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Research paper

An Exploratory Study on AI Adoption Challenges in A Telecom Organization

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Abstract

This is an empirical study conducted in two large organizations within the telecommunication sector. One of the organizations is providing telecom wireless services, and the other is in the manufacture of various devices such as handphones, set-top-boxes, telecommunication tower cores, routers, and the like. The study has used a qualitative research method, namely the grounded theory method by Corbin and Strauss. Semi-structured interviews were conducted with the leadership team members who decided to adopt AI technologies, and a focus group discussion (FGD) with the middle management team who were responsible for implementation. The respondents in the FGD included data engineers, data scientists, software developers, and end users. The organisations have implemented more than 150 AI applications. The key finding is that organisations need to be focused on data readiness, leadership drive, digital literacy across the workforce, technology infrastructure, overcoming resistance to change, and regulatory norms compliance. The study provides insight into how the barriers were overcome, and the outcome was growth in customer base and average revenue per user. The study can be expanded to include organisations within the domain of manufacturing and the service sector.

Keywords: *Adoption of AI; Customer Experience; Digital Literacy; Regulatory; Telecom.*

1. Introduction

There is a rapid surge across industries today to adopt AI technologies to transform operations, leading to greater productivity, innovation, eliminating variability in product and service, and gaining a sustainable competitive advantage. The study highlights several challenges to AI adoption and attempts to provide solutions to overcome those challenges by integrating AI applications in routine workflows. Technologies such as machine learning (ML), natural language processing (NLP), and the use of autonomous robots in machine vision are revolutionising several activities that previously required human intervention. These technologies can automate tasks, optimise complex operations, and most importantly, enable data-based decision making [1]. Specifically, in the telecom industry, AI can enhance field and device manufacturing productivity, eliminate quality proble,ms and substantially reduce costs [2]. However, organisations face challenges in legacy issues, such as aligning the workforce to new ways of working, technology obstacles, and culture change resistance [3]. Identifying challenges early in the adoption process and creating pathways to address them is crucial for successfully adopting AI technologies.

A review of related literature indicates that the quality of data and availability of the same in a manner that is technically and functionally correct and accurate, integration of legacy data with the requirements of algorithm and with new data being continuously generated by various methods such as sensors, probes, scanners, analogue meters or digital meters, manually entered data, is foundational for successful training of AI models to make them reliable and accurate [3]. This requires significant investment coupled with a robust data strategy to become data-ready for use in AI applications [4]. An organisation with an open, transparent culture that promotes entrepreneurship is likely to adopt accelerated AI technologies. In addition, unless the AI applications merge into the larger business strategy of the organisation, driving AI into the organisation poses a chall,enge [5], [2]. Widespread education on digital technologies encompassing every person within the organisation and key stakeholders is necessary for creating the required digital skills within the organisation's immediate ecosystem for smooth adoption of AI technologies [6].

The study focuses on challenges to adopting AI technologies in telecom organisations. The empirical study supports learning from real-life experiences to understand the key elements acting as challenges and gain actionable insights to overcome them. The study's first objective is to identify the challenges to adopting AI technologies in telecom organisations. The study's second objective is to suggest solutions to overcome the challenges. To achieve the stated objectives, the researchers conducted a teleological study to investigate the sources of the challenges. It also proposed heuristic solutions supported by related literature to enable proposals on creating quick solutions.

The grounded theory method (GTM) collected audio-recorded data, including semi-structured interviews and FGD. Each participant in the study gave a consent letter for participation and audio recording. The semi-structured interviews were conducted with the senior leaders who decided to adopt AI technologies, and the FGD was conducted with employees who implemented the AI models. The FGD also included the field and factory workforce, who were also a part of building the AI models and provided inputs for creating the 'use case.' Hence, the data is rich and thick from real-life situations. The method used to gather data has enabled the researcher to gain a nuanced understanding and credible insights into the challenges experienced by the team in rolling out the AI models. The data enabled the identification of themes and recurring trends influencing the adoption of AI technologies. The complex web of various parameters that influence the adoption of AI technologies thus offers valuable insights from an academic perspective and for practitioners in the industry.
The research provides a deep understanding of the complexities of adopting AI technologies in the telecom industry, providing actionable insights that can transform customer experience. Investing in data readiness, securing support from system integrators, upskilling the workforce in digital skills, and fostering a culture of innovation and entrepreneurship are crucial for overcoming the challenges of adopting AI technologies. The outcome for the organisation is in terms of enlarging the consumer base and gaining a larger market share, providing an outstanding consumer experience, and ultimately resulting in higher earnings per consumer.

