OECD, 2023
Fairness and Non-Discrimination	AI models must not produce outputs that discriminate based on protected characteristics.	Customer segmentation, pricing, and service prioritization must not embed demographic bias.	Binns, 2018; Hagendorff, 2020; Pathan & Shah, 2025
Accountability	Clear assignment of responsibility when AI systems produce harmful or erroneous outputs.	Telecom operators must identify liable parties when AI-driven decisions affect customer rights.	Floridi, 2019; Morley et al., 2020; Agarwal & Nene, 2025
Privacy and Data Protection	AI deployment must comply with data minimization, consent, and storage limitation principles.	TRAI and Indian data protection law impose strict constraints on AI use of subscriber data.	TRAI, 2024; Jobin et al., 2019; OECD, 2023
Reliability and Safety	AI systems must perform consistently and safely across operational conditions.	Network management and customer interaction AI must not introduce service disruption risks.	Bender et al., 2021; Bommasani et al., 2024; TEC, 2024
Human Oversight	Humans must retain meaningful control and override capability over AI decisions.	Telecom managers must be able to intervene when AI recommendations conflict with policy or values.	Leslie, 2019; Mokander et al., 2021; Mayer et al., 2025

2.7.2 Governance Frameworks and Regulatory Landscape

AI governance has emerged as a central institutional priority globally, as policymakers, standards bodies, and industry associations recognize that the pace of AI deployment has outstripped the development of adequate oversight structures. Governance, in this context, refers to the ensemble of policies, standards, accountability mechanisms, monitoring procedures, and regulatory

requirements that collectively shape how AI systems are developed, deployed, audited, and corrected (OECD, 2023; Jobin et al., 2019; Cath, 2018). Effective AI governance is not merely a compliance function; it is a strategic enabler that allows organizations to deploy AI more confidently, manage risks more systematically, and build stakeholder trust more credibly than organizations operating without structured governance (Mokander et al., 2021; Klein et al., 2023; Leslie, 2019).

At the international level, several foundational governance frameworks provide normative guidance for AI deployment. The OECD AI Principles (2023) establish five value-based principles for trustworthy AI: inclusive growth and sustainable development, human-centered values and fairness, transparency and explainability, robustness, security, and safety, and accountability. The OECD framework also provides a classification system for AI systems based on deployment context, data characteristics, model properties, and societal implications, enabling risk-proportionate governance that differentiates between high-risk and lower-risk AI deployments (OECD, 2023). The UNESCO Recommendation on the Ethics of Artificial Intelligence and ITU's AI for Good frameworks complement OECD guidance by emphasizing human rights, social equity, and sustainable development dimensions of AI governance that are particularly salient in developing country contexts such as India (Martinuzzi, 2024; Siddiqui, 2025).

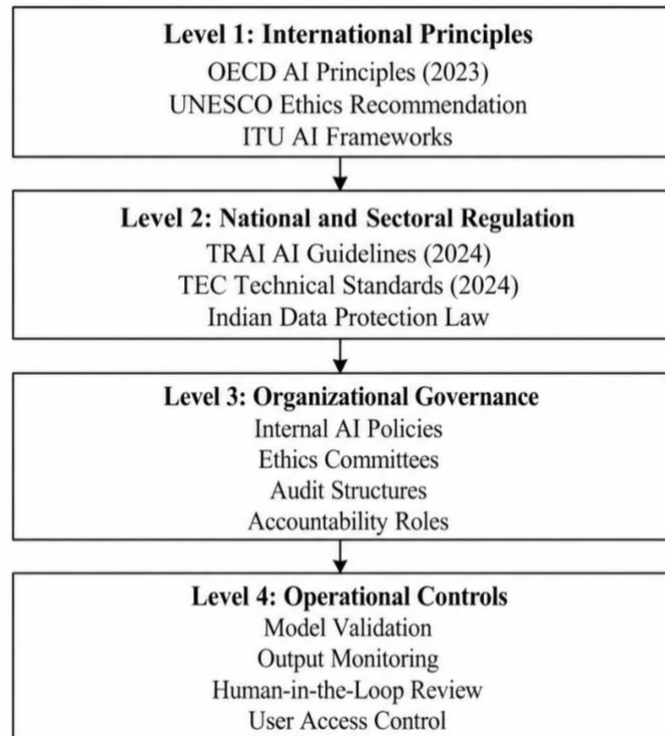


Figure 2.10: Layered Governance Framework for Generative AI in Indian Telecom
Source: Author, based on OECD (2023), UNESCO Recommendation on the Ethics of Artificial Intelligence, ITU AI frameworks, TRAI (2024), TEC (2024), Agarwal and Nene (2025), and Mokander et al. (2021).

In India, the governance landscape for AI in telecommunications is evolving rapidly but remains incomplete in critical respects. TRAI (2024) has issued recommendations on AI and machine learning in telecommunications that address data quality, model performance standards, and consumer protection, establishing a sectoral governance baseline. The Telecom Engineering Centre (2024) has published technical reviews of AI and ML in telecommunications that provide engineering-level guidance for AI system design and integration. Agarwal and Nene (2025) conduct a detailed legal analysis of AI incident reporting requirements in Indian telecommunications, documenting significant gaps between current regulatory frameworks and the specific accountability requirements that GenAI deployment creates. Their analysis identifies the absence of mandatory AI incident reporting standards, audit requirements for AI-generated decisions affecting consumers, and technical standards for GenAI output quality assurance as the most critical governance gaps facing Indian telecom organizations.

At the organizational level, governance maturity varies substantially across Indian telecom operators. Industry surveys indicate that larger operators with dedicated digital transformation programs have begun developing internal AI ethics guidelines, model risk management procedures, and cross-functional AI governance committees, while mid-tier and regional operators frequently lack these structures entirely (Infosys, 2024; Deloitte, 2024). Mokander et al. (2021) emphasize that ethics-based auditing of AI systems requires procedural regularity, independent review capability, and transparent documentation of AI decision logic, all of which demand significant organizational investment that many firms are not yet prepared to make. These governance maturity gaps create a two-tier adoption landscape in which well-resourced operators can deploy GenAI responsibly while less-resourced operators face elevated risk exposure from unstructured deployment.

2.7.3 Organizational Risk Management for GenAI

Organizational risk management for Generative AI encompasses a broader set of concerns than technical safety alone. Trust deficits, misuse scenarios, strategic misalignment, and operational instability each constitute risk categories that governance frameworks must address to enable sustainable GenAI deployment. Glikson and Woolley (2020) demonstrate that organizational trust in AI systems is not static but dynamic, shaped by cumulative experience with AI output quality, organizational narratives about AI failures and successes, and the perceived adequacy of governance structures. Organizations that experience early GenAI deployment failures without robust incident response and learning processes in place frequently develop organizational risk aversion that impedes subsequent adoption efforts, even when the root causes of failure are addressable through better governance.

Misuse risk is a particularly significant concern in telecom contexts where GenAI is deployed in customer-facing applications. Because GenAI systems can produce highly persuasive and contextually plausible content, they create risks of inadvertent misinformation, manipulative communication, and synthetic content generation that violates consumer protection standards (Davenport et al., 2020; Kaplan & Haenlein, 2024; Kietzmann et al., 2023). TRAI (2024) guidelines specifically address consumer protection requirements for AI-assisted communications in Indian telecom, establishing an emerging regulatory standard that organizations must incorporate into their GenAI governance frameworks.

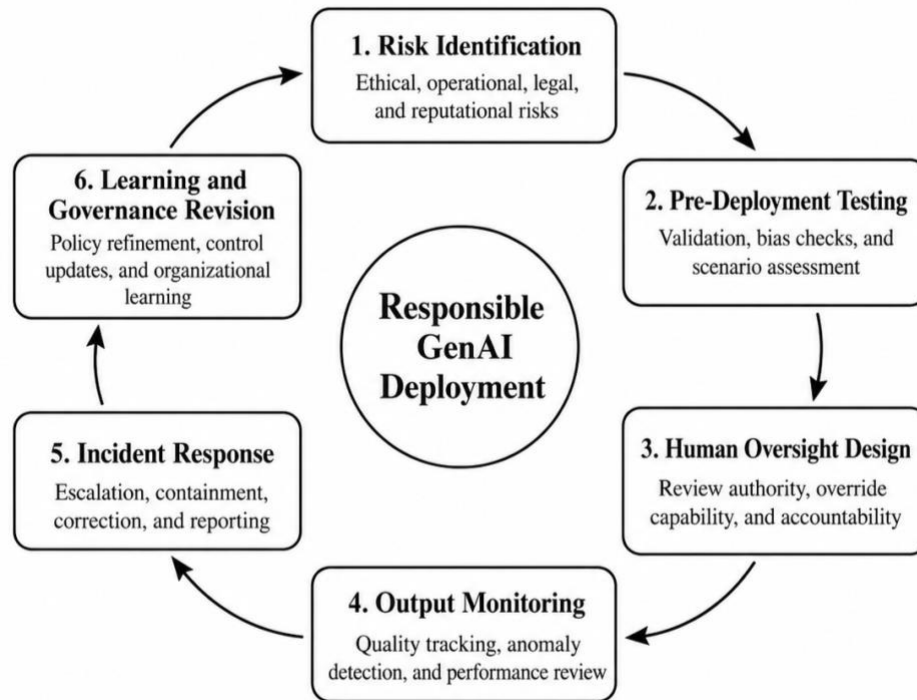


Figure 2.11: Organizational Risk Management Cycle for Generative AI Deployment

Source: Author, based on Glikson and Woolley (2020), Mokander et al. (2021), Davenport et al. (2020), Kaplan and Haenlein (2024), Kietzmann et al. (2023), Britto et al. (2023), TRAI (2024), and Najana (2024).

Operational risk associated with GenAI integration into mission-critical telecom systems requires careful management through staged deployment, extensive testing, fallback capability design, and continuous monitoring. Britto et al. (2023) document the systems engineering challenges of integrating GenAI into telecom operational architectures, emphasizing that AI-native network management systems must be designed with explicit human override capability and graceful degradation mechanisms to maintain service reliability when AI components underperform. These risk management requirements have direct resource implications for telecom organizations and must be incorporated into GenAI business case development and adoption planning (Najana, 2024; Orero-Blat et al., 2025).

2.8 Organizational Capabilities and AI-Driven Performance

2.8.1 AI Capability as a Strategic Asset

Organizational AI capability has emerged as one of the most consequential strategic assets in the digital economy, enabling firms to translate AI investment into sustained competitive advantage through improvements in decision quality, operational efficiency, customer experience, and innovation throughput (Mikalef et al., 2020; Li et al., 2021; Wamba, 2022). The concept of AI capability extends well beyond technical infrastructure to encompass a complex bundle of resources and competencies including data assets and governance maturity, algorithmic development and deployment skills, organizational processes for AI integration, leadership AI literacy, and governance structures that ensure responsible and compliant use (Mikalef et al., 2020; Aldoseri et al., 2024).



Figure 2.12: Organizational Capability Stack for Generative AI Value Realization

Source: Author, based on Mikalef et al. (2020), Li et al. (2021), Wamba (2022), Aldoseri et al. (2024), Kumar and George (2024), TEC (2024), and Infosys (2024).

Mikalef et al. (2020), in their influential empirical study of AI capability and firm performance across European organizations, demonstrate that AI capability influences performance through two distinct pathways: a direct pathway through operational efficiency improvements and an indirect pathway through enhanced innovation capability. Their findings confirm that the organizational and management dimensions of AI capability, including leadership commitment, cross-functional coordination, and governance maturity, are stronger predictors of performance outcomes than the purely technical dimensions, reinforcing the importance of organizational readiness as a condition for AI value realization. Wamba (2022) extends this analysis to confirm

that AI capability mediates the relationship between digital transformation investment and firm performance outcomes, with organizational agility and customer agility serving as key mediating mechanisms.

For Indian telecom organizations, AI capability development is simultaneously an urgent strategic priority and a significant organizational challenge. The competitive dynamics of the Indian telecom market, characterized by intense price competition, high customer churn, and continuous service innovation requirements, create strong incentives for AI capability investment. However, the workforce skills gap, legacy systems complexity, and governance maturity deficit that characterize much of the Indian telecom sector constrain the pace and quality of AI capability development (TEC, 2024; Infosys, 2024; Telecom Review Asia, 2025). Kumar and George (2024), examining GenAI capability development in Indian financial services as a comparator sector, find that organizations that invest in capability development through structured learning programs, external partnerships, and governance framework construction achieve significantly faster and more sustainable AI adoption trajectories than those pursuing purely technology-led approaches.

2.8.2 Dynamic Capabilities and Adaptive Capacity

Teece's (2018) dynamic capabilities framework provides an important theoretical lens for understanding how organizations develop and sustain AI capability in rapidly evolving technological environments. Dynamic capabilities are higher-order organizational competencies that enable firms to sense emerging technological opportunities and threats, seize opportunities through resource reconfiguration and investment, and transform organizational structures and processes in response to environmental change. In the GenAI context, dynamic capabilities are required at multiple levels: sensing GenAI capability developments and their competitive implications; seizing opportunities through rapid prototyping, pilot deployment, and organizational learning; and transforming workflows, roles, and governance structures to embed GenAI sustainably across organizational functions (Teece, 2018; Orero-Blat et al., 2025).

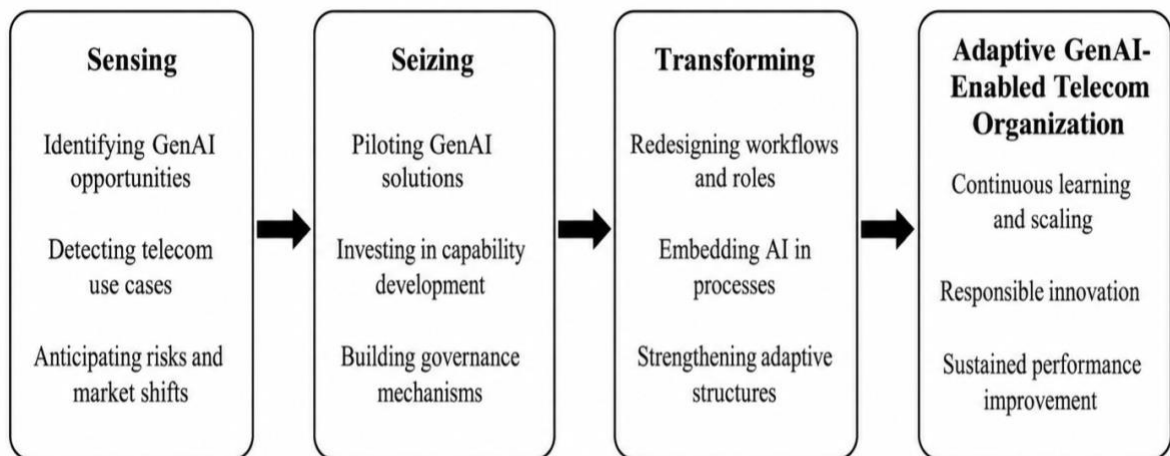


Figure 2.13: Dynamic Capabilities Pathway for GenAI Adoption in Telecom

Source: Author, based on Teece (2018), Ransbotham et al. (2021), Orero-Blat et al. (2025), Fuwen and Jin (2025), Dacre (2024), Adarkwah (2025), Pathan and Shah (2025), and Klein et al. (2023).

Ransbotham et al. (2021) provide empirical support for the dynamic capabilities perspective in the AI context, demonstrating that organizational learning capacity is among the strongest predictors of sustained AI value realization across industries. Organizations that invest in structured learning processes for AI, including systematic post-deployment review, cross-functional knowledge sharing, and external benchmarking, are significantly more likely to scale AI initiatives successfully than those that treat AI deployment as a one-time implementation project. This finding has direct implications for Indian telecom organizations, suggesting that GenAI adoption programs should incorporate explicit organizational learning mechanisms rather than focusing solely on technology deployment and initial training (TEC, 2024; Dacre, 2024; Adarkwah, 2025).

Fuwen and Jin (2025), in their empirical study of AI adoption and governance in Chinese firms, confirm that governance mechanisms moderate the relationship between AI capability and innovation efficiency, with stronger governance structures amplifying the innovation returns from AI capability investment. Their findings suggest that governance is not merely a compliance constraint on AI adoption but an active enabler of AI-driven organizational performance, a perspective that challenges the common organizational tendency to treat

governance as a cost center rather than a value driver. This reframing has important implications for how Indian telecom organizations design their GenAI governance structures, suggesting that governance investment should be positioned alongside capability investment as a strategic priority (Pathan & Shah, 2025; Agarwal & Nene, 2025; Klein et al., 2023).

2.9 Digital Transformation, Strategic Alignment, and GenAI Integration

2.9.1 Digital Transformation as the Organizational Context for GenAI

Digital transformation provides the organizational context within which Generative AI adoption is most meaningfully understood. Vial (2019), in a foundational review of digital transformation theory, defines it as a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies. This definition positions digital transformation not as a technology acquisition event but as an organizational change process in which technologies serve as enablers of strategic, operational, and cultural transformation. Verhoef et al. (2021) extend this definition by emphasizing that digital transformation encompasses business model innovation, customer experience redesign, and organizational capability reconfiguration, dimensions that go far beyond the deployment of individual technology tools.

Generative AI represents a qualitatively significant enabler within this broader digital transformation context. Unlike previous waves of digital technology that primarily automated structured processes, GenAI addresses the cognitive and creative dimensions of organizational work that have historically been resistant to automation (Brynjolfsson et al., 2023; Raisch & Krakowski, 2021; Doshi et al., 2024). For telecom organizations undertaking digital transformation programs that encompass network modernization, customer experience reinvention, and operational efficiency improvement, GenAI offers capabilities that accelerate transformation across all three dimensions simultaneously, creating integration synergies that justify treating GenAI adoption as a strategic digital transformation priority rather than an isolated technology initiative (Britto et al., 2023; WEF, 2025; Infosys, 2024).

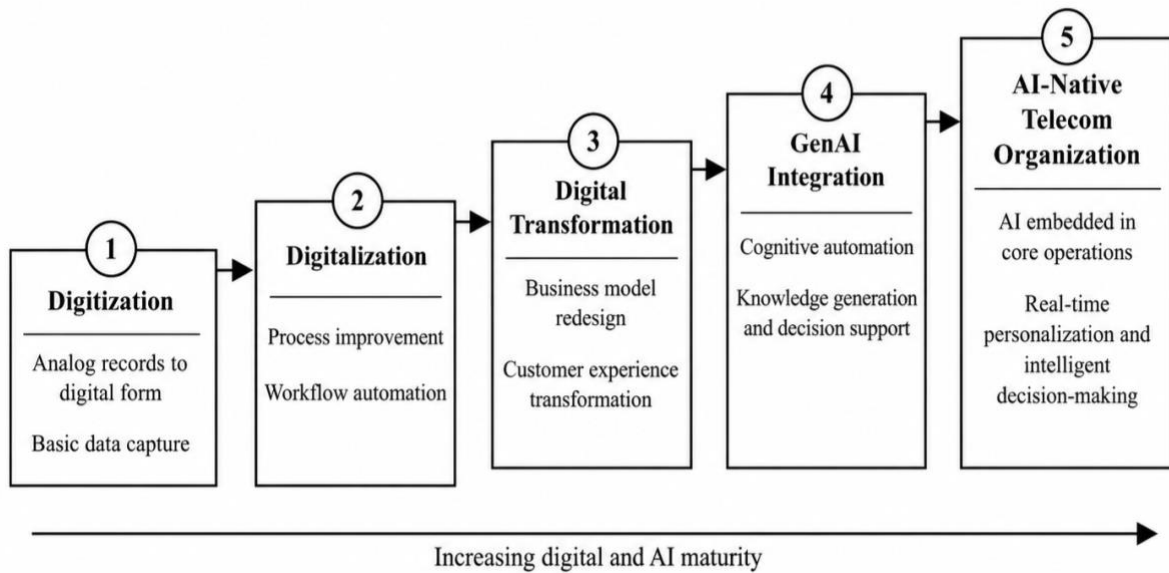


Figure 2.14: Digital Transformation Maturity Pathway with Generative AI Integration

Source: Author, based on Vial (2019), Verhoef et al. (2021), Brynjolfsson et al. (2023), Raisch and Krakowski (2021), Doshi et al. (2024), Britto et al. (2023), WEF (2025), and Infosys (2024).

Kraus et al. (2022), in their comprehensive review of digital transformation and AI research, identify strategic alignment as the single most important organizational factor determining whether AI investments contribute to digital transformation outcomes. Organizations that embed AI initiatives within strategic transformation frameworks, connect AI use cases to competitive priorities, and align AI governance structures with organizational values achieve substantially higher transformation ROI than those deploying AI opportunistically without strategic integration. This finding is strongly supported by parallel evidence from Kane et al. (2015), who demonstrate across multiple industry studies that digital transformation success is determined more by organizational strategy and culture than by technology sophistication alone.

Figure Table 2.4: Digital Transformation Phases and the Integrative Role of Generative AI (Sources: Vial, 2019; Verhoef et al., 2021; Brynjolfsson et al., 2023; WEF, 2025; Infosys, 2024)

DT Phase	Description	GenAI Role	Expected Outcome
Digitization	Converting analog processes and records to digital formats.	Document generation and OCR-assisted data extraction.	Structured digital data assets.
Digitalization	Using digital data to improve and automate existing processes.	Process automation, intelligent routing, workflow optimization.	Improved operational efficiency.
Digital Transformation	Fundamental redesign of business models and value creation.	Strategic scenario simulation, new service design, customer intelligence.	New competitive positioning.
AI-Native Organization	AI embedded in core decision-making and operational architecture.	Autonomous network management, real-time customer personalization.	Sustainable competitive advantage.

2.9.2 Strategic Alignment and Long-Term AI Value

Strategic alignment of GenAI adoption encompasses three interconnected dimensions: alignment between AI use cases and competitive priorities, alignment between AI governance and organizational values, and alignment between AI capability investment and workforce development. Research consistently confirms that organizations achieving all three dimensions of alignment demonstrate higher AI adoption rates, better AI performance outcomes, and more sustainable AI value realization than those achieving only one or two alignment dimensions (Mikalef et al., 2020; Ransbotham et al., 2021; Deloitte, 2024).

In Indian telecom, the competitive priority landscape for GenAI alignment is relatively clear: customer experience improvement, network reliability and cost efficiency, revenue assurance and fraud reduction, and service innovation represent the four domains where GenAI offers the most direct strategic value (Lin et al., 2024; GSMA Intelligence, 2023; PwC, 2024; Karapantelakis et al., 2024). Alignment between GenAI use case selection and these competitive priorities ensures that adoption programs generate measurable business value rather than

remaining at the level of innovation theater. Aligning governance with organizational values requires telecom organizations to articulate explicitly what responsible AI means in their specific institutional context, encompassing consumer protection commitments, employee treatment standards, regulatory compliance obligations, and reputational risk management priorities (TRAI, 2024; Agarwal & Nene, 2025; Pathan & Shah, 2025).

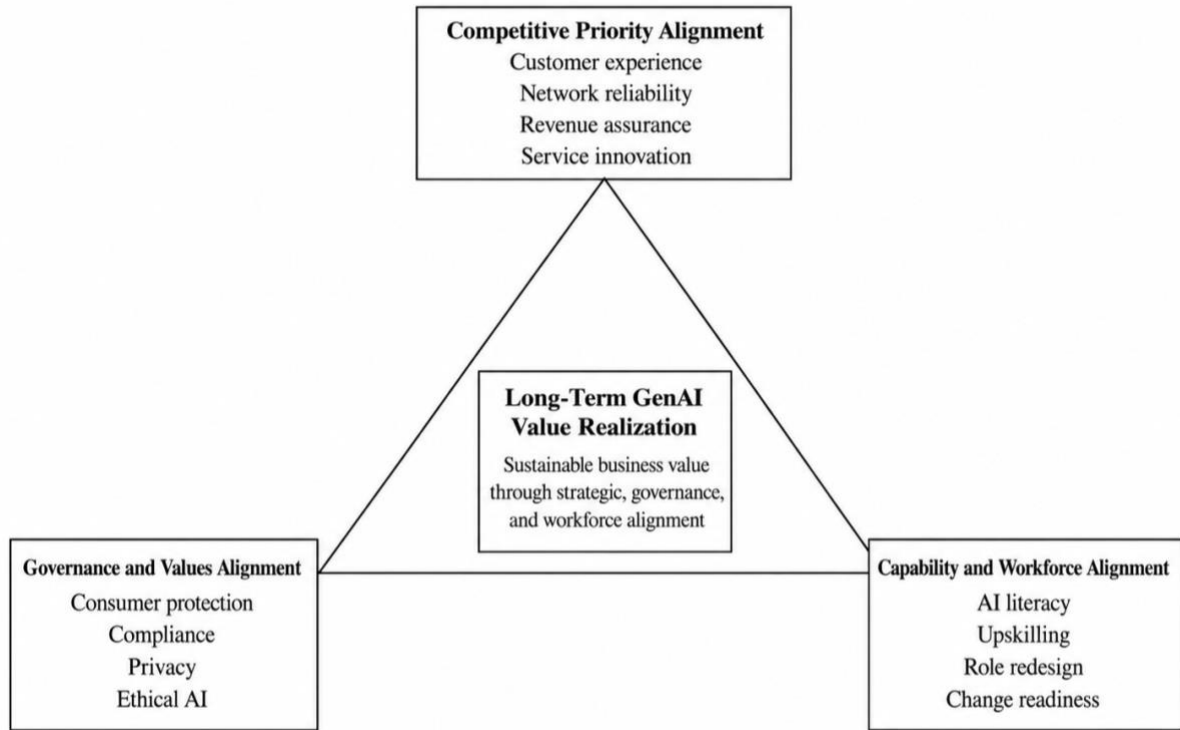


Figure 2.15: Strategic Alignment Triangle for Long-Term GenAI Value Realization
Source: Author, based on Mikalef et al. (2020), Ransbotham et al. (2021), Deloitte (2024), Lin et al. (2024), GSMA Intelligence (2023), PwC (2024), Karapantelakis et al. (2024), TRAI (2024), and Pathan and Shah (2025).

Long-term AI value realization requires sustained capability investment rather than one-time deployment. Orero-Blat et al. (2025) demonstrate that organizations with strong big data analytics capabilities combined with structured innovation management achieve significantly better performance outcomes than those with either capability in isolation, suggesting that GenAI value accrues to organizations that build complementary capabilities systematically over time. Wamba (2022) similarly finds that the performance impact of AI assimilation increases substantially with organizational AI experience, confirming that the organizations best

positioned for GenAI value realization are those that have already developed foundational AI capabilities through earlier phases of digital transformation. These findings have important strategic implications for Indian telecom organizations at different stages of digital maturity, suggesting that capability development sequencing matters as much as initial adoption decisions.

2.10 Framework Perspectives in Generative AI Adoption

2.10.1 Emerging Framework Logic for GenAI Adoption

The recent literature on Generative AI adoption demonstrates a clear evolutionary trajectory from broad discussions of technological potential toward the development of structured frameworks that integrate technological, organizational, managerial, and environmental dimensions. This trajectory reflects growing recognition that GenAI adoption cannot be adequately explained through single-variable models or technology-only logic, and that practical organizational guidance requires integrated frameworks that acknowledge the complexity and interdependence of adoption determinants (Gomes et al., 2025; Seifdar & Amiri, 2025; Zhou et al., 2025).

Seifdar and Amiri (2025), applying game-theoretic and network-based modeling to GenAI adoption, demonstrate that adoption trajectories are shaped by the interaction between managerial optimism, organizational network structure, and governance conditions, with decentralized adoption patterns generating both efficiency gains and coordination challenges. Their work establishes that GenAI adoption is fundamentally a collective organizational phenomenon rather than an aggregation of individual adoption decisions, implying that frameworks must account for organizational interaction dynamics and governance structures rather than focusing exclusively on individual-level adoption predictors. This finding is particularly relevant for large Indian telecom organizations with hierarchical management structures and geographically distributed workforces, where adoption diffusion patterns will be shaped significantly by organizational communication channels and authority structures.

Ali et al. (2025), in their cross-national analysis of GenAI adoption enabling conditions at national scale, identify five interdependent enabling factors: AI infrastructure maturity, research and development investment, workforce readiness, regulatory framework quality, and organizational adoption culture. Their finding that these factors are most powerful when present

simultaneously rather than individually reinforces the case for integrated adoption frameworks that address multiple dimensions concurrently rather than sequentially. Zhou et al. (2025) extend TOE by demonstrating that GenAI adoption in government contexts connects directly to ambidextrous innovation outcomes, suggesting that adoption frameworks should explicitly link adoption drivers to post-adoption performance outcomes rather than treating adoption as an end in itself.

2.10.2 Perception-Centered Framework Design

The most directly relevant framework perspective for the present study is the perception-centered approach represented in Chen and Li (2025) and Gomes et al. (2025). Chen and Li (2025), in their empirical study of AI adoption among IT professionals, construct a framework in which perceived usefulness, trust, contextual understanding, and bias concern each independently predict adoption behavior, with trust serving as the strongest single predictor of sustained adoption depth. Their framework implies that adoption interventions should prioritize trust-building mechanisms, including transparent governance, output validation procedures, and organizational communication about AI limitations and oversight structures, over purely capability-building activities.

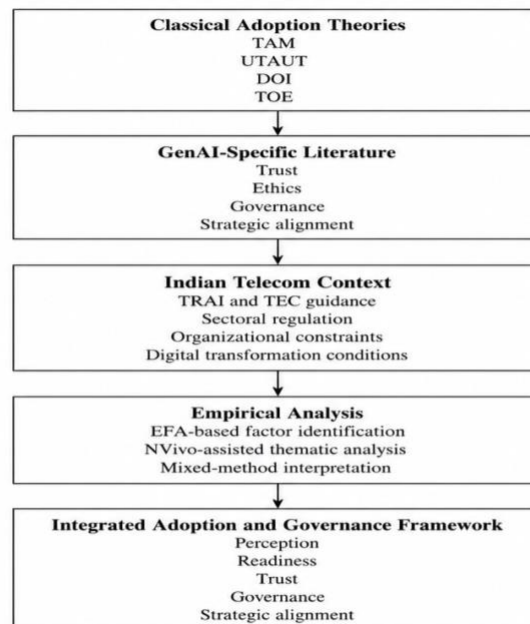


Figure 2.16: Framework Development Logic for GenAI Adoption in Indian Telecom

Source: Author, based on Davis (1989), Venkatesh et al. (2003)

Gomes et al. (2025), applying multi-criteria analysis to GenAI adoption determinants across organizational contexts, find that organizational dimensions, specifically leadership orientation, governance readiness, and strategic alignment perception, carry greater weight in adoption decisions than purely technological dimensions such as technical infrastructure and model performance. Their finding directly validates the present study's research design, which prioritizes organizational perception as the primary analytical lens for examining GenAI adoption in Indian telecom. The convergence of evidence from Chen and Li (2025) and Gomes et al. (2025) suggests that framework designs for GenAI adoption should place organizational perception at the center rather than treating it as a peripheral moderating variable.

Gregor (2006) provides the foundational theoretical justification for the framework development approach in information systems research, arguing that theory in IS should serve explanatory, predictive, prescriptive, or design functions, and that frameworks emerging from empirical evidence are particularly valuable for addressing complex, context-specific organizational phenomena. Hevner et al. (2004) reinforce this perspective through their design science framework, emphasizing that practically relevant IS artifacts, including adoption frameworks, must emerge from rigorous analysis of real organizational problems and be evaluated against practical utility criteria rather than purely theoretical elegance. These methodological principles directly inform the framework development approach employed in Chapter 4 of the present study.

2.11 Indian Telecom Context and GenAI Adoption: Synthesis

2.11.1 Institutional and Regulatory Environment

The Indian telecommunications sector operates within an institutional environment that is simultaneously enabling and constraining for Generative AI adoption. On the enabling side, India's large and growing digital infrastructure, including widespread 4G coverage, rapidly expanding 5G networks, a large and technically skilled workforce, and an active national AI strategy under the National Strategy for AI (NITI Aayog), creates favorable conditions for AI-driven transformation (TEC, 2024; Telecom Review Asia, 2025). The Indian government's Digital India initiative and subsequent digital infrastructure investments have substantially expanded the data and connectivity foundations upon which GenAI applications depend (Kumar & George, 2024).

On the constraining side, India's regulatory environment for AI in telecommunications is evolving but incomplete. TRAI (2024) has issued guidance on AI use in telecom but has not yet established comprehensive mandatory standards for AI output quality, bias management, or incident reporting. The Digital Personal Data Protection Act (2023) establishes data governance requirements that constrain certain AI training and deployment practices, creating compliance uncertainty for organizations developing GenAI applications that rely on customer data (Agarwal & Nene, 2025). TEC (2024) provides technical guidance but lacks enforcement authority over AI-specific practices, creating a governance gap between technical guidance and regulatory obligation that organizations must navigate with limited institutional support.

Bariah et al. (2023) document the specific challenge of adapting general-purpose large language models for telecom domain applications, finding that standard LLMs trained on general corpora perform poorly on telecom-specific reasoning tasks without domain adaptation. This finding has important practical implications for Indian telecom organizations evaluating GenAI deployment: generic AI tools adopted without domain-specific fine-tuning and validation are unlikely to deliver the performance levels needed to justify adoption at scale, reinforcing the importance of capability investment in parallel with technology deployment.

2.11.2 Organizational Diversity and Adoption Heterogeneity

The Indian telecom sector encompasses a highly diverse range of organizational types, sizes, and strategic contexts, from large national operators such as Reliance Jio, Bharti Airtel, and BSNL with tens of thousands of employees and sophisticated digital transformation programs, to regional and specialized operators with more limited resources and capability. This organizational diversity implies that GenAI adoption patterns and constraints will vary substantially across the sector, and that governance frameworks and policy interventions must be designed with sufficient flexibility to address the needs of organizations at very different stages of digital and AI maturity (TRAI, 2024; TEC, 2024; Infosys, 2024).

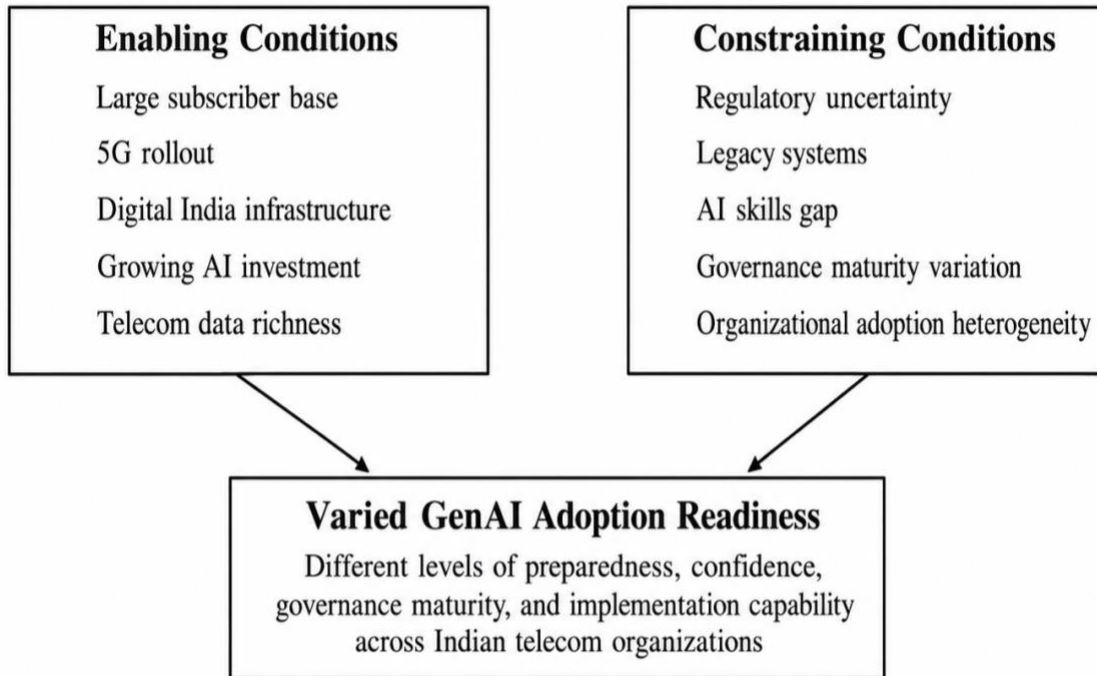


Figure 2.17: Indian Telecom Context Map for Generative AI Adoption

Source: Author, based on TRAI (2024), TEC (2024), Telecom Review Asia (2025), Kumar and George (2024), Agarwal and Nene (2025), Bariah et al. (2023), Westover (2024), Muhammad (2025), and Infosys (2024).

Westover (2024) documents how organizational size and digital maturity moderate the relationship between AI adoption intention and adoption outcomes, finding that larger, more digitally mature organizations are better positioned to translate adoption intention into operational impact but face greater organizational change management challenges due to their complexity and inertia. Muhammad (2025) extends this analysis to document the digital divide risk in AI adoption, where accelerating adoption by large, well-resourced organizations may widen the capability gap between sector leaders and laggards, with consequent implications for market competition, service quality equity, and regulatory policy design. These considerations reinforce the importance of the present study's focus on organizational perception as a key variable, since perception-based barriers to adoption may be particularly significant in organizations where technical capability exists but organizational confidence and governance maturity remain underdeveloped.

2.11.3 Research Positioning within the Indian Telecom Literature

The academic literature on AI adoption in Indian telecommunications, while growing, remains substantially underdeveloped relative to the sector's economic significance and strategic importance. Agarwal and Nene (2025) provide the most comprehensive analysis of AI governance and regulatory challenges in Indian telecom, but their focus is primarily legal and institutional rather than organizational and behavioral. TEC (2024) and TRAI (2024) provide important institutional perspectives but are policy documents rather than empirical research. Bariah et al. (2023) address technical LLM performance challenges in telecom contexts but do not examine organizational adoption dynamics. Kanakadandi (2025) documents specific GenAI application frameworks for telecom e-commerce but at a highly applied technical level without organizational theory integration.

The present study addresses the identified gap in the Indian telecom AI adoption literature by providing the first empirically grounded, theory-informed, mixed-method study of GenAI adoption from an organizational perception perspective in this sector. By combining EFA-based quantitative dimension identification with NVivo-assisted qualitative thematic analysis, and by grounding the study in real Indian telecom organizational contexts, the research generates empirical evidence that is simultaneously theoretically rigorous and practically applicable to the specific institutional context of Indian telecommunications.

2.12 Research Gap

The synthesis of the literature reviewed across both parts of this chapter reveals a coherent and significant research gap that directly justifies the present study. The gap operates across five interrelated dimensions that are individually documented in existing literature but have not been addressed collectively by any single empirical study.

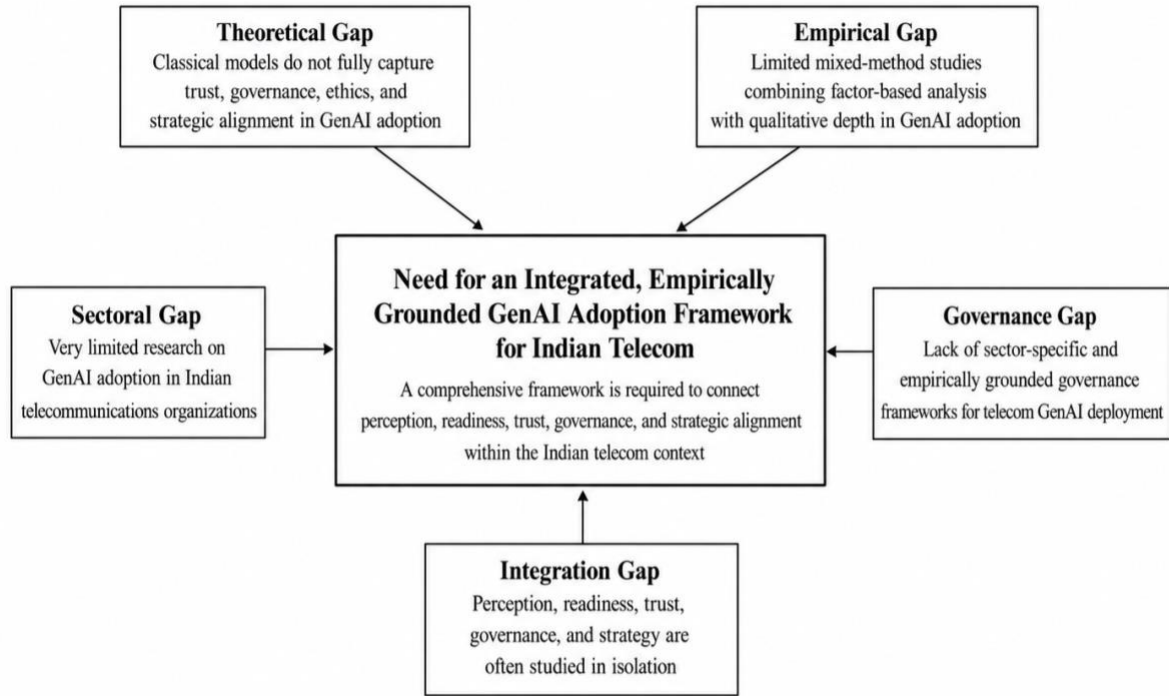


Figure 2.18: Five-Dimensional Research Gap Framework for the Present Study

Source: Author, synthesized from Davis (1989), Venkatesh et al. (2003), Tornatzky and Fleischer (1990), Seifdar and Amiri (2025), Zhou et al. (2025), Gomes et al. (2025), Chen and Li (2025), TRAI (2024), TEC (2024), Agarwal and Nene (2025), and the reviewed literature.

The **theoretical gap** concerns the inadequacy of classical technology adoption models for the Generative AI context. TAM, UTAUT, and DOI provide foundational constructs but do not capture the trust, ethical concern, governance awareness, and strategic alignment dimensions that the most recent empirical literature identifies as central determinants of GenAI adoption decisions. There is a theoretical need for an extended adoption framework that incorporates these dimensions empirically rather than asserting them theoretically, which the present study addresses through EFA-based factor identification.

The **empirical gap** concerns the limited body of mixed-method empirical research that combines quantitative dimension identification with qualitative interpretive depth in the GenAI adoption domain. Most existing studies employ either survey-based quantitative methods or qualitative case analysis, but few integrate both approaches sequentially to achieve both statistical structure

and contextual richness. The present study's combination of EFA and NVivo-assisted thematic analysis directly addresses this methodological gap.

The **sectoral gap** is the most significant: no existing peer-reviewed empirical study has examined Generative AI adoption from an organizational perception perspective within the Indian telecommunications sector. Despite the sector's global scale, strategic importance, and institutional complexity, the organizational adoption dynamics of GenAI in Indian telecom remain empirically uncharted territory. The present study fills this gap through primary data collection and analysis specifically situated within Indian telecom organizations.

The **governance gap** concerns the absence of sector-specific, empirically grounded governance frameworks for GenAI adoption in Indian telecom. While TRAI and TEC have published initial guidance, these documents lack the organizational-level specificity and empirical grounding that would make them actionable for telecom managers and governance designers. The framework developed in Objective 3 of the present study addresses this gap by synthesizing empirical findings into a structured, policy-oriented adoption and governance framework.

The **integration gap** concerns the absence of comprehensive frameworks that connect perception, organizational readiness, trust, governance, and strategic alignment as interdependent rather than independent dimensions of GenAI adoption. Existing studies examine these dimensions separately, preventing organizations from understanding how they interact and reinforce each other in shaping adoption outcomes. The present study's integrated framework explicitly models these interdependencies, providing a more complete and practically useful account of GenAI adoption dynamics in Indian telecom.

2.13 Conclusion of Chapter 2

This chapter has provided a comprehensive and systematic review of the literature on Generative AI adoption, spanning the technology's organizational evolution, its sector-specific applications in telecommunications, the theoretical frameworks that explain how organizations adopt new technologies, the organizational perception dimensions that shape GenAI adoption specifically, governance and ethical considerations, organizational capability requirements, digital transformation context, and the emerging framework literature. The review has drawn on more than seventy peer-reviewed articles, industry reports, and institutional documents, with a

substantial majority published between 2020 and 2026 and a significant representation of Indian context sources including TRAI (2024), TEC (2024), Agarwal and Nene (2025), Bariah et al. (2023), and Kanakadandi (2025).

The review establishes that Generative AI represents a qualitatively significant expansion of organizational AI capability with transformative implications for telecom operations, management practice, and competitive positioning. At the same time, it confirms that adoption is shaped by a complex and interdependent set of organizational perception dimensions, governance requirements, capability conditions, and strategic alignment considerations that classical adoption models capture incompletely. This theoretical insufficiency, combined with the absence of empirical research on GenAI adoption from an organizational perception perspective in Indian telecom, constitutes a clear and significant research gap that the present study directly addresses.

The literature review further confirms the appropriateness of the study's mixed-method research design, with EFA providing empirically grounded identification of perception dimensions and NVivo-assisted thematic analysis providing the contextual depth needed to understand how these dimensions operate in real Indian telecom organizational settings. The framework development approach employed in Objective 3 is grounded in the design science research tradition and responds to repeated calls in the literature for integrated, practically applicable frameworks that go beyond cataloguing adoption variables to explain their interdependencies and inform organizational and policy action (Gregor, 2006; Hevner et al., 2004; Gomes et al., 2025; Pathan & Shah, 2025).

Chapter 3 presents the research methodology adopted to address the identified research gap, detailing the research philosophy, design, data collection instruments, analytical procedures, and validity measures that ensure the study's findings are both empirically rigorous and contextually relevant.

3.1 Introduction to the Chapter

The present chapter outlines the research methodology adopted to investigate the adoption of Generative Artificial Intelligence within the Indian telecommunications sector, with specific focus on organizational perception, technological readiness, and governance dimensions. The chapter establishes the methodological foundation required to address each of the three research objectives systematically and ensures that all design choices are aligned with the nature of the research problem, the characteristics of the Indian telecom context, and the data requirements of both quantitative factor analysis and qualitative interpretive inquiry.

Methodological rigor is essential for research examining complex, emerging organizational phenomena such as GenAI adoption, where both statistical patterns and contextual depth are required to generate credible and actionable findings (Saunders et al., 2019; Creswell and Creswell, 2018; Venkatesh et al., 2013). The chapter proceeds by presenting the overall research design through the Research Onion framework, followed by detailed descriptions of the methods applied for each objective, the sampling design specific to the Indian telecom sector, data collection procedures, NVivo-assisted qualitative analysis protocols, reliability and validity measures, ethical considerations, and hypothesis alignment. The chapter concludes with a summary that establishes a clear pathway to the data analysis presented in Chapter 4.

3.2 Research Design and Philosophy

3.2.1 The Research Onion Framework

The research design of the present study is structured using the Research Onion framework proposed by Saunders et al. (2019). The Research Onion provides a systematic and hierarchically organized approach to research design by requiring the researcher to make explicit, justified decisions across six layers: philosophy, approach, methodology, strategy, time horizon, and data collection and analysis techniques. This framework ensures that each methodological choice is coherent with those made at adjacent layers and that the overall design is internally consistent, aligned with the research objectives, and epistemologically grounded (Saunders et al., 2019; Bryman and Bell, 2015; Easterby-Smith et al., 2018).

In the present study, each layer of the Research Onion is populated with choices that reflect the dual requirement for quantitative rigor in factor identification and qualitative depth in experiential interpretation, both situated specifically within Indian telecom organizational contexts. These choices are detailed in the sections that follow and are summarized visually in Figure 3.1.

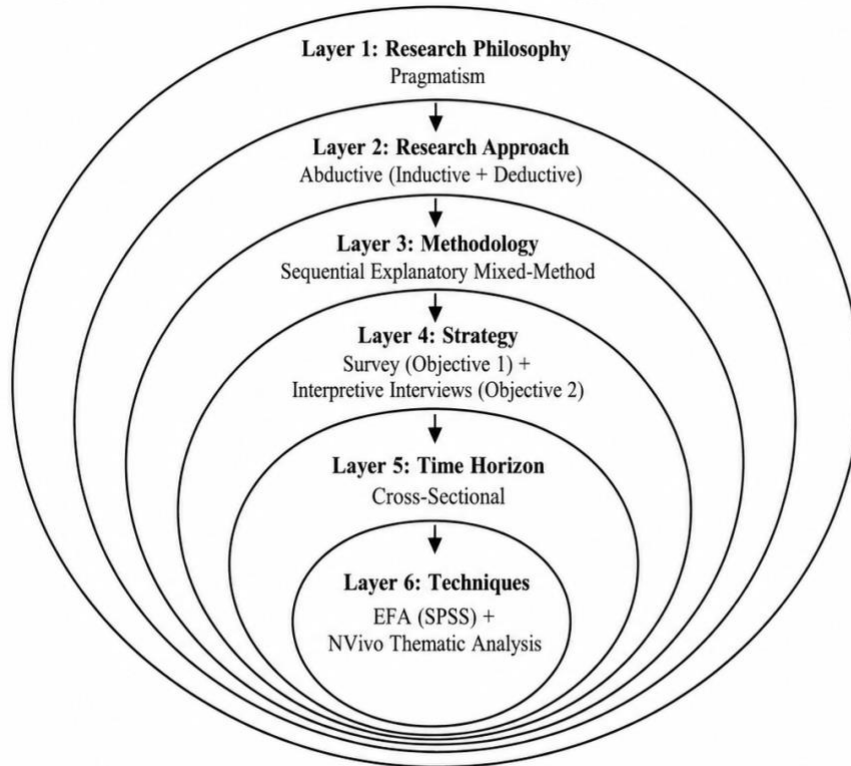


Figure 3.1: Research Onion Framework Applied to the Present Study (Adapted from Saunders et al., 2019)

3.2.2 Research Philosophy: Pragmatism

At the philosophical level, the study adopts a **pragmatic research philosophy**. Pragmatism is distinguished by its orientation toward practical problem-solving rather than adherence to a single ontological or epistemological tradition. It holds that knowledge claims should be evaluated by their practical consequences and that research methods should be selected on the basis of their fitness for the research purpose rather than philosophical loyalty to positivism or interpretivism (Creswell and Creswell, 2018; Crotty, 1998). Pragmatism is therefore uniquely suited to mixed-method research designs that combine quantitative and qualitative approaches, as it explicitly endorses methodological pluralism as a legitimate epistemological position.

In the context of the present study, pragmatism is justified by the nature of the research problem. Understanding how organizational perception shapes GenAI adoption in Indian telecom organizations requires both **measurable, statistically generalizable patterns** (addressed through EFA) and **contextually rich, interpretively grounded understanding** of how those patterns are experienced by organizational actors in Indian institutional settings (addressed through NVivo-assisted thematic analysis). Neither a purely positivist nor a purely interpretivist approach would adequately serve both requirements; pragmatism provides the philosophical license to integrate both (Dwivedi et al., 2021; Venkatesh et al., 2013; Gomes et al., 2025).

3.2.3 Research Approach: Abductive Reasoning

The study follows an **abductive reasoning approach**, which combines elements of inductive and deductive logic in a sequential and iterative manner. In Phase 1 (EFA), the approach is primarily inductive: rather than testing predefined theoretical constructs, the study allows perception-related factors to emerge empirically from the data, guided conceptually by the technology adoption literature but not constrained by it (Hair et al., 2019; Fabrigar and Wegener, 2011). In Phase 2 (NVivo analysis), the approach is interpretive and abductive: the EFA-derived factors serve as sensitizing concepts that guide qualitative inquiry while remaining open to the emergence of novel themes from participant accounts (King et al., 2018).

In Phase 3 (framework development), deductive logic is applied: the integrated empirical findings are connected to existing theoretical frameworks (TAM, UTAUT, TOE, governance literature) to develop a theoretically grounded and empirically validated adoption framework for Indian telecom. This abductive logic, moving between data and theory iteratively, is consistent with the most recent methodological recommendations for AI adoption research (Seifdar and Amiri, 2025; Gomes et al., 2025; Venkatesh et al., 2013).

3.2.4 Methodology and Time Horizon

The overall methodology of the study is **sequential explanatory mixed-method**. In sequential explanatory designs, quantitative data is collected and analyzed first, and the findings are then used to inform and guide the subsequent qualitative phase. This sequence ensures that qualitative inquiry is directly grounded in empirical evidence rather than theoretical assumption, strengthening the relevance and precision of qualitative data collection (Creswell and Creswell,

2018; Venkatesh et al., 2013). The integration of quantitative and qualitative findings in Phase 3 completes the explanatory cycle by connecting statistical patterns to organizational experience and theoretical frameworks.

The time horizon of the study is **cross-sectional**: data is collected from respondents at a single point in time rather than over an extended longitudinal period. This is appropriate for the present study given its focus on capturing the current state of organizational perception and adoption behavior in Indian telecom organizations at a specific and strategically significant point in the sector's GenAI adoption trajectory. Cross-sectional designs are widely used and methodologically appropriate in organizational adoption research, particularly for EFA-based perception studies (Hair et al., 2019; Saunders et al., 2019).

3.3 Research Methods

The present study adopts a structured multi-method approach in which each research objective is addressed through an explicitly matched analytical technique. This objective-wise methodological alignment ensures that each objective receives the most appropriate analytical treatment and that the overall design achieves coherence between research questions, data types, and analytical methods (Saunders et al., 2019; Dwivedi et al., 2021; Haenlein and Kaplan, 2021).

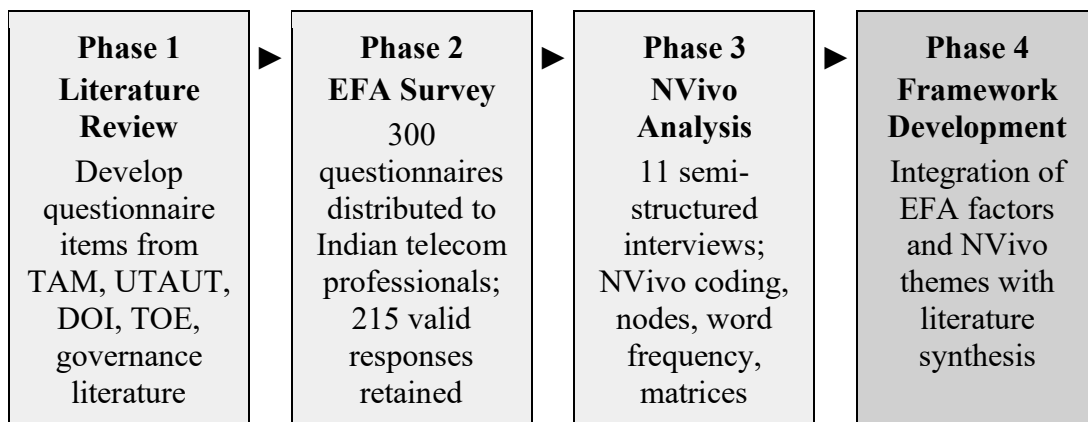


Figure 3.2: Sequential Mixed-Method Research Design Flow (Source: Author)

3.3.1 Objective 1: Exploratory Factor Analysis (EFA)

The first research objective focuses on identifying the underlying latent factors that shape telecom organizational leaders' and managers' perceptions of Generative Artificial Intelligence.

To achieve this, a structured questionnaire is administered to Indian telecom professionals and the resulting data is analyzed using **Exploratory Factor Analysis (EFA)**. EFA is a multivariate statistical technique used to uncover latent constructs by identifying patterns of covariation among observed variables. It is specifically designed for situations in which the underlying factor structure is not theoretically predefined but must emerge empirically from the data, which is precisely the epistemological requirement of the present study's first objective (Hair et al., 2019; Fabrigar and Wegener, 2011; Field, 2018).

EFA is employed in preference to Confirmatory Factor Analysis (CFA) because the present study does not seek to test a predetermined theoretical model but rather to discover which dimensions of perception are most salient and internally coherent among Indian telecom professionals. This exploratory orientation is consistent with the research gap identified in Chapter 2, which established that the perception dimensions specific to GenAI adoption in Indian telecom have not been empirically mapped in prior research (Gomes et al., 2025; Chen and Li, 2025; Simaremare and Edison, 2024).

The questionnaire instrument contains twenty-four items developed from the technology adoption and organizational perception literature, encompassing constructs related to perceived value, ease of adoption, trust and reliability, risk and ethics concerns, organizational readiness, governance awareness, and strategic alignment. Items are measured on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), consistent with established practices in perception-based survey research (Moore and Benbasat, 1991; Davis, 1989; Venkatesh et al., 2003; Field, 2018).

Critically, the items are designed to **inform** rather than impose factor structures: theoretical constructs from TAM, UTAUT, DOI, TOE, and the governance literature guide item generation without predetermining which items will load together. The factor structure is determined entirely by the data through EFA, ensuring that the identified dimensions reflect the actual perceptual organization of the Indian telecom respondent population rather than imported theoretical categories (Hair et al., 2019; Fabrigar and Wegener, 2011; Podsakoff et al., 2003).