2. Literature review

2.1. The role of leadership

Davenport & Ronanki (2018) [3] stated that the availability, correctly and consistently coupled with data quality, is a key requirement for creating successful AI models. Top leadership commitment and drive, demonstrated through resource allocation, continuous periodic reviews, demonstrating and articulating the vision for the organisation, and ensuring that the AI models are aligned with the business strategy of the organisation, help create a culture conducive to innovation, risk taking, and accelerated implementation [4]. Studies by Brynjolfsson & McAfee (2014) [2] indicate that widespread inculcation of digital skills programs accelerates the adoption of AI technologies. It is common knowledge that adopting AI technologies supports gaining a competitive advantage for an organisation by enhancing operational efficiencies, reducing costs, reducing time to market for new offerings, and vastly improving innovation speed and capabilities. A literature review was conducted on recently published papers, focusing on themes such as data frameworks, organisational culture, technology choices, leadership, digital literacy among the workforce, and security and safety concerns related to regulatory matters.

2.2. Strategic foundations

Strategy on capturing data, creating a relevant data framework, and ensuring that the data is technically and functionally correct is the basis for successful adoption of AI technologies [7]. Nevertheless, another factor is data democratisation based on purpose and need, with due filters and safeguards to ensure the data is available to those needing it [8]. Organisation culture, a sustainable source of competitive advantage, must empower the workforce, encourage risk taking without fear of failure, and view every good intentioned failure as a learning opportunity. The zeal of the workforce to innovate and be creative will be significantly enhanced by such a work environment [9]. The leadership plays a critical role in building such a culture and fostering a transparent, honest work environment.

2.3. Workforce readiness and continuous learning

The readiness to adopt AI technologies, albeit starting at the very apex level in the organisation, requires several markers to be satisfied before embarking on the journey to adopt AI. One such critical marker is the alignment of AI initiatives with the organisation's overall business strategy, as this will enable identification of relevant 'use cases' that support the creation of capabilities to execute the business strategy [10]. Widespread education, training for upskilling and right-skilling workforce on digital technologies, and providing opportunities to use the skills are critical components in the design for the adoption of AI. Particularly in the telecom sector, as in other similarly circumstanced industries, the associate at the ground level is as much, if not more, critical than the one in the offices dealing with customer experience. At the ground level, productivity increases result in more defects being attended to and repaired in the field or factory floor, directly correlating with customer experience and device quality as per the NVIDIA Survey Report, 2024 [11]. Every organisation in the age of AI needs to adopt continuous learning that includes knowledge acquisition, knowledge transfer (putting it to the jobbjobowledge sharing (making others knowledgeable). Such initiatives at ground level enhance confidence, build competence, and provide learning and growth opportunities, thereby enhancing engagement and reducing attrition among the workforce [12].