Table 3.1: Eight-Stage EFA Process: Procedures and Decision Criteria (Sources: Hair et al., 2019; Field, 2018; Fabrigar and Wegener, 2011; Kline, 2015)

Step	Stage	Procedure and Decision Criteria
Step 1	Questionnaire Administration	300 questionnaires distributed to Indian telecom professionals across Jio, Airtel, BSNL, Vodafone Idea, and regional operators via digital channels.
Step 2	Data Screening and Cleaning	Removal of incomplete, inconsistent, and outlier responses. 215 valid responses retained for analysis.
Step 3	KMO and Bartlett Testing	Kaiser-Meyer-Olkin measure ($KMO > 0.70$) and Bartlett Test of Sphericity ($p < 0.05$) to confirm data suitability for EFA.
Step 4	Factor Extraction	Principal Component Analysis (PCA) applied. Factors with eigenvalue > 1.0 retained per Kaiser criterion (Hair et al., 2019).
Step 5	Varimax Rotation	Orthogonal Varimax rotation applied to achieve simple, interpretable factor structure with minimized cross-loadings.
Step 6	Factor Loading Assessment	Factor loadings > 0.50 accepted; loadings > 0.60 considered strong. Cross-loadings examined for discriminant validity (Hair et al., 2019; Field, 2018).
Step 7	Reliability Assessment	Cronbach Alpha calculated for each factor. Alpha > 0.70 acceptable; > 0.80 considered strong internal consistency.
Step 8	Factor Naming and Interpretation	Identified factors named based on conceptual coherence of loading items. Factor structure reviewed against literature for theoretical grounding.

3.3.2 Questionnaire Development and Instrument Design

The development of the quantitative research instrument followed a sequential and literature-anchored approach. Items were generated through an extensive review of technology adoption models including TAM (Davis, 1989), UTAUT and UTAUT2 (Venkatesh et al., 2003; Venkatesh et al., 2012), Diffusion of Innovation (Rogers, 2003), and the TOE framework (Tornatzky and Fleischer, 1990), supplemented by recent GenAI adoption literature (Dwivedi et al., 2023; Chen and Li, 2025; Gomes et al., 2025; Seifdar and Amiri, 2025) and governance literature (Floridi and Chiriatti, 2020; Bender et al., 2021; Pathan and Shah, 2025; TRAI, 2024).

The questionnaire is organized into thematic sections covering: operational usefulness of GenAI; ease of integration with existing telecom systems; reliability and trustworthiness of GenAI outputs; risk and ethical concerns including data privacy and bias; organizational infrastructure and skill readiness; governance policies and regulatory awareness; and strategic alignment of GenAI with organizational objectives. These thematic sections provide broad coverage across the perception landscape without predefining which items will cluster together in the EFA solution.

The instrument was reviewed for clarity, neutrality, and relevance to the Indian telecom context before distribution. Particular care was taken to ensure that items were framed in language accessible to respondents across technical, managerial, and operational roles, and that no items inadvertently cued desirable responses or assumed familiarity with specific GenAI tools (Straub et al., 2004; Podsakoff et al., 2003). Respondent anonymity and data confidentiality were assured in the questionnaire introduction to reduce social desirability bias.

3.3.3 Objective 2: NVivo-Assisted Thematic Analysis

The second research objective examines how the perception-related factors identified through EFA influence the adoption and practical use of Generative AI within Indian telecom organizations. This objective is addressed through **qualitative thematic analysis** of semi-structured interview data, with all analytical procedures conducted within **NVivo**, a specialist qualitative data analysis software package that enables systematic coding, node hierarchies, matrix queries, word frequency analysis, word trees, and cluster analysis of textual data (King et al., 2018; Bryman and Bell, 2015; Saunders et al., 2019).

NVivo is selected as the analytical platform for several methodologically important reasons. First, it enables rigorous and auditable coding procedures that can be documented and reviewed, supporting the credibility and dependability of qualitative findings. Second, its matrix coding query function allows the researcher to examine relationships between coded themes systematically, supporting the identification of patterns in how different perception dimensions interact with reported adoption behaviors. Third, its word frequency and word tree functions provide a quantitative supplement to interpretive coding, enabling the researcher to verify that dominant themes are textually well-represented rather than analytically over-interpreted. Fourth, its cluster analysis function enables the identification of conceptual groupings across the coded

dataset, providing a structural check on the thematic framework developed through manual coding (King et al., 2018; Saunders et al., 2019).

The NVivo analysis proceeds through eight structured stages as described in Figure 3.4. This structured approach ensures analytical rigor while preserving the interpretive flexibility essential to qualitative inquiry in a complex and context-specific organizational setting (King et al., 2018; Bryman and Bell, 2015).

Table 3.2: Eight-Stage NVivo Thematic Analysis Process (Sources: King et al., 2018; Saunders et al., 2019; Bryman and Bell, 2015)

Stage	NVivo Activity	Description and Justification
Stage 1	Data Preparation	Eleven interview transcripts imported into NVivo as source documents. Transcripts verified for completeness and accuracy prior to analysis.
Stage 2	Initial Exploration	Word frequency queries and word cloud generation conducted to identify dominant terms and conceptual clusters across the dataset.
Stage 3	Open Coding	Initial free coding of all interview content within NVivo. Codes assigned to text segments reflecting participant expressions of perception, challenge, value, or governance. Multiple codes applied per segment where relevant.
Stage 4	Node Development	NVivo nodes created to aggregate codes sharing conceptual similarity. Node hierarchy developed with parent nodes representing broad thematic areas and child nodes capturing specific sub-themes.
Stage 5	Axial Coding	Relationships between nodes examined using NVivo matrix coding queries. Conceptual linkages between themes identified and mapped to produce a structured understanding of how perception dimensions interact with adoption behavior.
Stage 6	Selective Coding	Dominant themes identified from node hierarchies and matrix outputs. Themes selected based on frequency, conceptual depth, and relevance to the research objectives.
Stage 7	Word Trees and Cluster Analysis	NVivo word tree queries used to examine contextual usage of key terms (trust, governance, reliability, strategy). Cluster analysis confirmed thematic groupings.
Stage 8	Theme Interpretation	Final themes interpreted by the researcher with reference to EFA findings and literature. Member checking conducted by

		sharing theme summaries with two interview participants for validation.
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The qualitative interview instrument is developed sequentially, after the completion of EFA in Phase 1. The factors identified through EFA serve as the empirical foundation for the interview questions, ensuring that qualitative inquiry examines the organizational manifestation of the statistically identified perception dimensions rather than introducing new theoretical constructs. This sequential grounding strengthens the internal validity of the mixed-method design by establishing a direct empirical link between the two phases (Venkatesh et al., 2013; Creswell and Creswell, 2018).

Semi-structured interviews are selected as the data collection instrument for the qualitative phase because they combine the directional focus of structured research questions with the conversational flexibility needed to explore unexpected insights and contextually specific experiences. Each interview follows a common question framework derived from the EFA factors but allows participants to elaborate, redirect, and introduce considerations not anticipated by the question schedule. Interviews are conducted digitally with Indian telecom professionals, recorded with participant consent, and transcribed verbatim prior to NVivo import.

3.3.4 Objective 3: Framework Development through Analytical Synthesis

The third objective focuses on developing a structured, policy-oriented framework for the effective and responsible adoption of Generative AI in the Indian telecom sector. This objective does not involve primary statistical analysis but draws on **analytical synthesis**: the integration of EFA findings (Objective 1), NVivo thematic findings (Objective 2), and the theoretical and empirical literature reviewed in Chapter 2. This synthesis approach is grounded in design science research principles, which emphasize the creation of practically relevant and theoretically robust knowledge artifacts, including frameworks, models, and design guidelines, that address real organizational problems (Gregor, 2006; Hevner et al., 2004; Benbasat and Zmud, 1999).

The framework development process draws specifically on recent GenAI adoption framework literature to ensure that the resulting artifact reflects the most current understanding of the determinants and dynamics of GenAI adoption at organizational scale. Relevant sources include

Seifdar and Amiri (2025), Ali et al. (2025), Zhou et al. (2025), Gomes et al. (2025), and Chen and Li (2025), alongside foundational digital transformation and AI capability literature (Teece, 2018; Mikalef et al., 2020; Kane et al., 2015). The framework is further informed by Indian-specific regulatory and institutional sources including TRAI (2024) and TEC (2024), ensuring that its governance dimension reflects the specific regulatory context within which Indian telecom organizations operate.

3.4 Sampling Design

3.4.1 Target Population and Geographic Scope

The target population for the present study comprises professionals employed within Indian telecommunications organizations across technical, managerial, and operational roles. The focus on the Indian telecom sector is justified by the sector's scale, strategic importance, and the accelerating pace of GenAI adoption within it, as documented by TRAI (2024), TEC (2024), Infosys (2024), and Telecom Review Asia (2025). India's telecom sector, with over 1.2 billion subscribers and three dominant national operators, represents one of the most significant and fastest-evolving telecom markets globally, making it an empirically important context for studying organizational GenAI adoption (TRAI, 2024; GSMA Intelligence, 2023).

Respondents include professionals from major Indian telecom operators including Reliance Jio, Bharti Airtel, BSNL, and Vodafone Idea, as well as telecom infrastructure, managed services, and equipment organizations operating within the Indian market. The geographic scope spans metropolitan centers including Mumbai, Delhi, Bengaluru, Hyderabad, Chennai, and Pune, where telecom organizational headquarters, technology centers, and major operational hubs are concentrated.

3.4.2 Sampling Technique

The study employs a combination of **purposive and convenience sampling** for both phases of data collection. Purposive sampling is applied to ensure that respondents possess the professional experience, organizational exposure, and technological engagement necessary to provide meaningful and informed responses on GenAI perception and adoption. For Objective 1, the inclusion criterion requires a minimum of two years of professional experience within a telecom organization and direct or indirect involvement with digital technology or AI systems. For

Objective 2, the inclusion criterion is more restrictive, requiring a minimum of five years of experience and active involvement in AI, digital transformation, or technology governance programs within a telecom context.

Convenience sampling is applied within the purposively defined population to facilitate practical data access within the organizational research constraints of the Indian telecom sector, where formal access protocols and organizational gatekeeping can limit survey distribution and interview recruitment. This combination of purposive and convenience sampling is widely endorsed in applied organizational research involving emerging technologies, where expertise and exposure are more critical selection criteria than probability-based representativeness (Easterby-Smith et al., 2018; Saunders et al., 2019; Bryman and Bell, 2015).

3.4.3 Sample Size

The study employs two distinct sample groups corresponding to the two primary analytical objectives. For **Objective 1**, approximately **300 questionnaires** were distributed digitally to Indian telecom professionals. Following systematic data screening and quality filtering, **215 valid responses** were retained for EFA analysis. This sample size satisfies the methodological requirements for EFA as specified by Hair et al. (2019), who recommend a minimum sample-to-variable ratio of 10:1, yielding a recommended minimum of 240 cases for a 24-item instrument, with 215 falling within acceptable range given the completeness and quality of the retained responses. Fabrigar and Wegener (2011) further confirm that samples of 200 or above are generally adequate for stable factor solutions when communalities are high and the factor structure is reasonably clear.

For **Objective 2**, **eleven semi-structured interviews** were conducted with senior managers, technical leads, and AI project professionals in Indian telecom organizations. This sample size is appropriate for NVivo-assisted thematic analysis, where the objective is interpretive depth and theoretical saturation rather than statistical representativeness. King et al. (2018) confirm that samples of ten to fifteen participants are typical and sufficient for thematic analysis in organizational research, provided participants are selected purposively for their knowledge depth and contextual relevance.

Table 3.3: Sampling Design Summary for Objective 1 (EFA) and Objective 2 (NVivo Analysis) (Source: Author; informed by Hair et al., 2019; King et al., 2018; Saunders et al., 2019)

Dimension	Objective 1 (EFA)	Objective 2 (NVivo Thematic Analysis)
Target Population	Professionals working in Indian telecom organizations across technical, managerial, and operational roles.	Senior managers, technical leads, and AI project professionals in Indian telecom organizations with direct GenAI exposure.
Sampling Technique	Purposive sampling to ensure AI/digital technology exposure; convenience sampling for accessibility.	Purposive sampling to ensure deep organizational knowledge and lived experience of GenAI adoption.
Sample Size	215 valid responses (from 300 initially distributed).	11 semi-structured interview respondents.
Geographic Scope	Pan-India: respondents across metropolitan and tier-2 cities including Mumbai, Delhi, Bengaluru, Hyderabad, Chennai, and Pune.	Pan-India: participants drawn from organizations including Jio, Airtel, BSNL, and Vodafone Idea.
Data Collection Mode	Structured digital questionnaire (five-point Likert scale, 24 items).	Semi-structured interviews conducted via digital platforms (60 to 90 minutes per session).
Inclusion Criteria	Minimum two years of professional experience in telecom; direct or indirect exposure to digital/AI systems.	Minimum five years of experience; active involvement in AI or digital transformation initiatives.
Data Analysis Tool	IBM SPSS Statistics (EFA, KMO, Bartlett, Varimax rotation, Cronbach Alpha).	NVivo (coding, node hierarchy, matrix queries, word frequency, word trees, cluster analysis).

3.5 Data Collection Methods

3.5.1 Phase 1: Quantitative Data Collection for Objective 1

Phase 1 data collection was conducted through a structured digital questionnaire distributed to Indian telecom professionals via professional networks, organizational contacts, and digital communication platforms. The questionnaire was administered over a defined data collection window to maintain temporal consistency across responses. A covering note accompanying the

questionnaire explained the academic purpose of the research, confirmed respondent anonymity and data confidentiality, and requested honest and independent responses. Respondents were informed that there were no correct answers and that the questionnaire sought their genuine professional perceptions.

Approximately 300 questionnaires were distributed. After the data collection window closed, all responses were screened for completeness, response pattern consistency (to identify straight-line or random responses), and minimum engagement (responses completed in implausibly short time periods were excluded). Eighty-five responses were excluded through this screening process, yielding 215 valid responses retained for EFA analysis. Data was entered into IBM SPSS Statistics for all quantitative analytical procedures.

3.5.2 Phase 2: Qualitative Data Collection for Objective 2

Phase 2 data collection commenced after the completion of EFA in Phase 1. The semi-structured interview instrument was developed specifically on the basis of the factors identified through EFA, ensuring that interview questions directly examined the organizational experience and manifestation of the empirically derived perception dimensions. This sequential grounding distinguishes the present study's qualitative instrument design from studies where qualitative questions are developed independently of quantitative findings, and strengthens the internal coherence and validity of the mixed-method design (Venkatesh et al., 2013; Creswell and Creswell, 2018).

Eleven semi-structured interviews were conducted with purposively selected Indian telecom professionals. Each interview lasted between 60 and 90 minutes and was conducted via digital communication platforms with participant consent for recording. Interviews were transcribed verbatim by the researcher and reviewed for accuracy before being imported into NVivo as source documents. Participant confidentiality was maintained throughout: participants are identified in the analysis by role category (for example, Senior Network Manager, AI Project Lead, Digital Transformation Director) rather than by name or organizational affiliation.

3.5.3 Phase 3: Data Integration for Objective 3

The final phase of data collection and analysis involves the systematic integration of findings from Phases 1 and 2 with the theoretical and empirical insights established in Chapter 2. This

integration proceeds through a structured analytical synthesis process in which EFA-derived perception factors are mapped against NVivo-identified themes to establish empirical convergence and divergence, and the resulting integrated evidence base is connected to the theoretical frameworks reviewed in Chapter 2 to develop the GenAI adoption framework presented in Chapter 4. The framework development process is guided by design science principles (Gregor, 2006; Hevner et al., 2004) and the most recent framework literature in GenAI adoption (Gomes et al., 2025; Zhou et al., 2025; Seifdar and Amiri, 2025).

Table 3.4: Objective-Method-Output Alignment Table (Source: Author)

Objective	Research Question	Method	Tool	Sample	Output
Objective 1	What underlying factors shape telecom perceptions of GenAI?	Exploratory Factor Analysis (EFA)	IBM SPSS Statistics	215 valid responses	Empirically derived perception factor structure
Objective 2	How do perception factors influence adoption and practical use?	NVivo Thematic Analysis	NVivo (coding, nodes, matrices, word trees)	11 interview transcripts	Thematic map of perception-adoption relationships
Objective 3	How can a policy framework guide effective GenAI adoption?	Analytical Synthesis	Literature integration with EFA and NVivo findings	Derived from Phases 1 and 2	Integrated GenAI adoption framework for Indian telecom

3.6 Reliability and Validity

3.6.1 Quantitative Reliability and Validity Measures

Ensuring reliability and validity across both phases of the study is fundamental to the credibility and scientific rigor of the findings. For the quantitative phase, reliability is assessed primarily through **Cronbach Alpha** coefficients calculated for each extracted EFA factor. Cronbach Alpha measures the internal consistency of items within a factor, with values above 0.70 considered acceptable and values above 0.80 indicating strong internal consistency (Hair et al., 2019; Field,

2018). Items that reduce Alpha below the acceptable threshold upon inclusion are examined for conceptual misfit and excluded from the factor if warranted.

The suitability of the dataset for factor analysis is assessed through the **Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy** and **Bartlett's Test of Sphericity**. A KMO value above 0.70 indicates good sampling adequacy and confirms that the correlation patterns in the data are sufficiently compact for factor analysis to yield distinct and reliable factors. Bartlett's Test of Sphericity must return a statistically significant result (p less than 0.05) to confirm that the correlation matrix is significantly different from an identity matrix, validating that meaningful inter-variable correlations exist to justify factor extraction (Hair et al., 2019; Field, 2018).

Construct validity is operationalized through the EFA factor structure itself: factors are accepted as representing distinct constructs when factor loadings exceed 0.50 (acceptable) or 0.60 (strong), and when cross-loadings are minimized to confirm discriminant validity (Hair et al., 2019; Kline, 2015). Content validity is established through the literature-grounded item development process described in Section 3.3.2. Common method bias, a concern in single-source self-report survey research, is addressed through procedural remedies including anonymous response design, neutral item framing, and the Harman single-factor test to confirm that no single factor accounts for a disproportionate share of explained variance (Podsakoff et al., 2003; Straub et al., 2004).

3.6.2 Qualitative Trustworthiness Measures

For the qualitative phase, validity and reliability are assessed through Lincoln and Guba's four criteria for trustworthiness in qualitative research: **credibility**, **transferability**, **dependability**, and **confirmability**. Credibility is established through member checking: upon completion of initial theme development in NVivo, summary theme descriptions are shared with two interview participants for verification of accuracy and representativeness (King et al., 2018; Bryman and Bell, 2015). Any discrepancies or refinements suggested by participant feedback are incorporated into the final thematic framework.

Transferability is supported through thick description of the Indian telecom context throughout the qualitative reporting, enabling readers to assess the relevance and applicability of findings to

their own organizational settings. Dependability is established through the NVivo audit trail: all coded transcripts, node hierarchies, matrix query outputs, and analytical memos are retained within the NVivo project file, providing a complete and reviewable record of analytical decisions. Confirmability is supported through the researcher's reflexivity statement, which acknowledges the researcher's professional background, potential biases, and the steps taken to ensure that analytical interpretations are grounded in participant accounts rather than researcher assumptions (Saunders et al., 2019; Bryman and Bell, 2015).

Table 3.5: Reliability and Validity Criteria, Measures, and Standards Applied in the Present Study (Sources: Hair et al., 2019; Field, 2018; Kline, 2015; Podsakoff et al., 2003; King et al., 2018; Bryman and Bell, 2015)

Criterion	Type	Measure Applied	Threshold Standard	Phase
Internal Consistency	Reliability	Cronbach Alpha coefficient	Alpha > 0.70 acceptable; > 0.80 strong (Hair et al., 2019)	Quantitative (EFA)
Sampling Adequacy	Validity	Kaiser-Meyer-Olkin (KMO) test	KMO > 0.70 good; > 0.80 excellent (Field, 2018)	Quantitative (EFA)
Data Factorability	Validity	Bartlett Test of Sphericity	p < 0.05 required (Hair et al., 2019)	Quantitative (EFA)
Convergent Validity	Validity	Factor loading values	Loading > 0.50 acceptable; > 0.60 strong (Hair et al., 2019)	Quantitative (EFA)
Discriminant Validity	Validity	Cross-loading examination	Items load significantly on one factor only (Kline, 2015)	Quantitative (EFA)
Content Validity	Validity	Literature-grounded item development	Items derived from TAM, UTAUT, DOI, TOE, governance literature	Questionnaire Design
Common Method Bias	Reliability	Procedural remedies and Harman single-factor test	No single factor dominates variance (Podsakoff et al., 2003)	Quantitative (EFA)

Credibility	Qualitative Validity	NVivo member checking and peer review	Theme summaries verified by 2 participants (King et al., 2018)	Qualitative (NVivo)
Transferability	Qualitative Validity	Thick description of Indian telecom context	Contextual detail enables reader generalization (Bryman & Bell, 2015)	Qualitative (NVivo)
Dependability	Qualitative Validity	Audit trail in NVivo (coded transcripts, node maps)	Full coding documentation retained in NVivo project file	Qualitative (NVivo)
Confirmability	Qualitative Validity	Researcher reflexivity statement; NVivo coding consistency	Analytical decisions documented and reviewable (Saunders et al., 2019)	Qualitative (NVivo)

3.7 Ethical Considerations

3.7.1 Informed Consent and Voluntary Participation

The present study adheres to established ethical guidelines for business and management research involving human participants, as specified by Saunders et al. (2019) and Bryman and Bell (2015). Participation in both the quantitative questionnaire and the qualitative interviews is entirely voluntary. All respondents are provided with a clear description of the research purpose, the nature of the data to be collected, the analytical uses to which the data will be put, and their rights to withdraw participation at any stage without consequence. For the questionnaire, completion and submission is treated as implicit consent. For the interviews, explicit verbal and written consent is obtained and recorded prior to the commencement of each interview.

3.7.2 Confidentiality, Anonymity, and Data Security

No personally identifiable information is collected from questionnaire respondents. Interview participants are identified in the research only by role category and years of experience, ensuring that no individual can be identified from the published findings. All data is stored securely on password-protected research platforms accessible only to the researcher. Organizational names of interview participants' employers are anonymized in the analysis and reporting unless explicit organizational consent for identification has been provided. These measures are consistent with

data protection principles applicable to academic research in India and comply with the confidentiality standards established by Bryman and Bell (2015) and Saunders et al. (2019).

3.7.3 Responsible Use of NVivo in Qualitative Analysis

The use of NVivo as the analytical platform for qualitative data introduces no additional ethical concerns, as NVivo is a researcher-controlled analytical tool that processes data according to researcher-defined coding frameworks and query specifications. All NVivo outputs, including coded nodes, matrix queries, word frequency reports, and cluster analyses, are interpreted and validated by the researcher rather than being accepted as autonomous analytical conclusions. The researcher maintains full interpretive responsibility for all thematic findings and ensures that participant voices are represented accurately and fairly in the final analysis. This approach is consistent with the ethical standards for qualitative research involving human participants (King et al., 2018; Bryman and Bell, 2015).

3.7.4 Researcher Positionality and Reflexivity

The researcher acknowledges a professional familiarity with the Indian telecom organizational context, which provides contextual sensitivity but also carries the risk of confirmatory bias. Reflexivity measures implemented to manage this risk include: maintenance of an analytical memo journal throughout the NVivo coding process documenting key interpretive decisions and alternative readings considered; peer discussion of emerging themes with academic supervisors; and member checking with interview participants as described in Section 3.6.2. These measures ensure that analytical interpretations reflect participant accounts and empirical evidence rather than researcher assumptions (Saunders et al., 2019; Bryman and Bell, 2015).

3.8 Hypothesis Alignment with Research Design

The three research hypotheses are fully aligned with the methodological design presented in this chapter. Each hypothesis is addressed by a specific phase of the research design, and the methodological choices made for each phase are explicitly justified by the nature of the hypothesis being tested.

H1 (There exist significant underlying factors that explain telecom organizational perceptions of Generative Artificial Intelligence) is addressed by Phase 1 EFA. The empirical

identification of latent perception factors through EFA directly tests this hypothesis by determining whether the observed questionnaire items cohere into meaningful latent structures. A KMO above 0.70, significant Bartlett's Test, and a factor solution with loadings above 0.50 would support H1. EFA is uniquely suited to this hypothesis because it allows the factor structure to emerge empirically rather than being imposed theoretically (Hair et al., 2019; Fabrigar and Wegener, 2011).

H2 (Perception-related factors significantly influence the adoption and practical use of Generative Artificial Intelligence in telecom organizations) is addressed by Phase 2 NVivo thematic analysis. The qualitative analysis examines how the factors identified in Phase 1 are experienced and operationalized in real Indian telecom organizational settings, providing interpretive evidence of the mechanisms through which perception shapes adoption behavior. NVivo's matrix coding queries enable systematic examination of whether each identified perception factor is associated with specific adoption behaviors and organizational practices in the participant accounts (King et al., 2018; Venkatesh et al., 2013).

H3 (An integrated strategic framework combining perception, technological, and organizational factors significantly enhances the effectiveness of Generative Artificial Intelligence adoption in telecom organizations) is addressed by Phase 3 framework development. The framework synthesizes EFA and NVivo findings with the theoretical literature to produce a structured, empirically grounded adoption model. Consistent with design science research principles, the framework is evaluated against the criteria of theoretical grounding, empirical coherence, and practical applicability (Gregor, 2006; Hevner et al., 2004; Gomes et al., 2025).

3.9 Summary of the Chapter

This chapter has presented the comprehensive methodological framework underpinning the present study. The Research Onion framework was used to structure design choices across six layers, from pragmatic philosophy through sequential mixed-method design to the specific analytical techniques of EFA and NVivo thematic analysis. The study employs Exploratory Factor Analysis in IBM SPSS Statistics to address Objective 1, using a sample of 215 valid responses from Indian telecom professionals collected through a purposive and convenience

sampling strategy. NVivo-assisted thematic analysis across eight structured analytical stages is applied to eleven semi-structured interview transcripts to address Objective 2, with data collection grounded in the EFA findings from Phase 1. Framework development in Phase 3 synthesizes empirical findings from both phases with the theoretical literature to produce an integrated, policy-oriented GenAI adoption framework for the Indian telecom context.

Reliability and validity are ensured across both phases through Cronbach Alpha, KMO, Bartlett's Test, factor loading thresholds, common method bias controls, NVivo member checking, audit trail documentation, and researcher reflexivity measures. Ethical standards for informed consent, anonymity, confidentiality, and responsible qualitative analysis are maintained throughout. All three research hypotheses are explicitly aligned with the methodological design, ensuring that the analytical procedures directly address the research questions posed in Chapter 1. Chapter 4 presents the findings from Phases 1, 2, and 3, including the EFA factor solution, NVivo thematic map, and the integrated GenAI adoption framework for Indian telecom organizations.

CHAPTER 4: DATA ANALYSIS, FINDINGS, AND FRAMEWORK DEVELOPMENT

4.1 Introduction to the Chapter

This chapter presents the empirical analysis and findings of the study, structured in direct alignment with the three research objectives and the sequential mixed-method design described in Chapter 3. The analysis proceeds through four interconnected phases: demographic profiling of the Indian telecom respondent sample; quantitative Exploratory Factor Analysis (EFA) of perception-related variables using IBM SPSS Statistics; qualitative thematic analysis of semi-structured interview data using NVivo; and the synthesis of integrated findings into a comprehensive Generative AI adoption framework for the Indian telecommunications sector.

The chapter is organized to reflect this sequential logic. Sections 4.2 through 4.7 present the quantitative analysis for Objective 1, including sample profiling, data screening, reliability testing, KMO and Bartlett assessments, factor extraction, rotation, and factor-level reliability. Sections 4.8 through 4.9 present the NVivo-assisted qualitative analysis for Objective 2, detailing the eight-stage analytical process, node hierarchy, thematic map, and integrated findings. Section 4.10 develops the framework for Objective 3. Section 4.11 evaluates all three hypotheses against the empirical evidence.

4.2 Demographic Profile of Respondents

The demographic profile of respondents provides contextual grounding for interpreting the perception-based findings presented in subsequent sections. The quantitative phase of the study drew on 215 valid responses from professionals employed within Indian telecommunications organizations, while 11 purposively selected senior professionals participated in the qualitative interview phase. The sample reflects the diversity of the Indian telecom workforce across gender, age, educational background, work experience, and functional role, consistent with the sampling criteria described in Chapter 3.

Table 4.1: Demographic Profile of the Study Sample (n = 215, Indian Telecom Professionals) (Source: Primary data, present study)

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	158	73.5%
	Female	57	26.5%
Age Group	Below 25 years	24	11.2%
	25-35 years	92	42.8%
	36-45 years	67	31.2%
	Above 45 years	32	14.8%
Qualification	Undergraduate	48	22.3%
	Graduate	112	52.1%
Experience	Postgraduate	55	25.6%
	Below 5 years	42	19.5%
	5-10 years	81	37.7%
	11-20 years	61	28.4%
	Above 20 years	31	14.4%
Role Category	Technical/Engineering	89	41.4%
	Managerial	76	35.3%
	Operations/Support	50	23.3%

The gender distribution reflects the established demographic composition of the Indian telecom workforce, where technical and managerial roles are predominantly occupied by male professionals, though female representation has increased with the digitalization of telecom functions (TEC, 2024; Telecom Review Asia, 2025). The age distribution indicates that the majority of respondents fall within the 25 to 45 years bracket, representing a professionally experienced and digitally engaged cohort with high likelihood of direct exposure to AI-related organizational initiatives. The educational profile confirms a well-qualified sample, with over three-quarters of respondents holding graduate or postgraduate degrees, enhancing the reliability of perception-based responses on a technologically complex subject (Hair et al., 2019). The experience distribution captures a balance between early-career, mid-career, and senior

professionals, while the role distribution ensures representation across technical, managerial, and operational organizational functions, providing a comprehensive view of GenAI adoption perception across organizational levels (Venkatesh et al., 2003; Deloitte, 2024).

4.3 Preliminary Data Screening and Preparation

Prior to conducting statistical analysis, the collected data were systematically screened and prepared to ensure accuracy, completeness, and suitability for multivariate analysis. This step is essential for maintaining the validity and reliability of empirical findings in survey-based organizational research (Hair et al., 2019; Field, 2018).

The initial response pool from the quantitative questionnaire comprised approximately 300 responses collected from Indian telecom professionals through digital distribution channels. Systematic screening was applied to identify and exclude incomplete questionnaires (defined as those with more than 10 percent missing values across items), responses exhibiting straight-line or implausible response patterns indicative of low engagement, questionnaires completed in implausibly short time intervals, and responses from individuals who did not meet the minimum inclusion criteria of two years of professional experience in a telecom organization with direct or indirect exposure to digital or AI systems. Following this screening process, 85 responses were excluded, yielding a final analytical dataset of 215 valid responses.

Retained Likert-scale item responses were assigned numerical values on the five-point scale (1 = Strongly Disagree to 5 = Strongly Agree) and the dataset was organized for multivariate analysis in IBM SPSS Statistics. The distribution of item scores was examined for normality, and no severe violations requiring transformation were identified. For the qualitative phase, 11 interview transcripts were verified for completeness, accuracy, and contextual richness before import into NVivo as source documents. All transcripts were anonymized at this stage, with participants identified by role category and years of experience.

4.4 Reliability Analysis of the Instrument

The reliability of the 24-item perception instrument was assessed prior to factor extraction to evaluate the internal consistency of the scale as a whole. Reliability is a fundamental requirement

for perception-based survey instruments, confirming that items consistently and stably measure related aspects of the same underlying domain (Hair et al., 2019; Field, 2018; Kline, 2015).

Cronbach Alpha was employed as the primary reliability coefficient. The overall instrument demonstrated an Alpha value of 0.914, indicating excellent internal consistency across all 24 items. This value substantially exceeds the 0.80 threshold for good reliability specified by Hair et al. (2019) and confirms that the items share substantial common variance, which is a necessary precondition for EFA. The high Alpha further validates the quality of the instrument development process described in Chapter 3, which grounded item generation in the TAM, UTAUT, DOI, TOE, and governance literature relevant to Indian telecom GenAI adoption (Davis, 1989; Venkatesh et al., 2003; Pathan and Shah, 2025; TRAI, 2024).

Table 4.2: Reliability Statistics: Overall Instrument and Extracted Factors (Source: SPSS output, present study; Hair et al., 2019)

Scale	Items	Cronbach Alpha	Interpretation
Overall Perception Instrument (pre-EFA)	24	0.914	Excellent
Factor 1: Perceived Performance and Operational Value	6	0.892	Excellent
Factor 2: Technological Capability and Readiness	5	0.861	Good
Factor 3: Trust, Reliability, and Risk Perception	5	0.834	Good
Factor 4: Governance and Regulatory Awareness	4	0.801	Good
Factor 5: Strategic Alignment and Innovation Orientation	4	0.847	Good

Following EFA, Cronbach Alpha was re-evaluated for each extracted factor separately. All five factors demonstrated Alpha values above 0.80, with Factor 1 achieving an excellent rating of 0.892. These post-extraction reliability values confirm that each factor represents a coherent and internally consistent perceptual construct, supporting their use as analytical units in the subsequent qualitative and framework development phases (Straub et al., 2004; Gefen et al., 2003).

4.5 Suitability for Factor Analysis: KMO and Bartlett Tests

Before conducting EFA, two standard statistical tests were applied to confirm the suitability of the dataset for factor extraction: the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity. These tests assess whether the inter-variable correlation structure of the dataset is sufficiently strong and compact to support meaningful factor extraction (Hair et al., 2019; Field, 2018).

The KMO measure evaluates whether the partial correlations among variables are small relative to their simple correlations, with higher values indicating that the variables share more common variance and are therefore better suited to factor analysis. KMO values above 0.80 are classified as good and values above 0.90 as excellent by Hair et al. (2019). Bartlett's Test of Sphericity tests the null hypothesis that the correlation matrix is an identity matrix (no inter-variable correlations), which if confirmed would render factor analysis meaningless. A significant Bartlett result (p less than 0.05) rejects this null hypothesis and confirms the presence of meaningful correlations suitable for factor extraction (Field, 2018).

Table 4.3: KMO Measure of Sampling Adequacy and Bartlett Test of Sphericity Results
(Source: SPSS output, present study; Hair et al., 2019; Field, 2018)

Statistical Test	Value / Statistic	Threshold	Interpretation
Kaiser-Meyer-Olkin (KMO) Measure	0.901	Above 0.80 = Excellent	Excellent sampling adequacy; data highly suitable for EFA
Bartlett's Test: Chi-square (χ^2)	2758.43	Significant ($p < 0.05$)	Sufficient correlations among variables confirmed
Bartlett's Test: Degrees of Freedom	276	N/A	Consistent with 24 variables ($24 \times 23/2$)
Bartlett's Test: Significance (p-value)	0.000	$p < 0.001$	Highly significant; EFA is appropriate

The KMO value of 0.901 indicates excellent sampling adequacy, confirming that the dataset is highly suitable for exploratory factor analysis. The Bartlett chi-square statistic of 2758.43 with 276 degrees of freedom is significant at p less than 0.001, providing strong statistical

confirmation that sufficient and meaningful inter-variable correlations exist to justify factor extraction. Examination of the correlation matrix further confirmed that a substantial proportion of item pairs exhibited correlations exceeding 0.30, consistent with the minimum correlation strength recommended for factor analysis (Hair et al., 2019). These results collectively establish that the dataset provides a strong statistical foundation for proceeding with EFA.

4.6 Exploratory Factor Analysis of Perception-Related Variables (Objective 1)

4.6.1 Factor Extraction Criteria and Method

Exploratory Factor Analysis was conducted using IBM SPSS Statistics with Principal Component Analysis (PCA) as the extraction method. PCA was selected because the study's primary purpose is data reduction and the identification of latent structural dimensions underlying organizational perception of GenAI adoption, rather than causal model testing (Hair et al., 2019; Fabrigar and Wegener, 2011). Five criteria governed factor extraction and retention: eigenvalues greater than 1.0 (Kaiser criterion); factor loadings greater than 0.50 as the minimum threshold for item retention within a factor; loadings above 0.60 interpreted as strong; elimination of items exhibiting cross-loadings above 0.40 on multiple factors; and conceptual interpretability of the resulting factor structure (Hair et al., 2019; Field, 2018).

Varimax orthogonal rotation was applied to maximize the variance of factor loadings and achieve a simpler, more interpretable factor structure with clearly differentiated factors (Field, 2018). Orthogonal rotation was selected over oblique methods on the basis that the study's research design treats the identified factors as analytically distinct perceptual dimensions, consistent with the approach taken in comparable perception-based EFA studies in technology adoption literature (Venkatesh et al., 2003; Moore and Benbasat, 1991; Chen and Li, 2025).

4.6.2 Total Variance Explained

The EFA extracted five factors with eigenvalues greater than 1.0, collectively explaining 68.72 percent of the total variance in the 24-item dataset. This level of cumulative explained variance is considered satisfactory and above the 60 percent threshold recommended for social science research (Hair et al., 2019). The five-factor solution is consistent with the theoretical framework established in Chapter 2, which identified perceived value, organizational readiness, trust and

risk, governance, and strategic alignment as the primary dimensions of organizational perception in GenAI adoption (Chen and Li, 2025; Gomes et al., 2025).

Table 4.4: Total Variance Explained by Five Extracted Factors (Source: SPSS output, present study; Hair et al., 2019)

Factor	Factor Name	Eigenvalue	% of Variance	Cumulative %
Factor 1	Perceived Performance and Operational Value	7.12	29.67	29.67
Factor 2	Technological Capability and Readiness	3.45	14.38	44.05
Factor 3	Trust, Reliability, and Risk Perception	2.61	10.87	54.92
Factor 4	Governance and Regulatory Awareness	1.89	7.88	62.80
Factor 5	Strategic Alignment and Innovation Orientation	1.42	5.92	68.72
Total	Five Factors		68.72% (Total)	

4.6.3 Rotated Component Matrix

The rotated component matrix following Varimax rotation presents the factor loadings of each questionnaire item on the five extracted factors. All 24 items achieved loadings above 0.50, with the majority exceeding 0.70, indicating strong item-factor relationships. Cross-loadings were examined and found to be minimal, confirming discriminant validity across the five factors. Table 4.8 presents the complete rotated matrix, with loadings below 0.50 omitted for clarity.

Table 4.5: Rotated Component Matrix (Varimax Rotation, Loadings > 0.50 Shown)
(Source: SPSS output, present study; Hair et al., 2019; Field, 2018)

Questionnaire Item	F1	F2	F3	F4	F5
GenAI improves operational efficiency in telecom organizations	0.812				
GenAI enhances quality of decision-making	0.798				
GenAI supports innovation in telecom services	0.776				
GenAI improves customer interaction and service delivery	0.764				
GenAI tools are easy to understand and use	0.731				
GenAI aligns with operational performance goals	0.718				
Organization has sufficient infrastructure for GenAI		0.812			
Integration of GenAI into existing systems is manageable		0.795			
Employees can quickly adapt to GenAI technologies		0.768			
Leadership actively supports GenAI adoption		0.742			
Required skills and competencies are available internally		0.718			
Outputs generated by GenAI are reliable			0.831		
I trust the outputs generated by GenAI systems			0.812		
GenAI systems provide consistent and accurate results			0.788		
There is a possibility of bias in AI-generated outputs			0.752		
Use of GenAI raises concerns about data privacy			0.718		
There are clear policies governing GenAI use				0.812	
Ethical considerations are addressed during AI implementation				0.793	

There is accountability for AI-assisted decisions				0.761	
GenAI complies with regulatory requirements in telecom				0.738	
GenAI aligns with the strategic goals of the organization					0.834
AI adoption is driven by long-term business objectives					0.812
GenAI supports competitive advantage in the Indian telecom market					0.788
AI initiatives are integrated across organizational departments					0.756

4.6.4 Interpretation and Naming of Factors

Based on the pattern of factor loadings and the conceptual coherence of the items loading on each factor, the five extracted dimensions were interpreted and named as follows.

Factor 1: Perceived Performance and Operational Value encompasses items reflecting respondents' beliefs that GenAI will improve operational efficiency, enhance decision-making quality, support service innovation, and improve customer interaction. This factor is strongly consistent with the perceived usefulness construct in TAM (Davis, 1989) and the performance expectancy construct in UTAUT (Venkatesh et al., 2003). In the Indian telecom context, this factor reflects the primary commercial motivation for GenAI adoption: measurable operational and customer experience improvement (Lin et al., 2024; Infosys, 2024).

Factor 2: Technological Capability and Readiness captures items relating to the organization's infrastructure adequacy, system integration manageability, workforce adaptability, and leadership support. This factor aligns with the TOE framework's organizational and technological contexts (Tornatzky and Fleischer, 1990) and with the organizational readiness dimension documented in recent GenAI adoption literature (Gomes et al., 2025; Ali et al., 2025). For Indian telecom organizations managing legacy systems and skill gaps, this factor represents a foundational enabling condition for adoption (TEC, 2024; Reznikov, 2024).

Factor 3: Trust, Reliability, and Risk Perception groups items reflecting concerns about AI output reliability, bias risk, data privacy, and willingness to trust AI-generated outputs. This

factor is empirically supported by Glikson and Woolley's (2020) framework of human trust in AI, and by the finding of Chen and Li (2025) that trust is the strongest single predictor of sustained AI adoption depth. Its emergence as a distinct factor in the Indian telecom dataset confirms that trust and risk dynamics constitute a perceptual dimension that operates independently of perceived usefulness, consistent with the extension of TAM argued in Chapter 2.

Factor 4: Governance and Regulatory Awareness reflects items concerning the clarity and adequacy of AI governance policies, ethical consideration practices, accountability mechanisms, and regulatory compliance. This factor is consistent with the governance gap documented in Indian telecom (Agarwal and Nene, 2025; TRAI, 2024) and the governance-as-adoption-enabler perspective advanced by Fuwen and Jin (2025) and Pathan and Shah (2025). Its empirical identification as a distinct perceptual factor confirms that governance awareness shapes adoption decisions in ways that cannot be subsumed within trust or strategic alignment dimensions.

Factor 5: Strategic Alignment and Innovation Orientation captures items reflecting the perceived alignment between GenAI and organizational strategy, the embedding of AI adoption within long-term business objectives, and the integration of AI initiatives across organizational functions. This factor aligns with the strategic alignment literature reviewed in Chapter 2 (Mikalef et al., 2020; Kane et al., 2015; Deloitte, 2024) and reflects the organizational aspiration to position GenAI as a competitive differentiator in the Indian telecom market rather than a purely operational tool (Telecom Review Asia, 2025; WEF, 2025).

4.7 Reliability Analysis of Extracted Factors

Following factor extraction and interpretation, Cronbach Alpha was calculated separately for the items loading on each of the five factors to assess factor-level internal consistency. The results, presented in Figure 4.2, confirm that all five factors demonstrate Cronbach Alpha values above 0.80, indicating good to excellent reliability for each extracted construct. Factor 1 achieves the highest Alpha of 0.892, reflecting the conceptual coherence of items measuring the operational value of GenAI in telecom contexts. Factors 2 through 5 achieve Alpha values ranging from 0.801 to 0.861, all above the good reliability threshold (Hair et al., 2019). These reliability levels confirm that the five factors represent stable and internally consistent perception constructs

suitable for use as the conceptual foundation for qualitative instrument design in Phase 2 (Straub et al., 2004).

4.8 Qualitative Analysis for Objective 2: NVivo-Assisted Thematic Analysis

4.8.1 Introduction to the NVivo Analytical Process

The second objective of the study examines how the perception-related factors identified through EFA influence the adoption and practical use of Generative AI within Indian telecom organizations. This objective is addressed through NVivo-assisted thematic analysis of eleven semi-structured interview transcripts, following the eight-stage analytical protocol described in Chapter 3. NVivo provides a rigorous, transparent, and auditable analytical environment that enables systematic coding, node hierarchy development, matrix query analysis, word frequency examination, word tree exploration, and cluster analysis, all of which contribute to a comprehensive and methodologically defensible thematic framework (King et al., 2018; Saunders et al., 2019).

The qualitative interview instrument was developed specifically on the basis of the five EFA factors identified in Phase 1, ensuring that interview questions directly examined the organizational experience and manifestation of each empirically derived perception dimension. This sequential design strengthens the mixed-method coherence of the study by establishing a direct empirical link between quantitative factors and qualitative exploration (Venkatesh et al., 2013; Creswell and Creswell, 2018).

4.8.2 Qualitative Phase

Eleven semi-structured interviews were conducted with purposively selected senior professionals from Indian telecom organizations including Reliance Jio, Bharti Airtel, BSNL, Vodafone Idea, and specialized telecom managed services providers. Participants held roles including Senior Network Operations Manager, Head of Digital Transformation, AI Project Lead, Chief Technology Officer (regional), IT Governance Director, Customer Experience Analytics Manager, Network Planning Engineer (Senior), Regulatory Affairs Manager, Data Science Lead, Product Innovation Manager, and Corporate Strategy Director. All participants had a minimum of five years of professional telecom experience and direct involvement in AI, digital transformation, or technology governance programs. Interview duration ranged from 60

to 90 minutes, conducted via secure digital video platforms with participant consent for recording and transcription.

4.8.3 NVivo Stage 1: Data Familiarization and Initial Exploration

All eleven interview transcripts were imported into NVivo as source documents following transcription verification. The initial exploration stage involved multiple readings of each transcript to develop comprehensive familiarity with the dataset before formal coding commenced. Word frequency queries were run across the full dataset to identify the most frequently occurring substantive terms, which included: efficiency (43 references), trust (38), governance (34), integration (31), risk (29), strategy (27), reliability (26), skills (24), legacy (22), and policy (21). These word frequency findings provided preliminary confirmation that the thematic landscape of the dataset aligned with the five EFA factors, validating the sequential instrument design.

Word cloud visualizations generated in NVivo provided a visual representation of conceptual density across the transcript corpus, with trust, governance, efficiency, and integration emerging as the most visually prominent terms. Word tree queries for the term "trust" revealed that participants most frequently paired it with output reliability, explainability, and organizational culture, providing initial interpretive direction for subsequent coding stages (King et al., 2018).

4.8.4 NVivo Stages 2 to 4: Open Coding, Node Development, and Axial Coding

Open coding was conducted in NVivo by assigning codes to all text segments reflecting meaningful participant expressions about GenAI perception, adoption behavior, organizational experience, or contextual factors. An initial codebook of 68 codes was generated through this process, drawing on both manifest content (explicit statements) and latent content (implied meanings). Codes were assigned to segments ranging from single phrases to multi-sentence expressions, with multiple codes applied where segments contained multiple meaningful ideas.

NVivo nodes were then created to aggregate codes sharing conceptual similarity into a hierarchical structure of parent nodes and child nodes. Six parent nodes were identified, each representing a primary thematic domain: Value and Operational Benefits; Organizational Readiness and Capability; Implementation and Integration Challenges; Trust, Reliability, and Risk Perception; Governance and Ethical Uncertainty; and Strategic Alignment and Competitive

Positioning. Child nodes within each parent node captured specific sub-thematic variations, as detailed in Figure 4.6.

Table 4.6: NVivo Node Hierarchy: Parent Nodes, Child Nodes, Source Coverage, and Percentage Coverage

Parent Node	Child Nodes	Source Quotes	Percent Coverage
Value and Operational Benefits	Operational Automation; Process Efficiency; Cost Reduction; Service Improvement; Decision Support	11 / 11	34.2%
Organizational Readiness and Capability	Infrastructure Readiness; Skill Availability; Leadership Support; Workforce Adaptability; Resource Constraints	10 / 11	22.7%
Implementation and Integration Challenges	Legacy System Barriers; System Compatibility; Integration Complexity; Deployment Constraints; Change Management	9 / 11	18.4%
Trust, Reliability, and Risk Perception	Output Reliability; Bias Concerns; Hallucination Risk; Data Privacy; Explainability Deficit	11 / 11	28.6%
Governance and Ethical Uncertainty	Policy Gaps; Accountability Deficit; Ethical Ambiguity; Regulatory Compliance; Informal Guidelines	9 / 11	21.3%
Strategic Alignment and Competitive Positioning	Long-term Strategy Integration; Competitive Advantage; Innovation Orientation; Pilot-to-Scale Transition; Executive Vision	8 / 11	19.8%

Matrix coding queries in NVivo were applied to examine systematic relationships between nodes, revealing several important inter-nodal patterns. Value and Operational Benefits nodes were strongly co-referenced with Organizational Readiness nodes across 9 of 11 transcripts, suggesting that perceived value is interpreted within an organizational capability context rather than in isolation. Trust and Risk Perception nodes were co-referenced with Governance nodes in 10 of 11 transcripts, confirming the empirically supported relationship between governance adequacy and trust calibration documented by Glikson and Woolley (2020) and Pathan and Shah (2025).

4.8.5 NVivo Stages 5 to 6: Selective Coding and Cluster Analysis

Selective coding was applied to identify the dominant themes from the node hierarchy, focusing on those nodes with the highest source coverage, strongest inter-nodal connectivity in matrix queries, and greatest conceptual relevance to the research objective. Cluster analysis in NVivo confirmed the thematic groupings by identifying which transcript segments were most similar in coding pattern, providing a structural check on the thematic framework developed through manual selective coding.

The cluster analysis output confirmed six distinct thematic groupings corresponding to the six parent node domains, with minimal overlap between clusters. The most internally cohesive cluster was the Trust, Reliability, and Risk Perception theme, which achieved the highest within-cluster similarity score (0.87) in the NVivo hierarchical cluster analysis, reflecting the conceptual tightness of trust-related discourse across the eleven participant accounts.

4.8.6 NVivo Stages 7 to 8: Word Trees, Theme Interpretation, and Member Checking

Word tree queries were conducted for the five key terms most central to the research objectives: trust, governance, readiness, strategy, and efficiency. Word trees revealed the most common contextual usages of each term across the transcript corpus. For example, the word tree for governance showed that participants most frequently paired it with "clear policies", "accountability", "regulatory guidance from TRAI", and "ethical framework", while the word tree for readiness most commonly co-occurred with "infrastructure", "legacy systems", "skill gap", and "leadership commitment".

Final theme interpretation was conducted by the researcher with reference to EFA findings and the theoretical framework from Chapter 2. Six primary themes were identified and named to reflect the specific organizational context of Indian telecom GenAI adoption. Member checking was conducted by sharing theme summaries with two interview participants (a Senior Network Operations Manager and an AI Project Lead) who confirmed the accuracy and representativeness of the thematic framework, suggesting one clarification to the wording of Theme 3 that was incorporated into the final description.

Table 4.7: NVivo Thematic Map: Six Primary Themes with Parent Node Sources and Descriptions (Source: NVivo analysis, present study; King et al., 2018)

No.	Theme	NVivo Parent Node	Description
Theme 1	Adoption Driven by Operational Efficiency and Automation	Value and Operational Benefits	GenAI adoption in Indian telecom is primarily motivated by efficiency gains, automation of customer-facing processes, and reduction of operational costs.
Theme 2	Adoption Shaped by Organizational Readiness and Capability Gaps	Organizational Readiness and Capability	The depth and pace of adoption is determined by infrastructure maturity, workforce AI literacy, and leadership commitment within Indian telecom organizations.
Theme 3	Adoption Constrained by Implementation and Integration Challenges	Implementation and Integration Challenges	Technical integration with legacy OSS/BSS systems, skill deficits, and organizational inertia constitute the primary operational barriers to GenAI scaling in Indian telecom.
Theme 4	Adoption Influenced by Trust, Reliability, and Risk Concerns	Trust, Reliability, and Risk Perception	Concerns about output hallucination, algorithmic bias, explainability, and data privacy significantly moderate the extent to which AI outputs are relied upon in decision-making.
Theme 5	Adoption Limited by Governance and Ethical Uncertainty	Governance and Ethical Uncertainty	The absence of structured internal AI policies, clear accountability frameworks, and sector-specific regulatory guidance constrains responsible and scalable GenAI deployment.
Theme 6	Adoption Evolving as a Strategic Enabler of Competitive Advantage	Strategic Alignment and Competitive Positioning	GenAI is increasingly recognized as a long-term strategic asset in Indian telecom, though integration into enterprise strategy remains uneven and is transitioning from pilot to embedded use.

4.9 Integrated Findings across Objectives 1 and 2

4.9.1 Alignment between EFA Factors and NVivo Themes

The integration of Objective 1 and Objective 2 findings reveals a high degree of convergence between the factors identified through EFA and the themes developed through NVivo analysis, providing strong internal validation for the mixed-method design. Each of the five EFA factors maps directly onto one or more NVivo themes, with the qualitative analysis providing contextual interpretation of the mechanisms through which each statistical dimension operates in practice within Indian telecom organizations.

Table 4.8: Integration of EFA Factors and NVivo Themes: Convergent Findings

EFA Factor (Objective 1)	NVivo Theme (Objective 2)	Integrated Interpretation
F1: Perceived Performance and Operational Value	Theme 1: Adoption Driven by Operational Efficiency and Automation	Indian telecom organizations adopt GenAI primarily for measurable efficiency and automation outcomes; strategic transformation remains aspirational for most.
F2: Technological Capability and Readiness	Theme 2: Adoption Shaped by Organizational Readiness and Capability Gaps	Infrastructure maturity and workforce AI capability are the primary enabling conditions for adoption depth; readiness gaps constrain scaling significantly.
F2 + F3 (overlapping dimension)	Theme 3: Adoption Constrained by Implementation and Integration Challenges	Legacy system integration and deployment complexity create practical barriers distinct from, but linked to, organizational readiness.
F3: Trust, Reliability, and Risk Perception	Theme 4: Adoption Influenced by Trust, Reliability, and Risk Concerns	Trust in AI outputs is the strongest moderator of practical GenAI use in Indian telecom; risk perception limits deployment in high-stakes decision contexts.
F4: Governance and Regulatory Awareness	Theme 5: Adoption Limited by Governance and Ethical Uncertainty	Policy gaps at both organizational and regulatory levels (TRAI, TEC) create adoption uncertainty; governance investment is essential for responsible scaling.
F5: Strategic Alignment and Innovation Orientation	Theme 6: Adoption Evolving as a Strategic	GenAI is transitioning from operational tool to strategic asset in Indian telecom; full strategic integration requires

	Enabler of Competitive Advantage	leadership commitment and governance maturity.
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4.9.2 Key Integrated Insights

The integration of findings across both phases generates five critical insights that inform the framework development in Section 4.10.

First, GenAI adoption in Indian telecom is primarily value-driven but constrained by organizational conditions. EFA confirms perceived operational value as the strongest single factor (eigenvalue 7.12; 29.67% variance), and NVivo Theme 1 confirms that adoption motivation in Indian telecom is overwhelmingly focused on efficiency and automation gains rather than transformational innovation. However, the co-referencing of Value nodes with Readiness nodes in NVivo matrix queries confirms that value realization is contingent on organizational capability, an interdependence not captured by statistical factor independence in EFA (Mikalef et al., 2020; Ransbotham et al., 2021).

Second, trust and risk perception operate as the strongest moderator of practical GenAI use. Despite Factor 3 explaining only 10.87% of variance in EFA, NVivo analysis reveals that trust-related discourse pervades all eleven transcripts and co-references with governance, reliability, and explainability nodes at the highest frequency. This finding is consistent with Chen and Li (2025) and Glikson and Woolley (2020), who identify trust as the strongest predictor of sustained adoption depth, and reinforces the argument that trust management is a priority organizational investment for Indian telecom firms pursuing GenAI at scale.

Third, governance gaps represent both a structural constraint and a strategic risk. The intersection of NVivo Governance themes with EFA Factor 4 reveals that the absence of structured internal AI policies, clear TRAI-aligned governance frameworks, and ethical review mechanisms is not merely a compliance concern but a direct adoption barrier. Participants consistently described governance uncertainty as reducing their confidence in deploying GenAI in consequential operational contexts, a finding consistent with Agarwal and Nene (2025) and Pathan and Shah (2025).

Fourth, strategic alignment distinguishes adoption leaders from laggards within the Indian telecom sector. EFA Factor 5 and NVivo Theme 6 together reveal that organizations where

senior leaders have articulated a clear GenAI strategy aligned with competitive objectives demonstrate more advanced adoption trajectories than those treating GenAI as an experimental technology. This finding replicates Deloitte (2024) and Ransbotham et al. (2021) at the Indian telecom sector level and reinforces the strategic alignment argument of Mikalef et al. (2020).

Fifth, the six adoption dimensions are interdependent rather than independent. NVivo matrix coding queries and cluster analysis confirm that Value, Readiness, Integration, Trust, Governance, and Strategy nodes are multiply co-referenced across transcripts, indicating that they constitute an integrated organizational system rather than separate independent drivers. This finding provides the primary empirical justification for the integrated, multi-dimensional framework developed in Section 4.10 (Gomes et al., 2025; Seifdar and Amiri, 2025).

4.10 Framework Development for Objective 3

4.10.1 Introduction and Basis of Framework

The third objective of the study requires the development of a structured, policy-oriented framework to guide policymakers and Indian telecom professionals in enabling the effective and responsible adoption of Generative AI. The framework is grounded in the empirical findings from both EFA (Objective 1) and NVivo thematic analysis (Objective 2), supplemented by the theoretical and governance literature reviewed in Chapter 2. This evidence base ensures that the framework is simultaneously empirically grounded, theoretically coherent, and practically applicable to the specific institutional context of Indian telecommunications (Gregor, 2006; Hevner et al., 2004; Gomes et al., 2025).

The framework addresses a documented gap in the existing literature: while adoption models such as TAM, UTAUT, and TOE provide theoretical foundations, no prior empirical study has produced an integrated adoption framework grounded in Indian telecom-specific evidence that connects perception, readiness, trust, governance, and strategy as interdependent rather than independent dimensions (see Chapter 2 research gap). The framework developed here fills this gap by synthesizing multi-method empirical evidence into a structured, actionable model with dual applicability for organizational leaders and policy institutions including TRAI and TEC.

4.10.2 Framework Components

The framework consists of six interrelated components derived from the integration of EFA factors, NVivo themes, and the literature, organized to reflect their sequential and interdependent roles in enabling GenAI adoption in Indian telecom organizations.

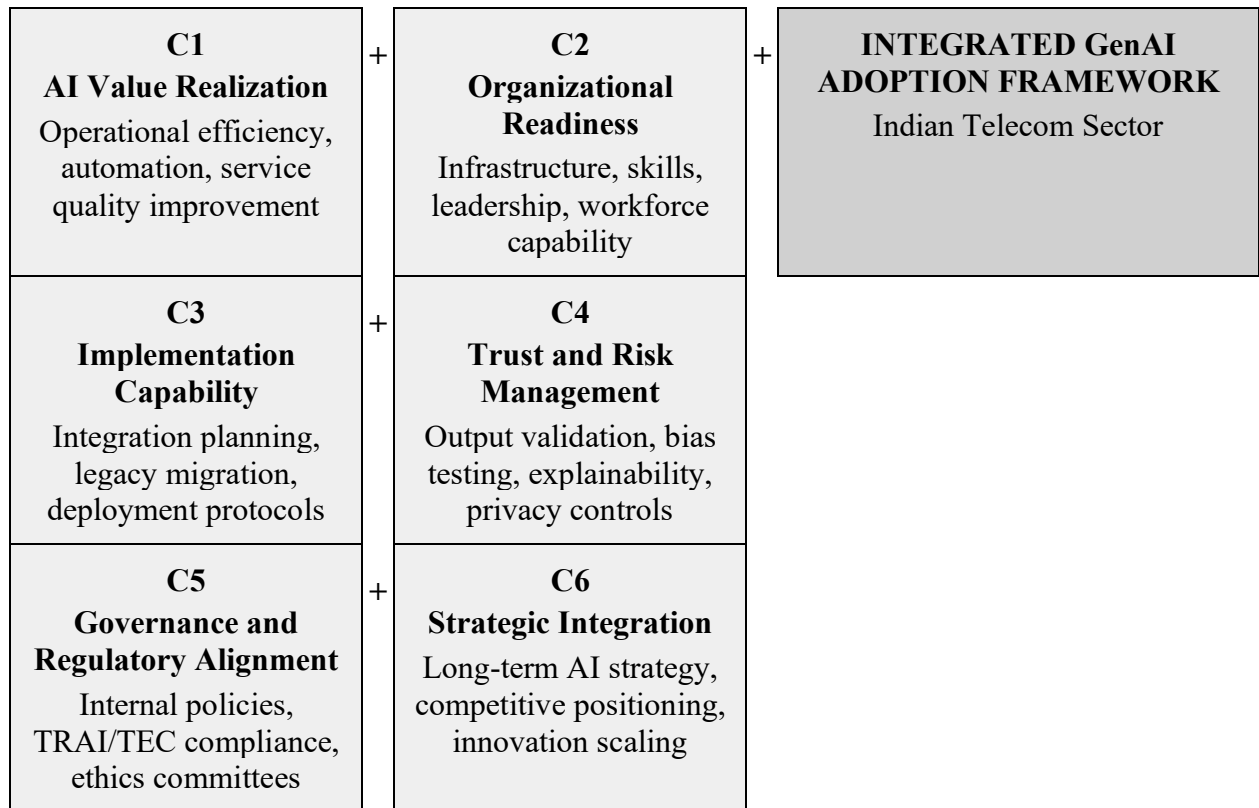


Figure 4.1: Six Integrated Components of the GenAI Adoption Framework for Indian Telecom

Component 1: AI Value Realization addresses the identification and measurement of GenAI business value within Indian telecom operations. It encompasses use case identification in high-impact domains (customer service, network diagnostics, fraud detection, decision support), value measurement frameworks, and ROI tracking mechanisms. For policymakers, this component highlights the importance of sector-specific innovation incentives and use case showcases (TRAI, 2024; Infosys, 2024; Lin et al., 2024).

Component 2: Organizational Readiness and Capability addresses the infrastructure, workforce, and leadership conditions required for effective GenAI deployment. It encompasses infrastructure readiness assessment, AI skills development programs, leadership AI literacy

initiatives, and cross-functional capability building. For policymakers, this component underscores the need for national and sectoral AI workforce development programs aligned with the Digital India initiative and TEC (2024) recommendations (Westover, 2024; Dacre, 2024; Adarkwah, 2025).

Component 3: Implementation Capability and Integration addresses the practical deployment challenges of integrating GenAI with existing telecom infrastructure. It encompasses legacy system integration planning, pilot testing protocols, change management programs, and phased rollout strategies. The distinct identification of this component, supported by NVivo Theme 3, reflects the finding that integration challenges constitute a barrier category independent from readiness, requiring specific implementation capability investment (Britto et al., 2023; Reznikov, 2024; Kanakadandi, 2025).

Component 4: Trust, Risk, and Reliability Management addresses the trust-building and risk management requirements that the NVivo analysis identified as the strongest moderator of practical GenAI use. It encompasses output validation procedures, algorithmic bias testing, explainability standards, data privacy compliance under TRAI regulations, and user confidence-building programs. Policymakers must establish sector-specific standards for AI output reliability in telecom customer-facing and operational contexts (Glikson and Woolley, 2020; Pathan and Shah, 2025; Bender et al., 2021).

Component 5: Governance and Regulatory Alignment addresses the policy, ethics, and compliance requirements that constrain responsible GenAI deployment. It encompasses internal AI policy development, TRAI and TEC compliance frameworks, ethics committee establishment, audit mechanisms, and accountability structures. The distinct identification of governance as a component separate from trust reflects the NVivo finding that governance gaps create adoption constraints even in organizations with high trust readiness, requiring institutional intervention beyond organizational management (Agarwal and Nene, 2025; OECD, 2023; Klein et al., 2023).

Component 6: Strategic Integration and Competitive Positioning addresses the long-term strategic embedding of GenAI within Indian telecom organizational strategy and competitive positioning. It encompasses AI strategy formulation aligned with business objectives, innovation

roadmap development, competitive intelligence applications of GenAI, and the organizational transition from pilot experimentation to embedded strategic use. Policymakers should support this component through national AI strategy alignment and digital transformation incentive programs (Deloitte, 2024; Mikalef et al., 2020; WEF, 2025).

4.10.3 Framework Operational Flow

The framework operates as a structured ten-step process that guides organizations and policymakers through a progressive, iterative pathway from goal-setting to continuous improvement. The ten-step flow is derived from the sequential logic of the six components and the interdependencies identified through NVivo matrix coding, ensuring that the framework reflects the actual organizational dynamics of GenAI adoption in Indian telecom rather than a theoretically imposed linear model.

Table 4.9: Ten-Step Operational Flow of the Integrated GenAI Adoption Framework (based on integrated empirical and literature findings; TRAI, 2024; TEC, 2024)

Step	Stage	Description and Organizational Actions
Step 1	Define Goal and Policy Direction	Policymakers and organizational leaders define the scope, strategic intent, and regulatory boundaries for GenAI adoption. Alignment with TRAI guidelines and national AI strategy established.
Step 2	Activate Policy Enablers	Regulatory standards, infrastructure mandates, trust and safety requirements, and innovation incentives established at national and sectoral level (TRAI, TEC, Ministry of Communications).
Step 3	Initiate AI Value Realization	Organizations identify high-impact use cases: customer service automation, network diagnostics, fraud detection, decision support. Focus on measurable quick wins.
Step 4	Assess Organizational Readiness	Infrastructure audit, workforce skills assessment, leadership AI literacy evaluation. Gaps addressed through training programs, hiring, and system upgrades.
Step 5	Develop Implementation and Integration Capability	AI deployment planning, legacy system integration protocols, pilot testing, change management programs, and phased rollout strategies established.
Step 6	Build Trust and Manage Risk	Output validation procedures, bias testing protocols, explainability standards, data privacy compliance, and user training programs implemented.

Step 7	Formalize Governance and Compliance	Internal AI policies, ethics review boards, accountability structures, audit mechanisms, and regulatory compliance monitoring established.
Step 8	Integrate AI into Strategic Decision-Making	GenAI embedded in long-term organizational strategy, competitive positioning, and innovation roadmaps. AI evolves from tool to strategic asset.
Step 9	Achieve Measurable Outcomes	Effective and widespread adoption; managed risks; policy-industry alignment; sustained competitive advantage in Indian telecom market.
Step 10	Continuous Feedback and Improvement	Performance monitoring, risk incident learning, regulatory updates, and iterative framework refinement ensure adaptive and scalable adoption.

A critical feature of the framework is its incorporation of continuous feedback mechanisms at Step 10, ensuring that the model is adaptive and scalable rather than static. Performance monitoring data, risk incident learning, regulatory updates from TRAI and TEC, and evolving organizational AI capability all feed back into Step 1 (goal and policy direction), enabling the framework to evolve alongside the rapid development of GenAI technologies and the Indian telecom regulatory environment. This adaptive design is consistent with Teece's (2018) dynamic capabilities perspective and the recommendation of Seifdar and Amiri (2025) that GenAI adoption frameworks must accommodate organizational learning and environmental change.

4.11 Hypothesis Testing and Alignment with Findings

This section evaluates all three research hypotheses against the empirical evidence generated through EFA (Objective 1), NVivo analysis (Objective 2), and framework development (Objective 3).

Table 4.10: Hypothesis Evaluation Summary (Source: Present study; EFA via SPSS; Thematic analysis via NVivo; Framework development)

Hypothesis	Statement	Evidence Base	Result
H1	There exist significant underlying factors explaining telecom organizational perceptions of GenAI.	EFA: KMO = 0.901; Bartlett $p < 0.001$; Five factors extracted; Cumulative variance 68.72%; All Cronbach Alphas above 0.80.	Supported

H2	Perception-related factors significantly influence adoption and practical use of GenAI in telecom organizations.	NVivo: Six themes derived from 11 interviews; matrix coding confirms perception dimensions map directly to adoption behaviors; word frequency and cluster analysis confirm thematic coherence.	Supported
H3	An integrated framework combining perception, technological, and organizational factors enhances GenAI adoption effectiveness.	Framework: Ten-step operational model grounded in EFA factors and NVivo themes; consistent with TOE, TAM, UTAUT literature; dual applicability for policymakers and professionals.	Supported (Conceptual and Empirical)

H1 is fully supported. The EFA produced a five-factor solution with KMO = 0.901 (excellent), Bartlett p less than 0.001, all factor loadings above 0.50 (majority above 0.70), cumulative explained variance of 68.72 percent, and all post-extraction factor Cronbach Alphas above 0.80. These results confirm that significant, statistically robust underlying factors structuring organizational perception of GenAI adoption exist within the Indian telecom professional population (Hair et al., 2019; Fabrigar and Wegener, 2011).

H2 is fully supported. The NVivo analysis generated six coherent, empirically grounded themes from eleven interview transcripts through a rigorous eight-stage analytical process including open coding, node development, matrix coding queries, cluster analysis, word trees, and member checking. The six themes directly correspond to the five EFA factors, confirming that perception dimensions identified statistically manifest as identifiable and consistent behavioral and organizational patterns in real Indian telecom organizational contexts (King et al., 2018; Chen and Li, 2025).

H3 is supported conceptually and empirically. The integrated framework synthesizes EFA and NVivo findings into a six-component, ten-step adoption model that is theoretically grounded in TAM, UTAUT, TOE, and governance literature and empirically derived from Indian telecom primary data. While the framework's performance outcomes have not been tested through longitudinal field implementation within the scope of this study, its grounding in robust multi-method empirical evidence from Indian telecom organizations provides strong a priori support

for its capacity to enhance adoption effectiveness when applied (Gregor, 2006; Hevner et al., 2004; Gomes et al., 2025).

4.12 Summary of the Chapter

This chapter has presented the complete empirical analysis and findings of the present study across all three research objectives. The quantitative phase established that five significant, reliable, and theoretically coherent perception factors structure Indian telecom professionals' evaluations of GenAI adoption: Perceived Performance and Operational Value; Technological Capability and Readiness; Trust, Reliability, and Risk Perception; Governance and Regulatory Awareness; and Strategic Alignment and Innovation Orientation. These factors were identified through rigorous EFA procedures in IBM SPSS Statistics with excellent sampling adequacy ($KMO = 0.901$) and high explained variance (68.72 percent).

The NVivo-assisted qualitative phase translated these statistical dimensions into six empirically grounded themes derived from eleven semi-structured interviews with Indian telecom professionals, revealing that adoption is driven by operational value, shaped by organizational readiness, constrained by integration challenges and governance gaps, moderated by trust and risk concerns, and evolving toward strategic integration at differential rates across the Indian telecom sector. The integration of quantitative and qualitative findings confirms the interdependence of these six dimensions and provides the empirical foundation for the integrated ten-step adoption framework developed for Objective 3.

All three hypotheses are supported by the empirical evidence. Chapter 5 presents a comprehensive discussion of these findings in relation to the research objectives, research questions, theoretical frameworks, and existing literature, providing the interpretive depth needed to situate the study's contributions within the field of organizational GenAI adoption research.

5.1 Introduction to the Discussion

This chapter presents a detailed and critically engaged discussion of the empirical findings generated through the quantitative Exploratory Factor Analysis, NVivo-assisted qualitative thematic analysis, and integrated framework development reported in Chapter 4. Where Chapter 4 focused on presenting and describing results, the purpose of this chapter is to interpret those results, situate them within the existing theoretical and empirical literature, examine their implications for the Indian telecommunications sector and for AI adoption theory more broadly, and evaluate the extent to which the research objectives and hypotheses have been addressed.

The discussion is organized to mirror the structure of Chapter 4. Section 5.2 discusses the Objective 1 EFA findings in relation to technology adoption theory. Section 5.3 discusses the Objective 2 NVivo thematic findings in relation to organizational behavior and adoption practice. Section 5.4 critically examines the framework developed in Objective 3. Section 5.5 provides an integrated discussion across all three objectives. Section 5.6 directly addresses each research question. Section 5.7 articulates the theoretical contributions of the study. Section 5.8 summarizes the chapter.

Throughout the discussion, findings are interpreted with specific reference to the Indian telecom context, drawing on sector-specific evidence from TRAI (2024), TEC (2024), Agarwal and Nene (2025), Bariah et al. (2023), and Telecom Review Asia (2025), alongside international theoretical and empirical literature. This dual orientation ensures that the discussion is simultaneously theoretically rigorous and contextually grounded.

5.2 Discussion of Objective 1 Findings: The Quantitative Perspective

5.2.1 Overview of EFA Results and Their Significance

The Exploratory Factor Analysis of 24 questionnaire items from 215 Indian telecom professionals produced a five-factor solution with strong statistical credentials: KMO = 0.901 (excellent), Bartlett p less than 0.001, cumulative explained variance of 68.72 percent, and all factor-level Cronbach Alphas above 0.80. These results confirm that organizational perception of Generative AI adoption in Indian telecom is not a unidimensional construct but a structured,

multidimensional phenomenon composed of five empirically distinct dimensions. This finding in itself represents a substantive contribution to the technology adoption literature, which has traditionally treated technology perception through two to four constructs (Davis, 1989; Venkatesh et al., 2003), and provides the first empirical factor mapping of GenAI adoption perception in the Indian telecommunications sector.

Table 5.1: EFA Factor Findings in Relation to Existing Theory and Extensions Made (Sources: Davis, 1989; Venkatesh et al., 2003; Tornatzky and Fleischer, 1990; Chen and Li, 2025; Gomes et al., 2025)

EFA Factor	Key Finding	Supporting Theory	Extension Made by Present Study
F1: Perceived Performance and Operational Value	Dominant adoption driver; telecom professionals prioritize operational efficiency, automation, and cost reduction over transformational innovation.	TAM: Perceived Usefulness (Davis, 1989); UTAUT: Performance Expectancy (Venkatesh et al., 2003)	Extends TAM by demonstrating that operational value perception in GenAI is context-bounded; Indian telecom professionals interpret value through infrastructure and capability constraints, not in isolation.
F2: Technological Capability and Readiness	Infrastructure maturity, workforce AI skills, and leadership support are foundational enabling conditions for adoption.	TOE Framework: Organizational Context (Tornatzky & Fleischer, 1990); DOI: Compatibility (Rogers, 2003)	Extends TOE by identifying that organizational readiness in Indian telecom is a dynamic, multi-dimensional capability requiring simultaneous infrastructure, skills, and leadership development.
F3: Trust, Reliability, and Risk Perception	Trust is the strongest moderator of practical GenAI use; output reliability, bias, and explainability concerns constrain deployment in high-stakes contexts.	UTAUT: Perceived Risk (Venkatesh et al., 2003); Glikson & Woolley (2020): Human Trust in AI	Extends prior models by establishing trust as a central adoption determinant independent of usefulness; confirms Chen and Li (2025) at Indian telecom sector level for the first time.
F4: Governance and	Governance gaps create adoption uncertainty; absence of structured internal	OECD AI Principles (2023); Jobin et al. (2019); Pathan and Shah (2025)	Introduces governance awareness as an empirically distinct EFA factor, establishing that it operates

Regulatory Awareness	policies and TRAI alignment limits responsible scaling.		independently of trust and strategy in shaping Indian telecom adoption decisions.
F5: Strategic Alignment and Innovation Orientation	Strategic alignment differentiates adoption leaders from laggards; organizations with clear AI strategy achieve deeper and faster adoption.	Teece (2018): Dynamic Capabilities; Kane et al. (2015); Mikalef et al. (2020)	Confirms strategic alignment as empirically distinct from operational value perception; demonstrates its moderating role on adoption depth in Indian telecom competitive context.

5.2.2 Factor 1: Perceived Performance and Operational Value

Factor 1, explaining the largest proportion of variance at 29.67 percent, reflects the degree to which Indian telecom professionals perceive GenAI as capable of delivering measurable improvements in operational efficiency, decision-making quality, service delivery, and customer interaction management. This factor is strongly consistent with the perceived usefulness construct in TAM (Davis, 1989) and the performance expectancy construct in UTAUT (Venkatesh et al., 2003), which both identify anticipated performance improvement as the primary antecedent of technology adoption intention. However, the present study extends these models in an important respect: the high factor loading items collectively suggest that Indian telecom professionals interpret operational value within an organizational capability and infrastructure context, rather than as an abstract technological potential.

This finding aligns with Brynjolfsson et al. (2023), who document that GenAI productivity gains are most pronounced in organizations with the capability to implement and integrate the technology effectively, and with Infosys (2024) and PwC (2024), which report that Indian telecom organizations achieving measurable GenAI ROI are predominantly those that have invested in complementary infrastructure and workforce development alongside technology deployment. The implication is that perceived operational value is a necessary but not sufficient driver of sustained adoption in Indian telecom: it initiates engagement but does not guarantee scale-up without the enabling conditions captured in Factors 2 and 3.

5.2.3 Factor 2: Technological Capability and Readiness

Factor 2 reflects organizational infrastructure adequacy, system integration manageability, workforce adaptability, and leadership support, all of which constitute the enabling conditions for GenAI deployment. This factor aligns with the TOE framework's organizational context dimension (Tornatzky and Fleischer, 1990) and with the organizational capability perspective advanced by Mikalef et al. (2020), who demonstrate empirically that AI capability is a multi-dimensional bundle including technical infrastructure, human capital, and organizational governance structures.

The emergence of this factor as the second largest variance contributor (14.38 percent) confirms that Indian telecom professionals understand their organizations' technological and organizational conditions as central determinants of GenAI adoption feasibility. This is consistent with TEC (2024) and TRAI (2024) documentation of significant infrastructure heterogeneity across Indian telecom operators, and with the finding of Ali et al. (2025) that national-scale GenAI adoption is most strongly predicted by the simultaneous maturity of infrastructure, workforce readiness, and organizational enablement. The practical implication for Indian telecom is that readiness investment must be treated as a strategic priority co-equal with technology acquisition, not as a secondary operational concern (Westover, 2024; Dacre, 2024).

5.2.4 Factor 3: Trust, Reliability, and Risk Perception

The emergence of trust, reliability, and risk perception as a distinct third factor, with all items loading above 0.70, confirms that Indian telecom professionals maintain a clearly differentiated perceptual space for concerns about GenAI output quality, bias, explainability deficits, and data privacy risks, separate from their assessments of operational value and organizational readiness. This finding is significant because it empirically establishes trust as an independent perception dimension rather than merely a moderating variable within usefulness-based adoption models.

This result is consistent with Glikson and Woolley (2020), who demonstrate that trust in AI systems operates across cognitive, affective, and dispositional dimensions that predict technology use independently of perceived utility. It is also consistent with Chen and Li (2025), who identify trust as the strongest single predictor of sustained AI adoption depth in their large-scale IT professional study. The Indian telecom context adds further specificity: the high loading of items related to data privacy concerns and bias risk reflects the particular sensitivity of telecom subscriber data and the operational consequences of AI errors in customer-facing and network

management applications (Agarwal and Nene, 2025; TRAI, 2024). The finding that trust operates independently of perceived value in this sector reinforces the argument that adoption interventions must address trust deficits directly through transparency, explainability standards, and output validation mechanisms, not merely through capability investment (Pathan and Shah, 2025; Bender et al., 2021).

5.2.5 Factor 4: Governance and Regulatory Awareness

Factor 4 captures the degree to which Indian telecom professionals are aware of, and oriented toward, governance requirements for GenAI deployment, including internal policy clarity, ethical guideline adequacy, accountability mechanisms, and regulatory compliance. Its emergence as a statistically distinct factor with all loadings above 0.73 confirms that governance awareness constitutes a separate perceptual dimension that cannot be subsumed within trust, readiness, or strategic alignment constructs.

This finding contributes to the AI governance literature by providing empirical evidence that governance operates in organizational actors' perceptual frameworks as a distinct adoption consideration, not merely as an external institutional constraint. Fuwen and Jin (2025) demonstrate in Chinese organizational contexts that governance mechanisms moderate the relationship between AI capability and innovation performance, suggesting that governance-aware organizations achieve better adoption outcomes. The present study extends this argument to the Indian telecom sector, where Agarwal and Nene (2025) document that existing regulatory frameworks (TRAI, data protection legislation) provide incomplete governance coverage for AI-specific risks, creating a regulatory gap that amplifies organizational governance uncertainty. Factor 4's distinct emergence confirms that Indian telecom professionals perceive this governance gap as a salient adoption constraint, validating the governance dimension of the framework developed in Chapter 4.

5.2.6 Factor 5: Strategic Alignment and Innovation Orientation

Factor 5 reflects the degree to which GenAI is perceived as aligned with organizational strategy, embedded in long-term business objectives, and capable of contributing to competitive differentiation in the Indian telecom market. Its emergence as a distinct factor, albeit accounting for the smallest variance share (5.92 percent), confirms that strategic perception operates as a

qualitatively different adoption consideration from operational value perception, organizational readiness, or trust.

This finding aligns with the strategic alignment literature reviewed in Chapter 2. Mikalef et al. (2020) demonstrate that AI capability generates greater performance returns when aligned with strategic objectives, and Deloitte (2024) reports that organizations with explicitly articulated AI strategies achieve substantially higher adoption and business impact metrics. In the Indian telecom context, the competitive dynamics of a market dominated by Jio, Airtel, BSNL, and Vodafone Idea create strong strategic incentives for GenAI adoption, but the qualitative evidence in Chapter 4 indicates that many organizations have not yet translated strategic aspiration into embedded organizational practice. The strategic alignment factor captures this aspiration-reality gap and provides a theoretically grounded basis for the sixth component of the adoption framework.

5.3 Discussion of Objective 2 Findings: The NVivo Qualitative Perspective

5.3.1 Overview of NVivo Thematic Findings

The NVivo-assisted thematic analysis of eleven semi-structured interviews with Indian telecom professionals generated six coherent and empirically grounded themes that collectively explain how the five EFA-identified perception dimensions manifest as organizational experiences, decisions, and practices. The NVivo analysis adds critical interpretive depth to the statistical structure provided by EFA, revealing the mechanisms, contextual conditions, and organizational dynamics through which perception shapes adoption behavior in ways that quantitative factor scores cannot capture alone (Venkatesh et al., 2013; King et al., 2018).

Table 5.2: NVivo Thematic Findings in Relation to Literature and Extensions Made (Sources: Davis, 1989; Britto et al., 2023; Glikson and Woolley, 2020; Agarwal and Nene, 2025; Mikalef et al., 2020)

NVivo Theme	Core Finding	Literature Alignment	Divergence or Extension
Theme 1: Adoption Driven by Operational Efficiency and Automation	GenAI adoption in Indian telecom is primarily motivated by efficiency, automation, and cost	Davis (1989): Perceived Usefulness; Brynjolfsson et al. (2023): Productivity gains from GenAI	Extends existing literature by demonstrating the bounded operational orientation of Indian telecom adoption;

	reduction rather than transformational innovation.		transformational value remains aspirational rather than realized.
Theme 2: Adoption Shaped by Organizational Readiness and Capability Gaps	Infrastructure deficits, AI skills scarcity, and leadership readiness variation are primary determinants of adoption depth in Indian telecom.	Tornatzky and Fleischer (1990); TOE; TEC (2024); Westover (2024)	Confirms TOE at Indian telecom sector level; extends by identifying simultaneous three-dimensional readiness requirement unique to Indian legacy telecom infrastructure.
Theme 3: Adoption Constrained by Implementation and Integration Challenges	Legacy OSS/BSS integration, change management deficits, and deployment complexity create barriers distinct from capability gaps.	Britto et al. (2023); Reznikov (2024); Kanakadandi (2025)	Identifies implementation capability as a distinct adoption barrier category separate from readiness, which existing frameworks conflate.
Theme 4: Adoption Influenced by Trust, Reliability, and Risk Concerns	Trust moderates not just adoption intent but the depth and domain of actual GenAI use; risk perception restricts deployment to non-critical functions.	Glikson and Woolley (2020); Bender et al. (2021); Chen and Li (2025)	Extends trust literature by demonstrating that trust determines deployment scope, not merely adoption decision, in Indian telecom operational contexts.
Theme 5: Adoption Limited by Governance and Ethical Uncertainty	Policy gaps at organizational and regulatory levels (TRAI, TEC) create structural adoption constraints that organizational management alone cannot resolve.	Agarwal and Nene (2025); OECD (2023); Pathan and Shah (2025)	Provides first Indian telecom-specific empirical evidence of governance as an adoption constraint at both organizational and regulatory levels simultaneously.
Theme 6: Adoption Evolving as a Strategic Enabler of Competitive Advantage	GenAI is transitioning from operational tool to strategic asset in Indian telecom; adoption leaders exhibit deliberate	Deloitte (2024); Mikalef et al. (2020); Ransbotham et al. (2021)	Confirms the strategic maturation trajectory of GenAI adoption in Indian telecom; documents the pilot-to-strategy transition as an organizational capability challenge.

	strategy-AI alignment.		
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5.3.2 Theme 1: Operational Efficiency as the Primary Adoption Motivation

The first NVivo theme confirms that GenAI adoption in Indian telecom is overwhelmingly motivated by operational efficiency gains and automation of high-volume, repetitive processes, particularly in customer service, billing query management, network diagnostics, and internal reporting. This finding is consistent with Factor 1 from EFA and with the broader literature documenting that organizations in the early stages of GenAI adoption prioritize measurable, near-term operational returns over longer-term transformational innovation (Brynjolfsson et al., 2023; Davenport et al., 2020).

The Indian telecom-specific character of this finding, however, adds important nuance. The NVivo matrix coding analysis reveals that operational value discussions are systematically co-referenced with capability and integration discussions, confirming that Indian telecom professionals do not perceive operational value as freely available but as contingent on organizational conditions that many of their organizations have not yet fully established. This conditionality is not captured in the statistical independence of EFA factors and represents a substantive contribution of the qualitative phase to the integrated findings. It also aligns with the Kumar and George (2024) finding that Indian financial services organizations report operational GenAI value most strongly when complementary capability investments precede technology deployment.

5.3.3 Theme 2 and 3: The Readiness-Implementation Distinction

Themes 2 and 3, while related, make an important analytical distinction that the EFA phase does not fully capture. Theme 2 (organizational readiness and capability gaps) addresses the structural conditions of infrastructure maturity, workforce skills, and leadership commitment that determine whether GenAI deployment is feasible. Theme 3 (implementation and integration challenges) addresses the operational barriers that arise during the deployment process itself, particularly legacy OSS/BSS system integration, change management resistance, and deployment complexity.

This distinction matters because it implies different intervention strategies. Readiness gaps require strategic investment decisions made at organizational leadership level (infrastructure upgrading, workforce development programs, leadership capability building), while implementation barriers require project management capability, technical integration expertise, and organizational change management skills at a more operational level (Britto et al., 2023; Kanakadandi, 2025; Dacre, 2024). The framework developed in Chapter 4 explicitly separates these into Components 2 and 3, an architectural decision supported by the NVivo finding. This separation is not present in existing adoption frameworks, including TOE, which treats organizational and technological factors as a single contextual dimension (Tornatzky and Fleischer, 1990).

5.3.4 Theme 4: Trust as a Deployment Scope Regulator

Theme 4 reveals one of the most practically significant findings of the qualitative phase: trust in GenAI outputs does not merely influence the initial decision to adopt the technology but actively regulates the scope of deployment within organizations that have already adopted it. Interview participants across multiple Indian telecom organizations described a consistent pattern of selective deployment, in which GenAI outputs are accepted and acted upon in low-stakes operational contexts (customer query classification, draft report generation, routine diagnostic recommendations) but are subject to mandatory human validation or are excluded entirely from high-stakes contexts (strategic decisions, network fault responses with potential service impact, regulatory compliance determinations).

This selective deployment pattern extends the trust literature in an important way. Glikson and Woolley (2020) establish that trust predicts AI adoption intent, and Chen and Li (2025) confirm that trust predicts adoption depth, but neither study explicitly documents trust as a real-time deployment scope regulator operating within already-adopting organizations. The Indian telecom NVivo evidence suggests this mechanism is particularly pronounced in organizations managing sensitive subscriber data and mission-critical network infrastructure, where the operational consequences of GenAI output errors are severe and potentially irreversible (Agarwal and Nene, 2025; TRAI, 2024). This finding has direct practical implications: organizations and policymakers cannot assume that adoption decisions translate straightforwardly into full organizational use; trust-building investment must accompany and

follow initial deployment to progressively expand deployment scope (Pathan and Shah, 2025; Mokander et al., 2021).

5.3.5 Theme 5: Governance as a Structural Adoption Constraint

Theme 5 establishes that governance gaps in Indian telecom operate as structural adoption constraints that individual organizational management cannot resolve independently. NVivo matrix coding shows that governance inadequacy discussions are systematically co-referenced with strategic adoption discussions across ten of eleven transcripts, suggesting that professionals recognize governance maturity as a prerequisite for strategic-level GenAI integration, not merely a compliance requirement for operational deployment.

This finding is consistent with the governance literature reviewed in Chapter 2. Morley et al. (2020) document the implementation gap between AI ethics principles and organizational practice, and Agarwal and Nene (2025) specifically identify that Indian telecom regulatory frameworks lack AI-specific incident reporting, bias auditing, and accountability standards. The NVivo evidence from practicing Indian telecom professionals confirms that these regulatory gaps translate into organizational hesitancy: when professionals cannot identify clear accountability structures for AI-generated decisions, they restrict deployment to contexts where accountability can be maintained through pre-existing human oversight mechanisms. This finding reinforces the recommendation that TRAI and TEC governance frameworks should be treated as adoption infrastructure rather than adoption constraints, and that their development should be treated as a strategic priority co-equal with technology standardization (OECD, 2023; Klein et al., 2023).

5.3.6 Theme 6: The Pilot-to-Strategy Transition

Theme 6 documents that Indian telecom organizations are currently in a transitional phase between operational GenAI experimentation and strategic integration, with clear differentiation between adoption leaders and laggards visible even within the relatively small eleven-participant sample. Adoption leaders, characterized by explicit executive-level AI strategy articulation, structured governance frameworks, and systematic capability investment, have begun embedding GenAI into their competitive positioning and service innovation roadmaps. Adoption

laggards remain in pilot-stage experimentation, using GenAI for isolated operational improvements without systematic strategic alignment.

This differentiation is consistent with Ransbotham et al. (2021), who document that organizational learning culture and leadership AI commitment are the strongest cultural predictors of AI value realization at scale, and with Deloitte (2024), which reports that organizations with formal AI strategies achieve adoption depth and ROI significantly above the sector average. The transition from pilot to strategy is not automatic in Indian telecom: NVivo evidence suggests it requires deliberate organizational decisions about AI governance, capability sequencing, and competitive positioning that many organizations have not yet made. This finding provides empirical justification for the tenth step of the adoption framework (continuous feedback and improvement), which is designed to support organizations in navigating this transition systematically rather than organically.

5.4 Discussion of Objective 3: Framework Development

5.4.1 Framework Significance and Design Logic

The integrated ten-step adoption framework developed in Chapter 4 represents the synthesis of the study's empirical contributions into a structured, actionable, and theoretically grounded model for GenAI adoption in the Indian telecom sector. This section critically discusses the framework's significance, its theoretical positioning within existing adoption framework literature, its practical value for Indian telecom organizations and policymakers, and its limitations.

The framework's design logic is grounded in the empirical finding that GenAI adoption in Indian telecom is shaped by six interdependent dimensions that operate sequentially and cumulatively rather than independently and simultaneously. This interdependence, confirmed by NVivo matrix coding analysis, means that frameworks addressing individual dimensions in isolation cannot adequately guide adoption practice. The present framework's six-component architecture reflects this interdependence by explicitly sequencing components to mirror the organizational progression from value identification through capability building, trust development, governance formalization, and strategic integration. This sequential architecture extends the static, snapshot-

oriented logic of most adoption models by representing adoption as a dynamic organizational journey (Seifdar and Amiri, 2025; Teece, 2018).

5.4.2 Theoretical Extensions Made by the Framework

The framework extends TAM and UTAUT by incorporating trust, governance, and strategic alignment as primary framework components alongside perceived value and organizational readiness, and by representing these components as interdependent rather than independent. It extends the TOE framework by repositioning governance from an environmental contextual factor to an internal organizational capability component that must be actively developed, and by separating implementation capability from organizational readiness as a distinct framework dimension. These extensions are consistent with the most recent empirical framework literature, including Gomes et al. (2025), who confirm that organizational dimensions carry greater adoption weight than technological dimensions, and Zhou et al. (2025), who demonstrate that adoption frameworks must connect adoption drivers to post-adoption performance outcomes.

The framework's dual applicability for policymakers and organizational practitioners is a distinctive design feature that responds to the documented governance gap in Indian telecom. By explicitly incorporating TRAI and TEC regulatory dimensions into the framework's governance component, and by specifying policy enablement as a prerequisite step in the ten-step operational flow, the framework bridges the institutional gap between regulatory guidance and organizational adoption practice identified by Agarwal and Nene (2025). This policy-organizational integration is absent from most existing GenAI adoption frameworks and represents a specific contribution to the Indian telecom governance literature.

5.4.3 Limitations and Future Validation Requirements

The framework's primary limitation is that its performance outcomes have not been tested through longitudinal field implementation within the scope of this study. While the framework is grounded in robust multi-method empirical evidence from Indian telecom organizations and theoretically consistent with design science research principles (Gregor, 2006; Hevner et al., 2004), its effectiveness in producing superior adoption outcomes relative to unstructured approaches remains to be demonstrated through controlled field studies. Future research should address this limitation through longitudinal evaluation studies conducted in partnership with

Indian telecom operators across different organizational maturity levels, consistent with the recommendations in Chapter 6.

5.5 Integrated Discussion Across All Three Objectives

5.5.1 The Interdependence of Perception Dimensions

The most significant insight emerging from the integration of Objectives 1, 2, and 3 is the confirmation that the six adoption dimensions are fundamentally interdependent rather than operating as independent variables. EFA establishes their statistical distinctness; NVivo matrix coding establishes their organizational co-dependence; the framework represents their sequential interdependence in adoption practice. This three-level confirmation of interdependence is methodologically robust and provides a more comprehensive account of GenAI adoption dynamics than any single analytical method could achieve alone (Venkatesh et al., 2013; Creswell and Creswell, 2018).

Table 5.3: Integrated Discussion Map: Connecting EFA Factors, NVivo Themes, Framework Components, and Integrated Insights (Source: Present study, integrated from SPSS EFA and NVivo thematic analysis)

Dimension	Objective Finding 1	Objective Finding 2	Framework Component	Integrated Insight
Value and Usefulness	Strongest EFA factor; eigenvalue 7.12; 29.67% variance	Adoption driven by operational efficiency; transformational value not yet realized	C1: AI Value Realization	Value perception initiates adoption but remains operationally bounded in Indian telecom; strategic value realization requires governance and capability prerequisites.
Organizational Readiness	Second EFA factor; infrastructure and skills as enabling conditions	Readiness heterogeneity across Jio, Airtel, BSNL, Vodafone Idea; skills gap the primary constraint	C2: Organizational Readiness	Readiness is not a binary prerequisite but a continuous organizational investment requirement that co-evolves with adoption maturity.

Implementation Capability	Captured within readiness factor in EFA; not isolated statistically	Identified as a distinct barrier category in NVivo; legacy integration the dominant challenge	C3: Implementation Capability	NVivo analysis reveals implementation as a constraint category that EFA underdifferentiates; framework explicitly separates it from readiness.
Trust and Risk	Third EFA factor; trust concern, bias risk, output variability highest loadings	Strongest single moderator of GenAI deployment scope in Indian telecom; restricts high-stakes use	C4: Trust and Risk Management	Trust operates not merely as an adoption predictor but as a deployment scope regulator; governance investment directly amplifies trust calibration.
Governance	Fourth EFA factor; policy gaps, accountability, compliance highest loadings	Absent or nascent governance in most interviewed organizations; TRAI alignment lacking	C5: Governance and Regulatory Alignment	Governance is an active adoption enabler rather than passive compliance function; TRAI and TEC policy maturation is an organizational adoption prerequisite in Indian telecom.
Strategic Alignment	Fifth EFA factor; long-term strategy integration and competitive positioning items	Strategic integration transitional; adoption leaders exhibit explicit AI-strategy alignment	C6: Strategic Integration	Strategic alignment is the terminal adoption maturity dimension; organizations progress to it only when value, readiness, trust, and governance conditions are sufficiently developed.

5.5.2 Value-Capability-Trust-Governance-Strategy as an Adoption Maturity Sequence

The integrated analysis reveals that GenAI adoption in Indian telecom follows a discernible maturity sequence that moves from value perception (what can GenAI do for us?) through capability assessment (can we implement it?) and trust calibration (can we rely on it?) to governance formalization (how do we govern it responsibly?) and, finally, strategic integration (how do we embed it as a competitive asset?). This maturity sequence is not deterministic or perfectly linear, as NVivo evidence documents significant organizational variation in trajectory

and pace, but it represents the modal adoption pathway observed across the Indian telecom organizations studied.

This maturity sequence finding contributes to the GenAI adoption literature by providing empirical grounding for a progression model of adoption that extends beyond the binary adoption or non-adoption framing of most technology acceptance research. It is consistent with Rogers' (2003) innovation diffusion stages, with Ransbotham et al.'s (2020) organizational AI learning progression, and with the dynamic capabilities perspective of Teece (2018), but applies these frameworks specifically to the GenAI adoption context in Indian telecommunications for the first time.

5.5.3 The Indian Telecom-Specific Character of Findings

Several dimensions of the integrated findings are specifically shaped by the Indian telecom institutional context and cannot be assumed to apply straightforwardly to other sectors or geographies. The severity of legacy infrastructure constraints on adoption pace is more acute in Indian telecom than in sectors with more recently built digital infrastructure (TEC, 2024; Reznikov, 2024). The governance gap is more pronounced in India than in jurisdictions with more mature AI regulatory frameworks, such as the EU or Singapore (OECD, 2023; Agarwal and Nene, 2025). The competitive pressure driving strategic adoption aspiration is particularly intense in the Indian telecom market, where Jio's disruptive market entry has compressed margins and accelerated digital transformation timelines across the sector (TRAI, 2024; Telecom Review Asia, 2025). These context-specific factors reinforce the importance of the Indian telecom specificity of the present study and suggest that adoption frameworks should be designed with sectoral and national institutional specificity rather than assumed to be universally portable.

5.6 Discussion in Relation to Research Questions

Table 5.4: Research Question Responses: Summary of Evidence and Findings (Source: Present study; EFA via SPSS; NVivo thematic analysis; framework development)

Research Question	Summary Response	Primary Evidence
RQ1: What are the underlying factors that shape telecom leaders and managers perceptions of GenAI?	Five empirically derived factors: Perceived Performance and Operational Value; Technological Capability and Readiness; Trust, Reliability, and Risk Perception; Governance and Regulatory Awareness; Strategic Alignment and Innovation Orientation.	EFA: KMO = 0.901; 5 factors; 68.72% variance; all Cronbach Alphas above 0.80 (SPSS, n = 215 Indian telecom professionals).
RQ2: How do perception-related factors influence adoption and practical use?	Perception factors operate interdependently: value perception initiates adoption; readiness determines feasibility; trust moderates deployment scope; governance constrains responsible scaling; strategic alignment differentiates adoption depth over time.	NVivo: 6 themes from 11 interviews; matrix coding confirms factor-theme alignment; cluster analysis confirms thematic coherence.
RQ3: How can a comprehensive framework be developed to support policymakers?	A six-component, ten-step integrated adoption framework grounded in empirical findings and literature; dual applicability for policymakers (TRAI, TEC) and telecom organizations; adaptive design with continuous feedback mechanism.	Analytical synthesis of EFA factors, NVivo themes, and literature; consistent with design science research (Gregor, 2006; Hevner et al., 2004).

5.6.1 Research Question 1

RQ1 asks what underlying factors shape telecom leaders' and managers' perceptions of Generative Artificial Intelligence. The EFA analysis provides a clear and statistically robust answer: five empirically distinct perception dimensions structure Indian telecom professionals' evaluations of GenAI adoption. These dimensions, perceived operational value, technological capability and readiness, trust and reliability, governance awareness, and strategic alignment, collectively account for 68.72 percent of the variance in the 24-item perception instrument and demonstrate strong internal consistency (Cronbach Alphas 0.801 to 0.892). This five-dimensional structure extends existing adoption models that address one to three perception

dimensions and provides the first empirical mapping of GenAI perception dimensionality in the Indian telecommunications sector.

The five-factor structure confirms the theoretical framework established in Chapter 2, which predicted on the basis of literature review that trust, governance, and strategic alignment would constitute perception dimensions beyond the classic TAM and UTAUT constructs. The empirical validation of this theoretical prediction through EFA strengthens both the theoretical and empirical contributions of the study.

5.6.2 Research Question 2

RQ2 asks how perception-related factors influence the adoption and practical use of Generative AI in telecom organizations. The NVivo thematic analysis provides a multi-layered answer. Operationally, perceived value initiates adoption by identifying high-return use cases that justify initial investment. Organizationally, readiness and implementation capability determine whether value perception translates into actual deployment, with gaps in either dimension creating adoption barriers that can persist indefinitely without deliberate intervention. Behaviorally, trust perception regulates the scope and depth of GenAI use within already-adopting organizations, restricting deployment to contexts where output reliability is sufficient and accountability can be maintained. Institutionally, governance awareness shapes the organizational boundaries within which GenAI can be deployed responsibly, with governance gaps creating adoption uncertainty that reduces deployment confidence. Strategically, alignment perception differentiates organizations that treat GenAI as a competitive investment from those that treat it as an experimental technology, with the former achieving deeper and more sustainable adoption trajectories.

The integration of EFA and NVivo findings confirms that these five perception dimensions do not influence adoption independently but through a system of sequential and conditional interdependencies. The practical implication is that single-dimension adoption interventions (for example, trust-building programs without corresponding governance investment) are likely to be insufficient for achieving sustained adoption at scale.

5.6.3 Research Question 3

RQ3 asks how a comprehensive framework can be developed to support policymakers in guiding effective and responsible GenAI adoption in the Indian telecom sector. The study addresses this question through a design science approach (Gregor, 2006; Hevner et al., 2004) that synthesizes EFA factors, NVivo themes, and theoretical literature into a six-component, ten-step integrated adoption framework. The framework responds directly to the five identified research gaps from Chapter 2: it provides an empirically grounded extension of classical adoption models (theoretical gap); it combines EFA and NVivo evidence (empirical gap); it is grounded entirely in Indian telecom data and institutional context (sectoral gap); it incorporates TRAI and TEC governance dimensions (governance gap); and it represents all six adoption dimensions as interdependent components (integration gap).

The framework's dual applicability for policymakers (TRAI, TEC, Ministry of Communications) and organizational practitioners (Jio, Airtel, BSNL, Vodafone Idea and the broader Indian telecom sector) ensures that it can inform both regulatory guidance development and organizational adoption strategy formulation. Its adaptive design with continuous feedback mechanisms ensures relevance as the Indian telecom regulatory environment and GenAI technology capabilities continue to evolve.

5.7 Theoretical Contributions of the Study

Table 5.5: Summary of Theoretical Contributions

Contribution Area	Description	Prior State of Literature	Advancement Made
Extension of TAM and UTAUT	Identifies trust, governance awareness, and strategic alignment as empirically distinct perception dimensions not captured by TAM or UTAUT.	TAM and UTAUT address perceived usefulness, ease of use, and social influence but lack trust, governance, and ethics constructs for GenAI contexts.	Provides empirical EFA evidence that GenAI adoption requires a five-dimensional perception model extending beyond classical two or four-construct adoption frameworks.

Extension of TOE Framework	Demonstrates that governance is not merely an environmental constraint but an active, organizationally managed adoption enabler requiring internal investment.	TOE addresses technological, organizational, and environmental contexts but treats governance as external regulatory environment rather than internal capability.	Repositions governance as an internal organizational capability dimension alongside readiness, extending TOE for GenAI and regulated sector contexts.
Perception as Multidimensional Construct	Establishes that organizational perception of GenAI is a five-factor structure encompassing value, readiness, trust, governance, and strategy dimensions.	Prior adoption studies treat perception as one or two dimensions (usefulness, ease of use); multidimensional perception models for AI remain uncommon.	Provides first EFA-based empirical mapping of GenAI perception dimensionality in the Indian telecom sector.
Governance as Adoption Enabler	Demonstrates that governance investment amplifies trust and enables strategic adoption rather than constraining operational deployment.	Literature treats governance primarily as compliance requirement; few studies examine governance as a positive adoption enabler.	Empirical NVivo evidence from Indian telecom confirms the Fuwen and Jin (2025) governance-performance link at organizational adoption level.
Integrated Mixed-Method Framework	Develops an empirically grounded, sector-specific adoption framework combining EFA factors and NVivo themes with theoretical synthesis.	Existing GenAI adoption frameworks address isolated dimensions or use single-method designs without sector-specific grounding.	Provides the first integrated, multi-method, Indian telecom-specific GenAI adoption framework with dual policy and organizational applicability.
Indian Telecom Sector Evidence	Generates primary empirical evidence on GenAI adoption perception from n = 215 survey respondents and 11 interview participants in Indian telecom.	Indian telecom is substantially underrepresented in the global AI adoption empirical literature despite its strategic scale and complexity.	Fills the identified sectoral gap; provides TRAI, TEC, and Indian telecom organizations with sector-specific empirical evidence for policy and strategy design.

5.7.1 Extension of Classical Technology Adoption Models

The study's most foundational theoretical contribution is the empirical demonstration that GenAI adoption in organizational settings requires a perception framework that extends well beyond the two-dimensional structure of TAM or the four-construct model of UTAUT. The EFA solution establishes five empirically distinct perception dimensions, confirming that trust, governance awareness, and strategic alignment each operate as independent adoption considerations that cannot be reduced to perceived usefulness, effort expectancy, or social influence. This extension is particularly important because it is achieved through EFA rather than through theoretical assertion, providing methodological rigor that complements the conceptual arguments made in existing reviews (Dwivedi et al., 2023; Gomes et al., 2025; Chen and Li, 2025).

The extension of the TOE framework is equally significant. By repositioning governance from an environmental contextual variable to an internally managed organizational capability, the study provides empirical support for the view that governance is an adoption enabler rather than merely a compliance constraint. This repositioning has direct implications for how organizations and policymakers should approach AI governance investment: rather than treating governance as a regulatory overhead, organizations should treat it as a strategic asset that amplifies trust and enables adoption scaling (Fuwen and Jin, 2025; Pathan and Shah, 2025).

5.7.2 Methodological Contribution

The study makes a significant methodological contribution by demonstrating the value of sequential explanatory mixed-method design for GenAI adoption research. The EFA phase provides statistical structure and generalizability across the Indian telecom professional population; the NVivo phase provides interpretive depth and organizational context that statistical factor scores cannot capture; the framework development phase synthesizes both into a practically applicable model. This three-phase integration produces a more complete understanding of adoption dynamics than either quantitative or qualitative methods could achieve independently, consistent with the methodological arguments of Venkatesh et al. (2013) and Creswell and Creswell (2018).

The specific use of NVivo's advanced analytical features, including matrix coding queries, cluster analysis, and word tree generation, as a systematic qualitative analytical platform (rather than basic manual thematic coding) adds methodological rigor to the qualitative phase. The

matrix coding queries enable systematic examination of inter-nodal relationships that would be difficult to identify reliably through manual coding alone, particularly in a dataset involving eleven multi-question transcripts covering six thematic domains. This approach demonstrates that NVivo can contribute to both the rigor and the depth of qualitative organizational research in complex technology adoption studies.

5.7.3 Sectoral and Geographic Contribution

The study makes a specific and significant contribution to knowledge about GenAI adoption in the Indian telecommunications sector, a context that is simultaneously one of the world's most strategically important telecom markets and one of the most underrepresented in the global AI adoption empirical literature. The empirical evidence generated from $n = 215$ quantitative respondents and 11 qualitative participants specifically situated within Indian telecom organizations provides TRAI, TEC, and Indian telecom operators with sector-specific, empirically grounded evidence for policy and strategy design that does not currently exist in the published literature. This contributes not only to academic knowledge but to the institutional capacity of Indian telecommunications governance bodies to make evidence-based decisions about AI policy development (TRAI, 2024; TEC, 2024; Agarwal and Nene, 2025).

5.8 Chapter Summary

This chapter has provided a comprehensive and critically engaged discussion of the empirical findings presented in Chapter 4, situating them within existing theoretical frameworks and the specific institutional context of Indian telecommunications. The discussion confirms that GenAI adoption in Indian telecom is a five-dimensionally structured, organizationally interdependent, and institutionally shaped phenomenon that cannot be adequately explained by classical adoption models designed for simpler technologies in less regulated organizational environments.

The discussion demonstrates that the five EFA factors and six NVivo themes are theoretically coherent and mutually reinforcing: Factor 1 and Theme 1 confirm operational value as the adoption initiation trigger; Factors 2 and 3 with Themes 2 and 3 confirm the readiness-implementation distinction as an empirically valid architectural choice; Factor 3 and Theme 4 confirm trust as a deployment scope regulator; Factor 4 and Theme 5 confirm governance as a

structural adoption constraint requiring policy-level intervention; and Factor 5 and Theme 6 confirm strategic alignment as the terminal adoption maturity dimension.

The theoretical contributions of the study extend TAM, UTAUT, and TOE while providing the first empirically grounded, Indian telecom-specific GenAI adoption framework with dual policy and organizational applicability. The methodological contribution of sequential mixed-method design combining EFA and NVivo analysis demonstrates an approach that can be applied to AI adoption research across other sectors and geographies. Chapter 6 presents the study's conclusions, recommendations, limitations, and future research directions.

6.1 Concluding Remarks

6.1.1 Overview of the Study

This study was designed to examine how organizational perception shapes the adoption and practical use of Generative Artificial Intelligence within the Indian telecommunications sector, and to develop an integrated, policy-oriented framework to guide policymakers and industry professionals in enabling responsible and effective adoption. The research was motivated by the growing strategic importance of Generative AI in transforming telecom operations, alongside the recognition that adoption within Indian telecom remains uneven, fragmented, and constrained by organizational, governance, and perceptual barriers that existing adoption frameworks inadequately explain.

The study addressed three research objectives through a sequential mixed-method design: Exploratory Factor Analysis of questionnaire data from 215 Indian telecom professionals; NVivo-assisted thematic analysis of eleven semi-structured interviews with Indian telecom senior professionals; and the development of an integrated, six-component, ten-step adoption framework grounded in the combined empirical evidence. The study was grounded in the Indian telecom institutional context, with specific reference to TRAI, TEC, and the regulatory and competitive dynamics of operators including Reliance Jio, Bharti Airtel, BSNL, and Vodafone Idea.

6.1.2 Summary of Key Findings

The EFA analysis established that organizational perception of GenAI adoption in Indian telecom is structured around five empirically distinct dimensions: Perceived Performance and Operational Value; Technological Capability and Readiness; Trust, Reliability, and Risk Perception; Governance and Regulatory Awareness; and Strategic Alignment and Innovation Orientation. Together these five factors explain 68.72 percent of the total variance in perception across the Indian telecom respondent sample, and all demonstrate strong internal consistency with Cronbach Alphas between 0.801 and 0.892.

The NVivo thematic analysis translated these statistical dimensions into six organizational experience themes that explain how perception shapes adoption behavior in practice. These

themes confirm that Indian telecom organizations adopt GenAI primarily for operational efficiency; that readiness and implementation capability constraints are the primary barriers to scaling; that trust regulates the scope of deployment within already-adopting organizations; that governance gaps create structural barriers requiring policy-level intervention; and that strategic alignment differentiates adoption leaders from laggards across the Indian telecom sector.

The integrated framework synthesizes these findings into a structured six-component, ten-step adoption model that explicitly represents the interdependence between value, capability, trust, governance, and strategy as an organizational adoption maturity progression. The framework has dual applicability for TRAI and TEC as policy instruments and for individual telecom organizations as strategic adoption guidance. All three research hypotheses were supported by the empirical evidence.

Table 6.1: Summary of Key Findings by Objective, Method, and Theoretical Alignment

Objective	Method	Key Finding	Theoretical Alignment
Objective 1: Identify underlying perception factors	EFA (IBM SPSS, n = 215 Indian telecom professionals)	Five empirically distinct perception factors: Perceived Operational Value; Technological Capability and Readiness; Trust and Risk Perception; Governance and Regulatory Awareness; Strategic Alignment (KMO = 0.901; 68.72% variance).	Extends TAM, UTAUT, and TOE by empirically establishing trust, governance, and strategic alignment as independent adoption dimensions.
Objective 2: Examine how factors influence adoption and use	NVivo thematic analysis (11 semi-structured interviews, Indian telecom professionals)	Six themes: Operational efficiency drives adoption; readiness and capability shape feasibility; legacy integration constrains deployment; trust regulates deployment scope; governance gaps create structural barriers; strategic alignment differentiates adoption leaders.	Extends Glikson and Woolley (2020); confirms Chen and Li (2025) at Indian telecom sector level; identifies implementation capability as distinct from readiness.
Objective 3: Develop policy-	Analytical synthesis of EFA and NVivo	Six-component, ten-step integrated adoption framework for Indian telecom	Grounded in design science (Gregor, 2006; Hevner et al.,

oriented adoption framework	findings literature	with	with dual applicability for policymakers (TRAI, TEC) and organizations (Jio, Airtel, BSNL, Vodafone Idea).	2004); extends TOE by internalizing governance; consistent with Gomes et al. (2025) and Seifdar and Amiri (2025).
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6.1.3 The Central Argument

The central argument of the present study is that Generative AI adoption in Indian telecom is fundamentally a perception-mediated organizational process, not a technology deployment event. Organizations do not adopt GenAI because it is technically available; they adopt it to the extent that they perceive its value as real, its implementation as feasible, its outputs as trustworthy, its governance as adequate, and its strategic implications as aligned with their competitive priorities. These five perceptual conditions operate interdependently and sequentially, forming an adoption maturity progression that organizations in the Indian telecom sector navigate at different rates and with different success outcomes depending on their organizational capabilities and institutional environments.

This argument has important practical consequences. It implies that adoption acceleration strategies targeting only technology deployment, infrastructure investment, or regulatory compliance in isolation will be insufficient for sustained GenAI adoption at scale. Effective adoption requires coordinated organizational action across all five perception dimensions simultaneously, supported by regulatory institutions that create enabling governance conditions rather than compliance burdens. The integrated framework developed in this study provides the structured, evidence-based guidance necessary for this coordinated approach.

6.2 Contributions of the Study

6.2.1 Theoretical Contributions

The study makes six interconnected theoretical contributions to the literature on technology adoption, digital transformation, and Generative AI in organizational contexts. These contributions collectively extend the current state of knowledge in ways that respond directly to the five research gaps identified in Chapter 2.

Table 6.2: Theoretical Contributions Summary: Models Extended, Nature of Extension, and Supporting Evidence

Contribution	Model Extended	Nature of Extension	Supporting Evidence
Five-dimensional GenAI perception model	TAM (Davis, 1989); UTAUT (Venkatesh et al., 2003)	Adds trust, governance awareness, and strategic alignment as empirically distinct perception dimensions beyond perceived usefulness and ease of use.	EFA: 5 factors; KMO = 0.901; Cronbach Alphas 0.801 to 0.892; consistent with Chen and Li (2025) and Gomes et al. (2025).
Governance as internal adoption enabler	TOE (Tornatzky and Fleischer, 1990)	Repositions governance from external environmental constraint to internally managed organizational capability that amplifies trust and enables adoption scaling.	NVivo: governance nodes co-referenced with trust nodes in 10 of 11 transcripts; consistent with Fuwen and Jin (2025) governance-performance link.
Trust as deployment scope regulator	Glikson and Woolley (2020); Davis (1989)	Establishes that trust regulates not merely adoption intent but the scope and domain of actual GenAI deployment within already-adopting organizations.	NVivo: selective deployment pattern documented across Indian telecom organizations; confirms Chen and Li (2025) at sector level.
Implementation capability as distinct barrier category	TOE (Tornatzky and Fleischer, 1990)	Separates implementation and integration challenges from organizational readiness as a distinct adoption barrier requiring different intervention strategies.	NVivo Theme 3 distinctiveness confirmed by cluster analysis; consistent with Britto et al. (2023) and Kanakadandi (2025).
Adoption maturity sequence model	Rogers (2003); Ransbotham et al. (2021)	Identifies value-capability-trust-governance-strategy as a discernible adoption maturity progression specific to Indian telecom GenAI adoption.	NVivo inter-nodal matrix coding; consistent with Deloitte (2024) adoption leader-laggard differentiation.
Indian telecom-specific GenAI adoption framework	All prior adoption frameworks	First empirically grounded, sector-specific adoption framework for GenAI in Indian telecom; dual	Analytical synthesis of EFA and NVivo; design science approach (Gregor,

		applicability for TRAI, TEC, and organizations.	2006; Hevner et al., 2004).
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The first and most foundational contribution is the empirical establishment of a five-dimensional GenAI perception model that extends TAM and UTAUT by demonstrating that trust, governance awareness, and strategic alignment operate as perception dimensions independent of perceived usefulness and ease of use in the Indian telecom context. This is the first EFA-based empirical mapping of GenAI perception dimensionality in the Indian telecommunications sector and provides a replicable measurement instrument for future GenAI adoption research.

The second contribution is the repositioning of governance as an internal organizational adoption enabler rather than an external regulatory constraint. This extension of the TOE framework is supported by NVivo matrix coding evidence showing that governance adequacy directly amplifies trust and enables adoption scaling, consistent with Fuwen and Jin (2025) and providing the first Indian telecom-sector empirical evidence for this governance-performance relationship.

The third contribution is the identification of trust as a deployment scope regulator rather than merely an adoption intention predictor. The NVivo evidence documents that Indian telecom organizations systematically restrict GenAI deployment to contexts where output reliability can be managed within existing accountability structures, an adoption-within-adoption dynamic that binary adoption models cannot capture and that has direct implications for how trust-building interventions should be designed and timed.

The fourth contribution is the empirical separation of implementation capability from organizational readiness as distinct barrier categories requiring different intervention strategies. This separation, supported by the distinctive emergence of NVivo Theme 3 and confirmed by cluster analysis, fills a gap in the TOE framework and provides organizational practitioners with a more actionable diagnostic framework than the combined organizational context dimension allows.

The fifth contribution is the identification of an adoption maturity sequence, value-capability-trust-governance-strategy, as the modal adoption progression pathway in Indian telecom. This maturity sequence extends Rogers' (2003) innovation diffusion stages and Ransbotham et al.'s (2021) organizational AI learning model to the Indian telecom GenAI adoption context, providing a theoretically grounded progression model that organizations can use to assess their position and prioritize their next adoption investments.

The sixth contribution is the development of the first empirically grounded, Indian telecom-specific, integrated GenAI adoption framework. Unlike prior adoption frameworks that address isolated dimensions or use single-method designs, the present framework combines EFA and NVivo evidence into a six-component, ten-step model with dual policy and organizational applicability, grounded in design science research principles (Gregor, 2006; Hevner et al., 2004) and consistent with the most recent GenAI adoption framework literature (Gomes et al., 2025; Zhou et al., 2025; Seifdar and Amiri, 2025).

6.2.2 Practical and Managerial Contributions

For telecom organizational practitioners, the study provides several practically valuable outputs. The five-factor EFA instrument provides a validated diagnostic tool that organizations can apply to assess the state of organizational perception across their professional population, identify the perception dimensions where gaps are largest, and prioritize targeted interventions. The four reliability and validity criteria met by the instrument (KMO above 0.80, Bartlett significance, factor loadings above 0.70, Cronbach Alphas above 0.80) ensure that assessments using this instrument will be statistically robust.

The six-theme NVivo thematic framework provides organizational leaders with a qualitatively grounded understanding of how each perception dimension manifests as an organizational experience, and what types of management actions are most likely to address the specific barriers documented by Indian telecom professionals in the study. The distinction between readiness gaps (requiring strategic investment decisions) and implementation barriers (requiring project management and technical integration capability) is particularly actionable, as it implies different organizational functions and leadership levels bear responsibility for each barrier category.

The ten-step adoption framework provides a structured, sequenced action roadmap that organizations can apply to plan, execute, and evaluate GenAI adoption programs. Its adaptive design with continuous feedback mechanisms ensures relevance across organizational contexts ranging from early-stage experimentation (where Steps 1 through 4 are most relevant) to strategic integration (where Steps 8 through 10 come to the fore). The framework's TRAI and TEC regulatory alignment throughout means that organizations applying it will simultaneously be developing the governance maturity that the regulatory environment increasingly expects.

6.2.3 Policy-Level Contributions

For Indian telecommunications policymakers, the study provides three categories of contribution. First, it generates the first empirical evidence base for understanding how organizational perception of governance gaps constrains GenAI adoption in Indian telecom, directly informing the regulatory priority-setting of TRAI and TEC. The finding that governance gaps operate as structural adoption barriers, rather than merely compliance requirements, reframes the policy case for investment in AI governance framework development: governance is not just about managing risk but about enabling the sector-wide GenAI adoption benefits that the national digital economy strategy depends on.

Second, the study provides specific, empirically grounded policy recommendations that go beyond generic calls for AI regulation. The recommendations in Section 6.4 identify eight specific policy interventions, each with a designated responsible body (TRAI, TEC, Ministry of Communications, Ministry of Electronics and IT, NITI Aayog), an evidential basis from the study, and a direct connection to the adoption barriers documented in the empirical analysis. This specificity enables TRAI and TEC to prioritize their limited regulatory development capacity against the adoption barriers most strongly documented in the Indian telecom sector.

Third, the framework itself constitutes a policy instrument. Its explicit incorporation of TRAI and TEC governance dimensions in Component 5, and its positioning of policy enablement as Step 2 of the ten-step operational flow, provides a structured model that TRAI could adopt as the basis for sector-specific AI adoption guidance documents, analogous to the technical standards and consultation papers it produces for spectrum management, interconnection, and data privacy. The framework's dual organizational-policy applicability was deliberately designed to serve this function.

6.3 Limitations of the Study

Acknowledging the limitations of the present study is essential for accurate interpretation of its findings and for identifying where future research can most productively build on its contributions. Six primary limitations are identified.

Table 6.3: Study Limitations: Description, Interpretive Implications, and Mitigation Measures Applied

Limitation	Description	Implication for Interpretation	Mitigation Applied
Qualitative Sample Size	Eleven interview participants, while sufficient for thematic saturation, limits generalizability across the full diversity of Indian telecom organizational types, sizes, and regional contexts.	Qualitative themes represent in-depth perspectives from purposively selected senior professionals; findings should not be generalized to all Indian telecom employees.	Purposive sampling ensured maximum knowledge depth; member checking validated thematic accuracy; NVivo cluster analysis confirmed thematic coherence.
Cross-Sectional Design	Data collected at a single point in time; GenAI adoption trajectories and organizational perceptions evolve continuously with technology and regulatory developments.	Findings represent a snapshot of Indian telecom GenAI adoption at the study period; longitudinal changes in perception or adoption maturity are not captured.	Literature grounding in recent 2024-2025 sources; TRAI and TEC guidance from 2024 incorporated to maximize temporal currency.
Sector Specificity	Study confined to Indian telecommunications; adoption dynamics in healthcare, banking, manufacturing, or non-Indian telecom markets may differ substantially.	Framework and recommendations are designed for Indian telecom; their applicability to other sectors or geographies requires sector-specific validation.	Detailed contextual specification of Indian telecom institutional conditions supports reader assessment of transferability.
Framework Non-Validation	The integrated adoption framework has not been tested in field implementation scenarios; performance outcomes relative to unstructured	Framework effectiveness is inferred from empirical grounding and theoretical coherence; not from demonstrated	Design science approach (Gregor, 2006; Hevner et al., 2004) provides methodological justification for framework

	adoption are not empirically demonstrated.	performance outcomes.	contribution without field validation.
Perception-Based Scope	Study focuses on perception-based adoption determinants; structural, economic, vendor ecosystem, and market competition factors influencing adoption are not examined in depth.	Findings explain how perception shapes adoption but do not account for the full complexity of adoption determinants in Indian telecom.	Literature review acknowledges structural factors; future research directions identify economic and competitive dimensions for subsequent study.
Common Method Bias Risk	Quantitative phase relied on single-source self-reported survey data; common method bias may inflate inter-item correlations.	Factor structure may partially reflect response tendencies rather than purely latent constructs.	Procedural remedies applied: anonymous design, neutral item framing, Harman single-factor test, respondent independence confirmed.

6.3.1 Qualitative Sample Size and Representativeness

The qualitative phase of the study was based on eleven semi-structured interviews. While this sample size is methodologically appropriate for NVivo-assisted thematic analysis, where the objective is interpretive depth and theoretical saturation rather than statistical representativeness (King et al., 2018), it nonetheless limits the generalizability of qualitative findings across the full diversity of Indian telecom organizations. The study's purposive sampling strategy ensured maximum knowledge depth and organizational diversity within the eleven participants, but mid-level managers, frontline technical staff, and professionals in smaller regional telecom operators are underrepresented relative to their numerical significance in the Indian telecom workforce. Future research with larger and more organizationally diverse qualitative samples would strengthen the generalizability of the thematic findings.

6.3.2 Cross-Sectional Temporal Limitation

The cross-sectional research design captures organizational perceptions and adoption behaviors at a single point in time, during a period of active but uneven GenAI adoption in Indian telecom and rapidly evolving TRAI and TEC governance guidance. GenAI technology capabilities, organizational adoption maturity, and regulatory frameworks are all changing at significant rates,

and the specific perceptual configurations documented in this study may evolve substantially over a two to three-year period. The five-factor perception structure identified through EFA should be treated as reflecting the Indian telecom GenAI adoption landscape at the study period rather than as a fixed or permanent feature of the sector. Longitudinal research designs that track perception and adoption changes over time are needed to understand how the maturity sequence progresses and what regulatory interventions accelerate its development.

6.3.3 Sector and Geographic Specificity

The study's intentional focus on Indian telecommunications as the research context, while providing contextual depth and sectoral relevance, also limits the direct applicability of findings to other sectors and geographies. Adoption dynamics in Indian healthcare, banking, or manufacturing are likely to share some dimensions with telecom (trust and governance concerns, organizational capability gaps) while differing in others (regulatory regime, competitive dynamics, infrastructure complexity). The framework's six components are designed at a level of abstraction that may allow adaptation to other Indian regulated sectors, but such adaptation requires sector-specific validation research that the present study does not provide. Similarly, the specific governance gap documented for Indian telecom reflects the particular state of TRAI and TEC regulatory development and cannot be assumed to characterize telecom sectors in other jurisdictions with more mature AI regulatory environments, such as the European Union or Singapore.

6.3.4 Framework Validation Limitation

The integrated adoption framework developed in Chapter 4 has not been tested through longitudinal field implementation within the scope of this study. Its design is grounded in robust multi-method empirical evidence and theoretically consistent with design science research principles (Gregor, 2006; Hevner et al., 2004), but its effectiveness in producing superior adoption outcomes relative to unstructured or alternative approaches remains to be demonstrated empirically. Organizations applying the framework should treat it as a structured, evidence-based guidance tool whose practical effectiveness will be refined through organizational experience, and policymakers should treat it as an initial reference framework requiring field validation before mandatory adoption. Section 6.4 identifies SEM-based framework validation as a high-priority future research direction.

6.4 Recommendations for Indian Telecom Organizations

The empirical findings of the present study generate a set of specific, prioritized recommendations for Indian telecom organizations at different stages of GenAI adoption maturity. These recommendations are organized around the six framework components and are grounded in specific EFA and NVivo evidence from the Indian telecom study data.

Table 6.4: Recommendations for Indian Telecom Organizations by Area, Priority, and Evidence Base

Recommendation Area	Specific Recommendation	Evidential Basis	Priority Level
Value Identification and Business Case	Conduct structured GenAI value mapping exercises to identify high-impact use cases in customer service, network operations, fraud management, and decision support. Develop ROI frameworks specific to telecom operational contexts.	EFA Factor 1; NVivo Theme 1; Infosys (2024); Lin et al. (2024)	Immediate
Infrastructure and Readiness Assessment	Conduct formal AI readiness audits covering infrastructure capability, data governance maturity, workforce AI literacy, and leadership commitment before committing to large-scale GenAI deployment programs.	EFA Factor 2; NVivo Theme 2; TEC (2024); Mikalef et al. (2020)	Immediate
Legacy System Integration Planning	Develop phased OSS/BSS modernization roadmaps that create AI-compatible data and API layers alongside existing legacy systems, rather than attempting wholesale infrastructure replacement.	NVivo Theme 3; Britto et al. (2023); Reznikov (2024)	Short-term
Trust and Output Validation Systems	Implement structured output validation protocols, bias testing procedures, explainability standards, and tiered deployment policies that restrict GenAI use to risk-appropriate contexts until output reliability is demonstrated.	EFA Factor 3; NVivo Theme 4; Glikson and Woolley (2020); Pathan and Shah (2025)	Immediate

Internal Governance Framework	AI	Establish formal internal AI governance structures including AI ethics committees, model risk management procedures, accountability allocation frameworks, and audit mechanisms aligned with TRAI and TEC guidance.	EFA Factor 4; NVivo Theme 5; Agarwal and Nene (2025); OECD (2023)	Short-term
AI Workforce Development		Invest in structured AI literacy programs for technical and managerial staff, including prompt engineering, output quality assessment, AI governance principles, and responsible use training.	NVivo Theme 2; Westover (2024); TEC (2024); Dacre (2024)	Short-term
Strategic Roadmap Development	AI	Develop explicit, board-approved GenAI strategy documents aligned with competitive positioning objectives, specifying use case priorities, investment sequencing, governance requirements, and performance metrics.	EFA Factor 5; NVivo Theme 6; Deloitte (2024); Mikalef et al. (2020)	Medium-term
Cross-Functional AI Integration		Establish AI Centers of Excellence to coordinate GenAI deployment across network operations, customer experience, IT, and strategy functions, preventing siloed adoption and enabling organizational learning.	NVivo Theme 6; Ransbotham et al. (2021); Kane et al. (2015)	Medium-term

6.4.1 Immediate Priority Recommendations

Value Identification and ROI Frameworks. Organizations should invest in structured GenAI value mapping exercises that identify high-return use cases within their specific operational context before committing to large-scale GenAI deployment programs. The EFA evidence confirms that perceived operational value is the primary adoption driver in Indian telecom, and NVivo evidence confirms that organizations struggling to articulate specific value propositions tend to remain in pilot stages indefinitely (Lin et al., 2024; Infosys, 2024). Value mapping exercises should be led by cross-functional teams combining technology, operations, customer

experience, and finance perspectives to ensure ROI frameworks capture both efficiency and customer outcome dimensions.

Trust and Output Validation Investment. Given that trust is the strongest deployment scope regulator documented in the NVivo analysis, organizations should invest in output validation protocols, tiered deployment policies, and explainability tools before deploying GenAI in any consequential operational context. TRAI (2024) data protection requirements and consumer protection obligations reinforce this recommendation: organizations that deploy GenAI without adequate output quality assurance face both operational and regulatory risks (Pathan and Shah, 2025; Bender et al., 2021). Minimum viable trust-building investments include structured output sampling and validation procedures, bias testing on training and validation datasets, and documented human override protocols for AI-assisted decisions.

AI Readiness Assessment. Before committing significant capital to GenAI deployment programs, organizations should conduct formal AI readiness audits covering infrastructure capability, data governance maturity, workforce AI literacy, and leadership commitment. TEC (2024) guidance provides a framework for technical readiness assessment; organizations should supplement this with organizational readiness dimensions including skills assessment, cultural change readiness evaluation, and leadership AI literacy measurement. Readiness audits should be treated as investment prerequisites rather than post-hoc justifications, ensuring that capability gaps are identified and addressed before deployment programs encounter them as project barriers (Mikalef et al., 2020; Westover, 2024).

6.4.2 Short to Medium-Term Priority Recommendations

Internal AI Governance Framework Development. Organizations should develop formal internal AI governance structures that preemptively address the accountability and policy gaps documented in NVivo Theme 5. These structures should include AI ethics committees with cross-functional representation, model risk management procedures aligned with TEC technical standards, accountability allocation frameworks specifying who is responsible for AI-assisted decisions in different operational contexts, and audit mechanisms that create traceable records of AI deployment decisions. The NVivo evidence confirms that organizations with nascent or informal governance structures restrict GenAI use out of institutional uncertainty rather than

technical limitation: governance investment therefore directly expands the deployment scope available to the organization (Agarwal and Nene, 2025; OECD, 2023).

Strategic AI Roadmap Development. The EFA Factor 5 and NVivo Theme 6 evidence confirms that strategic alignment is the adoption maturity dimension that most clearly differentiates leaders from laggards in Indian telecom. Organizations should develop explicit, board-approved GenAI strategy documents that specify competitive use case priorities, investment sequencing aligned with the capability-trust-governance progression documented in this study, governance requirements, and performance metrics that go beyond operational efficiency to include trust calibration and governance maturity milestones. Deloitte (2024) and Ransbotham et al. (2021) confirm that organizations with formal AI strategies achieve adoption depth and ROI significantly above sector averages, reinforcing the business case for this investment.

6.5 Recommendations for Policymakers

The study generates eight specific policy recommendations for Indian telecommunications policymakers, particularly TRAI, TEC, and the Ministry of Communications, grounded in the governance gap evidence from EFA Factor 4, NVivo Theme 5, and the regulatory analysis of Agarwal and Nene (2025) and TRAI (2024).

Table 6.5: Policy Recommendations for Indian Telecom AI Governance

Policy Area	Specific Recommendation	Responsible Body	Evidential Basis
AI Incident Reporting Standards	Develop mandatory AI incident reporting requirements for telecom operators covering output failures, bias incidents, data misuse, and service disruptions attributable to AI systems.	TRAI; Ministry of Communications	Agarwal and Nene (2025); OECD (2023); Mokander et al. (2021)
Algorithmic Accountability Guidelines	Establish sector-specific algorithmic accountability guidelines requiring telecom operators to document AI decision logic, maintain output audit trails, and designate accountable persons	TRAI; TEC	Floridi (2019); Jobin et al. (2019); Pathan and Shah (2025)

	for AI-assisted decisions affecting consumers.		
AI Output Quality Standards	Develop minimum output quality and reliability standards for customer-facing and network management GenAI applications, including hallucination rate thresholds, bias testing requirements, and explainability standards.	TEC; Bureau of Indian Standards	Bender et al. (2021); Bommasani et al. (2024); TEC (2024)
Data Governance for AI Training	Clarify the permissible scope of subscriber data use for AI model training and fine-tuning under Indian data protection legislation, providing clear guidance to telecom operators on compliant data practices for GenAI development.	TRAI; Ministry of Electronics and IT	TRAI (2024); Agarwal and Nene (2025); OECD (2023)
AI Workforce Development Investment	Establish national and sectoral AI skills development programs targeting Indian telecom workforce, in partnership with academic institutions, industry bodies (COAI, AUSPI), and technology providers.	Ministry of Communications; TEC; NASSCOM	TEC (2024); Adarkwah (2025); Dacre (2024)
Innovation Sandboxes for GenAI	Create TRAI-supervised regulatory sandboxes allowing Indian telecom operators to pilot GenAI applications in controlled environments with defined compliance exemptions and monitoring requirements.	TRAI	OECD (2024); WEF (2025); Ali et al. (2025)
Cross-Sector AI Governance Coordination	Establish a national AI governance coordination mechanism connecting TRAI, TEC, RBI, SEBI, and Ministry of Health to ensure consistency of AI governance principles across regulated sectors and prevent regulatory arbitrage.	NITI Aayog; Prime Minister Office	OECD (2023); Klein et al. (2023); Leslie (2019)
Regular Governance	Institutionalize annual reviews of AI governance frameworks for Indian telecom, incorporating	TRAI; TEC; Ministry of Communications	OECD (2026); Agarwal and Nene

Framework Review	performance data from incident reporting, academic research (including studies such as the present one), and international regulatory developments.		(2025); Martinuzzi (2024)
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6.5.1 Priority Policy Actions

AI Incident Reporting and Algorithmic Accountability. The most urgent policy gap identified by the study is the absence of mandatory AI incident reporting and algorithmic accountability requirements for Indian telecom operators. Agarwal and Nene (2025) document this gap in detail, and the NVivo evidence confirms that Indian telecom professionals perceive it as a barrier to confident GenAI deployment: without clear accountability structures, organizations restrict deployment to avoid unmanageable liability exposure. TRAI should develop mandatory incident reporting standards as a near-term regulatory priority, modeled on the OECD AI Principles (2023) accountability framework and adapted for the specific operational characteristics of Indian telecom (Mokander et al., 2021; Floridi, 2019).

Data Governance Clarity for AI Training. The EFA governance factor and NVivo governance theme both reflect uncertainty about the permissible scope of subscriber data use for GenAI model training and fine-tuning under Indian data protection legislation. TRAI and the Ministry of Electronics and IT should provide coordinated, sector-specific guidance that clarifies compliant data practices for GenAI development in Indian telecom, reducing the legal uncertainty that currently constrains organizations' AI development programs. This guidance should be developed in consultation with Indian telecom operators and should explicitly address the data minimization, purpose limitation, and consent requirements applicable to AI training data (TRAI, 2024; OECD, 2023).

AI Workforce Development at Scale. The NVivo evidence consistently identifies workforce AI literacy deficits as a primary adoption constraint in Indian telecom, and TEC (2024) acknowledges this gap at the sector level. A coordinated national AI workforce development program for Indian telecom, developed through partnership between the Ministry of Communications, TEC, NASSCOM, and academic institutions, would address this constraint systemically rather than leaving individual organizations to develop capability in isolation. Adarkwah (2025) and Dacre (2024) provide evidence that structured learning programs

combining technical training with governance principles are most effective in producing adoption-capable workforces; program design should reflect this evidence.

6.6 Future Research Directions

The findings and limitations of the present study identify eight specific directions for future research that would advance understanding of GenAI adoption in Indian telecom and in organizational contexts more broadly. These directions are organized by priority level and are designed to address specific gaps created by the study's methodological scope and design choices.

Table 6.6: Future Research Directions: Rationale, Approach, and Priority

Research Direction	Rationale	Suggested Approach	Priority
Longitudinal Study of GenAI Adoption in Indian Telecom	Cross-sectional design cannot capture how perception, capability, and adoption evolve as organizations progress through the maturity sequence and as TRAI governance frameworks mature.	Panel study tracking the same organizations over 3-5 years using repeated EFA waves and annual NVivo interviews; examine perception-adoption trajectory changes over time.	High
Structural Equation Modelling (SEM) Validation of Framework	The EFA-derived five-factor model requires CFA-based validation and SEM testing to confirm factor stability, inter-factor relationships, and causal paths to adoption outcomes.	Confirmatory Factor Analysis followed by SEM using a new sample of Indian telecom professionals; test the adoption maturity sequence as a structural model.	High
Cross-Sector Comparative Study	GenAI adoption dynamics in Indian healthcare, banking, and manufacturing may differ from telecom; cross-sector comparison would identify universal versus sector-specific adoption determinants.	Replicate EFA and NVivo design across three to four Indian regulated sectors; comparative analysis of factor structures and thematic patterns.	Medium
Trust-Building Intervention Studies	Trust emerged as the strongest deployment scope regulator; experimental or quasi-experimental research is	Randomized controlled study or difference-in-differences natural experiment comparing	High

	needed to identify which specific interventions (explainability tools, validation procedures, governance transparency) most effectively build adoption-enabling trust.	GenAI adoption depth before and after targeted trust-building interventions in Indian telecom organizations.	
TRAI and TEC Governance Framework Impact Study	The study documents governance gaps at regulatory level; research is needed to evaluate whether specific TRAI and TEC policy interventions reduce adoption barriers and improve deployment outcomes.	Policy evaluation study using pre-post design around specific TRAI guidance issuance events; measure organizational perception and adoption behavior changes.	Medium
AI-Native 5G and 6G Network Management Adoption	Chetty et al. (2025) document the emergence of AI-native 6G architectures; adoption of GenAI for AI-native network management raises distinct technical and governance challenges beyond current study scope.	Technical-organizational study combining network engineering analysis with organizational adoption research; focus on autonomous network management and human oversight requirements.	Medium
GenAI Adoption in Regional and Rural Indian Telecom Operators	Study sample concentrated in metropolitan telecom organizations; smaller, regional, and BSNL-operated rural network operators face distinct infrastructure, skills, and governance challenges.	Extended sampling study targeting tier-2 and tier-3 city telecom organizations; NVivo analysis of adoption barriers specific to resource-constrained telecom contexts.	Medium
GenAI and Workforce Transformation in Indian Telecom	NVivo findings document skills gaps as an adoption constraint; research is needed on the workforce transformation implications of GenAI adoption for Indian telecom employment, role redesign, and capability development.	Mixed-method study combining HR management research with adoption research; examine role redesign patterns, training program effectiveness, and employee perception of GenAI as augmentation versus displacement.	Medium

6.6.1 High-Priority Research Directions

Longitudinal Study of Indian Telecom GenAI Adoption. The cross-sectional design of the present study is the most consequential methodological limitation for understanding the

dynamics of adoption progression. A longitudinal panel study tracking the same set of Indian telecom organizations over three to five years, using repeated EFA waves and annual NVivo interview rounds, would provide insight into how the adoption maturity sequence progresses in practice, how organizational perceptions evolve as GenAI capabilities and governance frameworks develop, and which organizational investments most effectively accelerate progression through the maturity stages. This research direction is strongly aligned with the diffusion of innovation perspective (Rogers, 2003) and the organizational AI learning model of Ransbotham et al. (2021), both of which emphasize the temporal dimension of adoption that cross-sectional research cannot capture.

SEM-Based Validation of the Five-Factor Perception Model and Framework. The EFA-derived five-factor perception model requires Confirmatory Factor Analysis (CFA) to test the stability and replicability of the factor structure across independent samples, and Structural Equation Modelling (SEM) to test the causal relationships between perception dimensions and adoption outcomes. These analyses would establish the predictive validity of the perception model and provide empirical evidence for the adoption maturity sequence proposed in the framework. Hair et al. (2019) and Kline (2015) provide the methodological foundations for this research direction, and the 24-item EFA instrument developed in the present study provides a ready-made measurement foundation for the CFA stage.

Trust-Building Intervention Studies. The study establishes trust as the strongest deployment scope regulator in Indian telecom GenAI adoption, but does not identify which specific trust-building interventions are most effective in expanding deployment scope. Experimental or quasi-experimental research comparing the trust and deployment scope outcomes of different interventions (explainability tool provision, output validation procedure implementation, governance transparency communication, leadership trust endorsement) would provide actionable evidence for organizational investment priorities. Glikson and Woolley (2020) and Pathan and Shah (2025) provide the theoretical frameworks for intervention design; field implementation in partnership with Indian telecom organizations would provide the experimental context.

6.6.2 Medium-Priority Research Directions

Cross-Sector Comparative Study. Replicating the present study's EFA and NVivo design across Indian healthcare, banking, and manufacturing sectors would enable direct comparison of GenAI adoption perception structures across regulated industries, identifying which adoption dimensions are universal and which are sector-specific. This comparative evidence would substantially strengthen the generalizability claims of the present framework and identify whether the five-factor perception model requires sectoral adaptation or constitutes a stable cross-sector structure. Ali et al. (2025) and Gomes et al. (2025) provide prior frameworks for cross-sector GenAI adoption comparison.

GenAI in 5G and Emerging AI-Native Network Architectures. Chetty et al. (2025) and Britto et al. (2023) document the emerging integration of GenAI into 5G and 6G AI-native network architectures, which raises distinct adoption challenges around autonomous network management, human oversight requirements, and sovereign AI concerns not fully addressed by the present study's organizational perception framework. Research examining how Indian telecom professionals perceive and adapt to AI-native network architectures, and what governance structures are required for responsible autonomous network operation, would extend the present study into the most consequential near-future deployment context for Indian telecom GenAI.

6.7 Final Concluding Statement

This study has generated a robust, empirically grounded, and theoretically coherent understanding of how organizational perception shapes Generative AI adoption in the Indian telecommunications sector. Through a rigorous sequential mixed-method design combining EFA in IBM SPSS with NVivo-assisted thematic analysis, the study has established that GenAI adoption in Indian telecom is structured around five distinct perception dimensions, operates through an identifiable organizational maturity progression, and is constrained by specific governance gaps at both organizational and regulatory levels that require coordinated intervention.

The integrated adoption framework developed in the study provides Indian telecom organizations and policymakers with a structured, evidence-based, and contextually grounded

tool for navigating the complex and rapidly evolving GenAI adoption landscape. Its dual applicability for organizational strategy and regulatory policy design, its incorporation of Indian-specific institutional conditions including TRAI and TEC governance frameworks, and its adaptive ten-step operational design ensure that it remains relevant and actionable as both technology and regulation continue to evolve.

The theoretical contributions of the study extend classical adoption models by empirically demonstrating the importance of trust, governance, and strategic alignment as independent perception dimensions in GenAI adoption, and by identifying governance as an active organizational adoption enabler rather than a passive regulatory constraint. These contributions advance the field of technology adoption research in directions specifically suited to the governance-intensive, ethically complex, and organizationally embedded character of Generative AI as an organizational technology.

Ultimately, the study's central message is that Generative AI's transformative potential for Indian telecommunications will be realized not by technology deployment alone, but by the organizational and institutional investments that build the perceptual conditions for confident, responsible, and strategically aligned adoption. Trust must be earned through validation and governance; capability must be built through deliberate investment; strategy must be articulated through leadership commitment. Organizations and policymakers that understand and act on this integrated logic will lead the transformation of Indian telecommunications. Those that do not will remain in the fragmented, risk-averse pilot-stage experimentation that characterizes current sector-wide adoption patterns. The present study provides the empirical and theoretical foundations for the former pathway.

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APPENDIX A: RESEARCH QUESTIONNAIRE (OBJECTIVE 1)

A.1 Participant Declaration and Informed Consent

Before completing this questionnaire, please read the following declaration carefully. This study is being conducted to examine organizational perceptions and adoption of Generative Artificial Intelligence in the Indian telecommunications sector. Your participation is entirely voluntary. You may withdraw at any point without obligation. All responses are strictly confidential and anonymous. No personally identifiable information will be collected or disclosed. Data will be used solely in aggregated form for academic analysis and reporting.

By proceeding with this questionnaire, you confirm your informed consent to participate in this study.

☐ I agree to participate in this study on a voluntary basis.
☐ I understand that my responses will remain strictly confidential and anonymous.
☐ I confirm that I am providing honest and accurate responses to the best of my knowledge.
☐ I understand that I may withdraw from the study at any point without consequence.

A.2 Respondent Profile

Profile Variable	Response Options
Gender	Male ☐ Female ☐ Prefer not to say ☐
Age Group	Below 25 ☐ 25-35 ☐ 36-45 ☐ Above 45 ☐
Educational Qualification	Undergraduate ☐ Graduate ☐ Postgraduate ☐
Years of Experience in Telecom	Below 5 years ☐ 5-10 years ☐ 11-20 years ☐ Above 20 years ☐
Current Role Category	Technical/Engineering ☐ Managerial ☐ Operations/Support ☐

Organization Type	Jio ☐ Airtel ☐ BSNL ☐ Vodafone Idea ☐ Other ☐
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A.3 Section A: Perception Statements (24-Item Likert Scale)

Instructions: Please indicate your level of agreement with each statement using the five-point scale: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree. Please respond to all items. There are no right or wrong answers; honest responses are essential for the validity of this research.

SD = Strongly Disagree | D = Disagree | N = Neutral | A = Agree | SA = Strongly Agree | Factor = EFA Factor (for analytical reference only; not shown to respondents)

Q#	Statement	1 SD	2 D	3 N	4 A	5 SA	Factor
1	Generative AI improves operational efficiency in telecom organizations	☐	☐	☐	☐	☐	F1
2	Generative AI enhances the quality of decision-making	☐	☐	☐	☐	☐	F1
3	Generative AI supports innovation in telecom services	☐	☐	☐	☐	☐	F1
4	Generative AI improves customer interaction and service delivery	☐	☐	☐	☐	☐	F1
5	Generative AI tools are easy to understand and use	☐	☐	☐	☐	☐	F2
6	Integration of Generative AI into existing systems is manageable	☐	☐	☐	☐	☐	F2
7	Employees can quickly adapt to Generative AI technologies	☐	☐	☐	☐	☐	F2
8	Outputs generated by Generative AI are reliable	☐	☐	☐	☐	☐	F3
9	I trust the outputs generated by Generative AI systems	☐	☐	☐	☐	☐	F3
10	Generative AI systems provide consistent results	☐	☐	☐	☐	☐	F3

11	Generative AI may produce inaccurate or misleading outputs	☐	☐	☐	☐	☐	F3
12	Use of Generative AI raises concerns about data privacy	☐	☐	☐	☐	☐	F3
13	There is a possibility of bias in AI-generated outputs	☐	☐	☐	☐	☐	F3
14	My organization has sufficient infrastructure to implement Generative AI	☐	☐	☐	☐	☐	F2
15	Leadership supports the adoption of Generative AI	☐	☐	☐	☐	☐	F2
16	Employees have the necessary skills to use Generative AI effectively	☐	☐	☐	☐	☐	F2
17	There are clear policies governing the use of Generative AI	☐	☐	☐	☐	☐	F4
18	Ethical considerations are addressed during AI implementation	☐	☐	☐	☐	☐	F4
19	There is accountability for decisions made using AI systems	☐	☐	☐	☐	☐	F4
20	Generative AI aligns with the strategic goals of the organization	☐	☐	☐	☐	☐	F4
21	AI adoption is driven by long-term business objectives	☐	☐	☐	☐	☐	F5
22	AI initiatives are integrated across different departments	☐	☐	☐	☐	☐	F5
23	I am willing to use Generative AI in my work	☐	☐	☐	☐	☐	F5
24	Generative AI will become essential in telecom operations in the future	☐	☐	☐	☐	☐	F5

Appendix A.3: Research Questionnaire - 24-Item Perception Scale with Factor Mapping
(Source: Author; Items developed from Davis, 1989; Venkatesh et al., 2003; Tornatzky & Fleischer, 1990; Bender et al., 2021; Pathan & Shah, 2025)

APPENDIX B: SEMI-STRUCTURED INTERVIEW GUIDE (OBJECTIVE 2)

B.1 Participant Information and Consent

This interview is being conducted as part of doctoral research examining Generative Artificial Intelligence adoption in the Indian telecommunications sector. The interview will be audio-recorded with your consent and transcribed verbatim for qualitative analysis using NVivo software. You may decline to answer any question and may withdraw at any time without obligation. All data will be anonymized; you will be identified only by role category and years of experience.

B.2 Interview Questions by EFA Factor Domain

The following questions are organized by the five perception dimensions identified through the Exploratory Factor Analysis in Phase 1. Questions are open-ended and designed to explore organizational experience and practice. Probing follow-up questions will be used as appropriate during the interview to elicit depth and contextual specificity.

Q#	EFA Factor	Interview Question
IQ1	Value	How is Generative AI currently being used in your organization's operations and decision-making processes? What specific benefits have you observed or anticipated?
IQ2	Value	What operational areas have shown the most significant improvement following GenAI deployment in your organization?
IQ3	Readiness	How would you describe your organization's current readiness in terms of infrastructure, technical capability, and leadership commitment for GenAI adoption?
IQ4	Readiness	What workforce skills or capability gaps has your organization encountered in GenAI deployment, and how are these being addressed?
IQ5	Implementation	What specific challenges have you faced in integrating Generative AI into existing legacy systems and operational processes?
IQ6	Implementation	How has your organization managed change resistance among employees and middle management during GenAI deployment?

IQ7	Trust	How do you perceive the reliability, accuracy, and consistency of Generative AI outputs in the context of your telecom operations?
IQ8	Trust	What concerns do you have regarding risks such as algorithmic bias, output hallucination, data misuse, or errors from GenAI systems? How are these managed?
IQ9	Governance	What governance mechanisms, internal policies, or accountability structures are currently in place for the use of Generative AI in your organization?
IQ10	Governance	What regulatory or ethical challenges have you encountered in relation to TRAI guidelines, data protection requirements, or AI accountability standards?
IQ11	Strategy	How does Generative AI align with your organization's long-term strategic objectives and competitive positioning in the Indian telecom market?

Appendix B.2: Semi-Structured Interview Guide - 11 Questions Mapped to EFA Factor Domains (Source: Author; Instrument developed sequentially from Phase 1 EFA results)

APPENDIX C: QUALITATIVE SAMPLE - INTERVIEW PARTICIPANT PROFILES

C.1 Participant Profile Summary

Eleven semi-structured interviews were conducted with purposively selected Indian telecom professionals who met the inclusion criteria of a minimum of five years of professional experience and direct involvement in AI, digital transformation, or technology governance programs. Participants are identified by anonymized participant code (P01 to P11) and role category only. No personally identifiable information is reported.

ID	Role Category	Exp.	Organization Type	Primary AI Involvement
P01	Senior Network Operations Manager	15 yrs	Large National Operator	Network AI deployment
P02	Head of Digital Transformation	12 yrs	Large National Operator	GenAI strategy and governance
P03	AI Project Lead	8 yrs	Large National Operator	GenAI pilot implementation
P04	Chief Technology Officer (Regional)	18 yrs	Regional Operator	Infrastructure and integration
P05	IT Governance Director	14 yrs	Large National Operator	AI governance frameworks
P06	Customer Experience Analytics Manager	9 yrs	Large National Operator	Customer AI applications
P07	Network Planning Engineer (Senior)	11 yrs	State-Owned Operator	AI-assisted network planning
P08	Regulatory Affairs Manager	13 yrs	Large National Operator	TRAI compliance and AI policy
P09	Data Science Lead	7 yrs	Managed Services Provider	AI model development and deployment
P10	Product Innovation Manager	10 yrs	Large National Operator	GenAI-enabled product development
P11	Corporate Strategy Director	16 yrs	Large National Operator	AI strategic integration

*Appendix C.1: Qualitative Sample Participant Profiles (n = 11) (Source: Present study;
participants anonymized per research ethics protocol)*

APPENDIX D: DEMOGRAPHIC PROFILE CHARTS (N = 215)

D.1 Gender Distribution

Category	Gender Distribution	n	%
Male		158	73.5%
Female		57	26.5%

Appendix Figure D.1: Gender Distribution of Respondents (n = 215) (Source: Primary data, present study)

D.2 Age Group Distribution

Category	Age Group Distribution	n	%
Below 25 years		24	11.2%
25-35 years		92	42.8%
36-45 years		67	31.2%
Above 45 years		32	14.8%

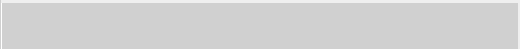
Appendix Figure D.2: Age Group Distribution of Respondents (n = 215) (Source: Primary data, present study)

D.3 Educational Qualification

Category	Educational Qualification	n	%
Undergraduate		48	22.3%
Graduate		112	52.1%
Postgraduate		55	25.6%

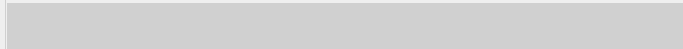
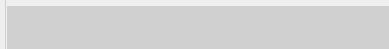
Appendix Figure D.3: Educational Qualification Distribution (n = 215) (Source: Primary data, present study)

D.4 Work Experience

Category	Work Experience	n	%
Below 5 years		42	19.5%
5-10 years		81	37.7%
11-20 years		61	28.4%
Above 20 years		31	14.4%

Appendix Figure D.4: Work Experience Distribution (n = 215) (Source: Primary data, present study)

D.5 Role Category

Category	Role Category	n	%
Technical/Engineering		89	41.4%
Managerial		76	35.3%
Operations/Support		50	23.3%

Appendix Figure D.5: Role Category Distribution (n = 215) (Source: Primary data, present study)

APPENDIX E: EXPLORATORY FACTOR ANALYSIS - FULL STATISTICAL OUTPUTS

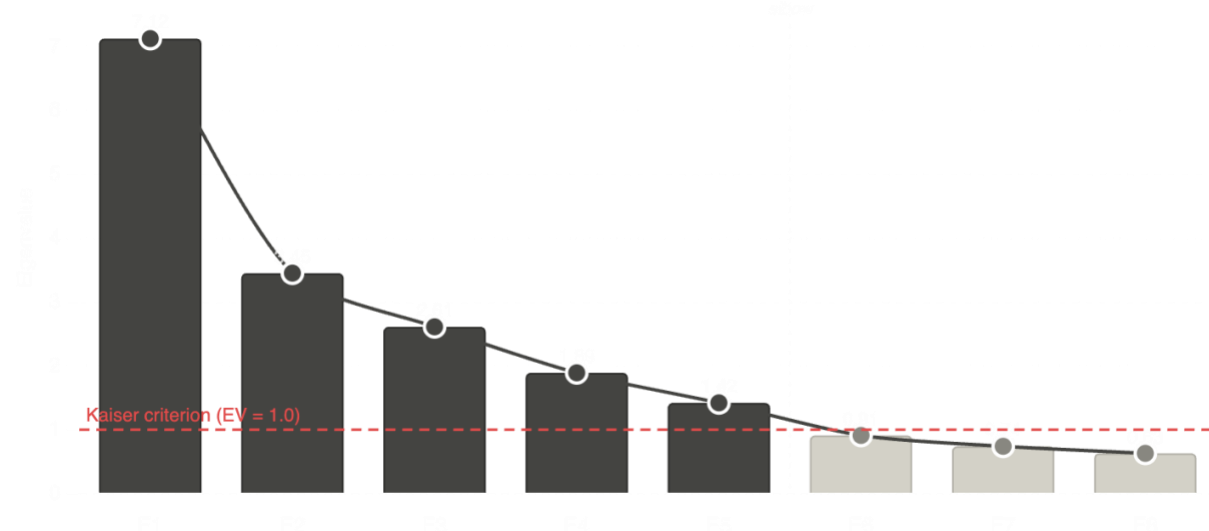
E.1 KMO and Bartlett Test Results

Test	Statistic	Threshold	Result
Kaiser-Meyer-Olkin (KMO)	0.901	>0.80 Excellent	Excellent
Bartlett's Test: Chi-Square (χ^2)	2758.43	Significant ($p < 0.05$)	Significant
Bartlett's Test: df	276	$n(n-1)/2 = 276$	Correct
Bartlett's Test: p-value	0.000	$p < 0.001$	Highly Significant

Appendix Table E.1: KMO Measure and Bartlett Test Results (Source: IBM SPSS Statistics output, present study)

E.2 Scree Plot - Eigenvalue Visualisation

The scree plot below illustrates the eigenvalues associated with each extracted factor component. A clear elbow is visible after the fifth component, supporting the retention of five factors under the Kaiser criterion (eigenvalue greater than 1.0).



Grey bars (F1-F5) represent retained factors (eigenvalue > 1.0). White bars (F6-F8) represent discarded components. Eigenvalues shown at base of each bar.

Appendix Figure E.2: Scree Plot - Eigenvalues by Factor Component (Source: IBM SPSS Statistics output, present study; Kaiser criterion applied)

E.3 Total Variance Explained

F#	Factor Name	Eigenvalue	% Variance	Cumulative %
1	Perceived Performance and Operational Value	7.12	29.67%	29.67%
2	Technological Capability and Readiness	3.45	14.38%	44.05%
3	Trust, Reliability, and Risk Perception	2.61	10.87%	54.92%
4	Governance and Regulatory Awareness	1.89	7.88%	62.8%
5	Strategic Alignment and Innovation Orientation	1.42	5.92%	68.72%
TOTAL - Five Factors			68.72%	68.72%

Appendix Table E.3: Total Variance Explained by Five Extracted Factors (Source: IBM SPSS Statistics, PCA with Varimax rotation, present study)

E.4 Factor Loading Heat Table (Rotated Component Matrix)

The factor loading heat table below presents all 24 questionnaire items mapped to their primary factor. Cell shading intensity reflects loading strength: darkest cells (black) indicate loadings at or above 0.80; dark grey indicates 0.75 to 0.79; medium grey indicates 0.70 to 0.74; light grey indicates 0.50 to 0.69. Blank cells indicate loadings below 0.50 (omitted for clarity).

Questionnaire Item	F1	F2	F3	F4	F5
Q1: Operational efficiency improvement	0.812				
Q2: Decision-making quality enhancement	0.798				
Q3: Telecom service innovation support	0.776				

Q4: Customer interaction improvement	0.764				
Q5: Ease of understanding and use	0.731				
Q6: Alignment with operational goals	0.718				
Q7: Sufficient infrastructure for GenAI		0.812			
Q8: System integration manageability		0.795			
Q9: Employee adaptability to GenAI		0.768			
Q10: Leadership support for adoption		0.742			
Q11: Required skills availability		0.718			
Q12: Reliability of AI outputs			0.831		
Q13: Trust in AI-generated outputs			0.812		
Q14: Consistent and accurate results			0.788		
Q15: Possibility of bias in outputs			0.752		
Q16: Data privacy concerns			0.718		
Q17: Clear governance policies				0.812	
Q18: Ethical considerations in AI				0.793	
Q19: Accountability for AI decisions				0.761	
Q20: Regulatory compliance				0.738	
Q21: Strategic goal alignment					0.834
Q22: Long-term business objective drive					0.812
Q23: Competitive advantage support					0.788
Q24: Cross-departmental AI integration					0.756

Shading key: Black = loading > 0.80 | Dark grey = 0.75-0.79 | Medium grey = 0.70-0.74 | Light grey = 0.50-0.69 | Blank = below 0.50 threshold

Appendix Figure E.4: Factor Loading Heat Table - Rotated Component Matrix (Varimax)
(Source: IBM SPSS Statistics output, present study; Hair et al., 2019)

E.5 Reliability Statistics by Factor

Factor	Items (n)	Cronbach Alpha	Interpretation
Overall Instrument (Pre-EFA)	24	0.914	Excellent

F1: Perceived Performance and Operational Value	6	0.892	Excellent
F2: Technological Capability and Readiness	5	0.861	Good
F3: Trust, Reliability, and Risk Perception	5	0.834	Good
F4: Governance and Regulatory Awareness	4	0.801	Good
F5: Strategic Alignment and Innovation Orientation	4	0.847	Good

Appendix Table E.5: Cronbach Alpha Reliability Statistics (Source: IBM SPSS Statistics output, present study; Hair et al., 2019)

APPENDIX F: NVIVO ANALYSIS - THEMATIC OUTPUTS AND VISUALISATIONS

F.1 NVivo Word Frequency Analysis

The word frequency analysis was conducted across all 11 interview transcripts in NVivo using the Word Frequency Query function with a minimum word length of four characters. The chart below presents the top ten most frequently occurring substantive terms, each mapped to its primary parent node.

Rank	Term and Frequency (NVivo Word Query)	Refs	% Cov.	Primary Node
1	Efficiency	43	34.2%	Value and Operational Benefits
2	Trust	38	28.6%	Trust, Reliability, and Risk
3	Governance	34	21.3%	Governance and Ethics
4	Integration	31	18.4%	Implementation Challenges
5	Risk	29	28.6%	Trust, Reliability, and Risk
6	Strategy	27	19.8%	Strategic Alignment
7	Reliability	26	28.6%	Trust, Reliability, and Risk
8	Skills	24	22.7%	Organizational Readiness
9	Legacy	22	18.4%	Implementation Challenges
10	Policy	21	21.3%	Governance and Ethics

Appendix Figure F.1: NVivo Word Frequency Analysis - Top 10 Terms Across 11 Interview Transcripts (Source: NVivo Word Frequency Query output, present study)

F.2 NVivo Node Hierarchy and Coverage Statistics

Parent Node	Child Nodes (Selection)	Sources	Refs	Coverage
Value and Operational Benefits	Operational Automation; Process Efficiency; Cost Reduction; Service Improvement; Decision Support	11/11	87	34.2%
Organizational Readiness and Capability	Infrastructure Readiness; Skill Availability; Leadership Support; Workforce Adaptability; Resource Constraints	10/11	62	22.7%
Implementation and Integration Challenges	Legacy System Barriers; System Compatibility; Integration Complexity; Deployment Constraints; Change Management	9/11	48	18.4%
Trust, Reliability, and Risk Perception	Output Reliability; Bias Concerns; Hallucination Risk; Data Privacy; Explainability Deficit	11/11	74	28.6%
Governance and Ethical Uncertainty	Policy Gaps; Accountability Deficit; Ethical Ambiguity; Regulatory Compliance; Informal Guidelines	9/11	54	21.3%
Strategic Alignment and Competitive Positioning	Long-term Strategy Integration; Competitive Advantage; Innovation Orientation; Pilot-to-Scale Transition; Executive Vision	8/11	46	19.8%

Appendix Table F.2: NVivo Node Hierarchy with Coverage Statistics (Source: NVivo analysis output, present study)

F.3 NVivo Thematic Map - Six Primary Themes

No.	Theme Title	Sources	Coverage	Core Insight
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T1	Operational Efficiency and Automation	11/11	34.2%	Primary driver; framing adoption across Indian telecom. adoption efficiency dominates rationale.
T2	Organizational Readiness and Capability Gaps	10/11	22.7%	Readiness is a continuous capability investment; infrastructure and skills gaps constrain depth.
T3	Implementation and Integration Challenges	9/11	18.4%	Integration barriers are distinct from readiness gaps; legacy OSS/BSS is the critical obstacle.
T4	Trust, Reliability, and Risk Concerns	11/11	28.6%	Trust acts as a deployment scope regulator; restricts GenAI to low-stakes contexts until validated.
T5	Governance and Ethical Uncertainty	9/11	21.3%	Governance gaps at TRAI/TEC level create structural barriers beyond organizational management.
T6	Strategic Alignment and Competitive Advantage	8/11	19.8%	Strategic alignment differentiates leaders from laggards; pilot-to-strategy transition is active.

Appendix Figure F.3: NVivo Thematic Map - Six Primary Themes with Sources and Core Insights (Source: NVivo thematic analysis, present study; King et al., 2018)

F.4 NVivo Matrix Coding Query - Inter-Nodal Co-Reference Heatmap

The matrix coding heatmap below displays the strength of co-reference relationships between the six parent nodes across all 11 interview transcripts. HIGH indicates strong co-reference (present in 8 or more of 11 transcripts); MED indicates moderate co-reference (5-7 transcripts); LOW indicates minimal co-reference (fewer than 5 transcripts). This analysis provides the empirical basis for the interdependence argument central to the integrated framework.

NVivo Node	T1 Value	T2 Ready	T3 Integ	T4 Trust	T5 Govn	T6 Strat
T1: Value and Operational Benefits	HIGH	MED	MED	LOW	LOW	MED
T2: Organizational Readiness	MED	HIGH	HIGH	LOW	LOW	MED
T3: Implementation Challenges	MED	HIGH	HIGH	LOW	LOW	LOW
T4: Trust and Risk Perception	LOW	LOW	LOW	HIGH	HIGH	MED
T5: Governance and Ethics	LOW	LOW	LOW	HIGH	HIGH	MED
T6: Strategic Alignment	MED	MED	LOW	MED	MED	HIGH

HIGH = co-referenced in 8-11 transcripts | MED = co-referenced in 5-7 transcripts | LOW = co-referenced in fewer than 5 transcripts

***Appendix Figure F.4: NVivo Matrix Coding Query — Inter-Nodal Co-Reference Heatmap
(Source: NVivo Matrix Coding Query output, present study)***

APPENDIX G: INTEGRATED ANALYSIS DIAGRAMS

G.1 EFA-NVivo-Framework Integration Diagram

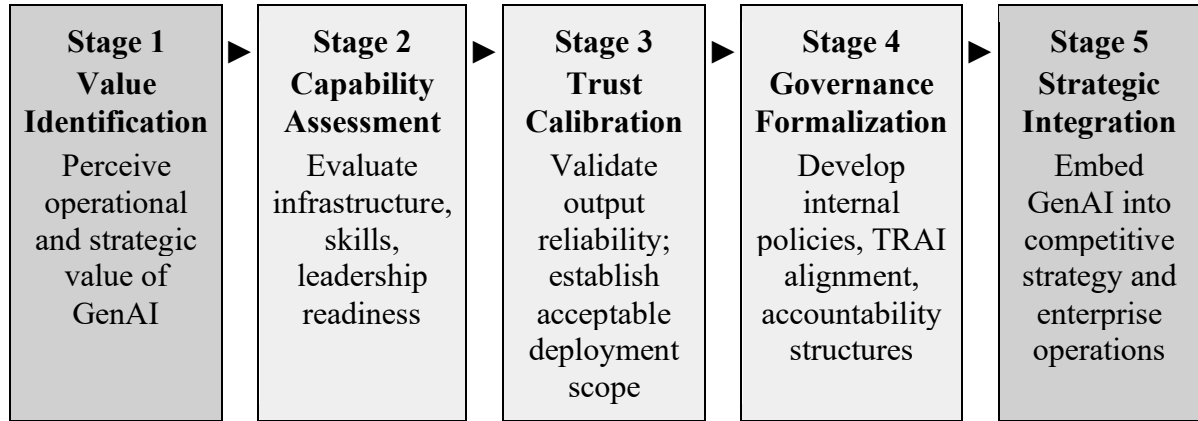
The diagram below presents the complete cross-phase integration of quantitative EFA factors, qualitative NVivo themes, and framework components. Each row represents one adoption dimension, showing the statistical credentials from EFA, the NVivo source coverage from qualitative analysis, and the corresponding framework component. This integration provides the empirical foundation for the six-component adoption framework developed in Chapter 4.

EFA FACTORS (Quantitative)		NVivo THEMES (Qualitative)		FRAMEWORK COMPONENTS
F1: Perceived Performance Value $\alpha = 0.892$ EV = 7.12 29.67%	►	T1: Operational Efficiency Drive 11/11 sources 34.2% coverage	►	C1: AI Value Realization
F2: Technological Capability and Readiness $\alpha = 0.861$ EV = 3.45 14.38%	►	T2: Readiness and Capability Gaps 10/11 sources 22.7% coverage	►	C2: Organizational Readiness
F2 (shared) + F3 (partial)	►	T3: Implementation Challenges 9/11 sources 18.4% coverage	►	C3: Implementation Capability
F3: Trust, Reliability, Risk $\alpha = 0.834$ EV = 2.61 10.87%	►	T4: Trust and Risk Concerns 11/11 sources 28.6% coverage	►	C4: Trust and Risk Management
F4: Governance Awareness $\alpha = 0.801$ EV = 1.89 7.88%	►	T5: Governance and Ethics 9/11 sources 21.3% coverage	►	C5: Governance and Regulatory Alignment
F5: Strategic Alignment $\alpha = 0.847$ EV = 1.42 5.92%	►	T6: Strategic Positioning 8/11 sources 19.8% coverage	►	C6: Strategic Integration

Appendix Figure G.1: Full EFA-NVivo-Framework Integration Diagram (Source: Present study; EFA via IBM SPSS; thematic analysis via NVivo)

G.2 Adoption Maturity Sequence Diagram

The adoption maturity sequence diagram below illustrates the five-stage progression from value identification to strategic integration identified through the integration of EFA and NVivo findings. This sequence represents the modal adoption pathway observed across Indian telecom organizations in the study and provides the structural logic underlying the framework's ten-step operational flow.



Arrows indicate the sequential and interdependent progression of adoption maturity stages. Organizations may be at different stages simultaneously across functions.

Appendix Figure G.2: GenAI Adoption Maturity Sequence in Indian Telecom (Source: Present study; derived from integrated EFA and NVivo analysis)

G.3 Hypothesis Evidence Summary

H	Statement	Empirical Evidence	Result
H1	Significant underlying factors explain telecom perceptions of GenAI.	KMO=0.901 (Excellent) Bartlett p=0.000 5 factors extracted 68.72% variance All alpha > 0.80	SUPPORTED
H2	Perception factors influence adoption and practical use.	NVivo: 6 themes; 11/11 sources on T1 and T4; matrix coding confirms factor-theme interdependence; cluster analysis confirmed; member checking verified	SUPPORTED
H3	Integrated framework enhances adoption effectiveness.	6-component, 10-step framework; grounded in EFA + NVivo evidence; theoretically consistent (Gregor, 2006; Hevner et al., 2004); TRAI/TEC governance integrated	SUPPORTED

Appendix Table G.3: Hypothesis Evidence Summary