2.4. Contrasting perspectives on AI-driven cultural change

The literature review has considered the emerging themes; a deeper engagement reveals important debates on the cultural impact on AI adoption in organisations. Maddula (2018) [27] asserts that AI implementation often triggers anxiety and hence resistance among employees due to fear of job loss and or loss of autonomy in their functioning. This necessitates concerted actions on the part of the organisation to negate the disruptive potential of AI through deliberate change management initiatives and culture building in the organisation to embed trust and maintain morale at a high level. Whilst Ekwueme et ., (2023) [28] present a more optimistic view since AI catalyses positive cultural transformation. Transparent communication, employee involvement at all levels, a culture of continuous learning, and opportunities to apply newly acquired skills all contribute to creating an environment that fosters the adoption of AI within an organisation. The focus of all such initiatives shifts from resistance and doubts to fostering a higher-level employee mindset through contributions to more skilled work and professional development. These contrasting views in literature amplify the complexity of inculcating an AI-driven culture. This is where the leadership role in culture building plays a pivotal role through the evolution of organisational strategies that encompass all employees,nsparently and diligently promote employee involvement in the development of use cases and subsequently demonstrate how the quality of work improves, making life more enriching to the employee. In this manner, transformation can be accelerated and gains at the personal level for the employees and the organisation come to life. To summarise, it is not so much of a technological problem but one where organisations need to tackle the contradictions competently, balancing efficiency gains with an empathetic change management initiative, thereby ensuring that AI adoption enhances a positive outlook-oriented organisation culture.

2.5. Infrastructure investments

Investment in data lakes, computing power, internet connectivity, storage capacity, and edge computing is essential for implementing AI. Making the infrastructure scalable and flexible enables the adoption of different technology platforms, integration with system integrators (SI) software, and processing large amounts of data. This is especially so in the telecom industry, where millions of data points are generated every second [13]. Developing long-term partnerships with SIs is paramount, as they possess a knowledge base that spans multiple industries. It can replicate solutions quickly without reinventing the wheel. SIs also possess off-the-shelf solutions that can be used with minor customisation, accelerating the adoption of AI technologies [14].

2.6. Regulatory compliance

In the telecom industry more so than in any other industry data security and compliance with regulatory norms is of utmost importance because of the critical personal data that is in the service provider's system and needs to be protected in line with the General Data Protection Regulations (GDPR in EU) and Digital Personal Data Protection Act, 2023 (DPDP) in India, besides as may be relevant in other geographies across the world. The regulations are evolving, and there needs to be a strong mechanism to ensure the security and safety of the data [15]. Telecom organizations can address evolving regulations like GDPR (EU) and DPDP (India) by implementing data protection impact assessments (DPIA) at regular time intervals to assess risks to personal data and document to mitigate risks, apply internationally accepted standards such as ISO/IEC 27701 for privacy information management, implement quarterly audits both internal and external to ensure adherence to data handling, consent, and breach notification requirements, establish a position of a 'Data Protection Officer' in the organization who will be accountable for compliance, training and ensuring prompt incident response and lastly, by keeping records of all data flows and processing actions/activities and monitoring external party sharing of data. These steps provide insight into the organisation's responsibility to ensure regulatory compliance and transparency in accountability.

2.7. Ethical guidelines

Ethical guidelines encompassing algorithm bias and accountability, especially where AI models make decisions, are mandatory in every organisation where personal data is stored, and the measures taken must be transparent and open to public scrutiny [16].
Adoption of AI technologies in the telecom industry, whether as a service provider or device manufacturer such as cell phones, set-top-boxes, routers, and the like, needs to incorporate mechanisms that ensure data quality, appropriate organisational culture, investment in infrastructure, workforce education and skill development, and compliance with jurisdictional data protection norms.

3. Methodology

The grounded theory method (GTM) by Strauss and Corbin (1990) [17] has been deployed for the research as the method enables the capture of nuanced knowledge from those who have been involved in the execution as well as in conceptualising the initiative. This approach is particularly relevant as no published literature provides any conceptual model or framework for adopting AI technologies. There are numerous theories and frameworks for adopting innovation, but none specifically focusing on AI. This is an empirical study, and the researcher collected the data in person at the location where the participants worked, thereby enabling a deep understanding of the difficulties, problems faced, and how the opportunities were exploited in adopting AI technologies [18].
Data was collected through three semi-structured interviews with members of the leadership team who were responsible for deciding on the adoption of AI technologies and a focus group discussion comprising 8 employees comprising including data engineers, data scientists, field technicians, platform and technology stack managers, and specialists in networks and infrastructure like data lakes [19]. All the participants in the study had a significant role in adopting AI technologies, whether at the conceptualisation stage, implementation stage, or end-user level. The data was collected by conducting several rounds of discussions, individually and separately, at times to seek clarifications until no new ideas emerged, thereby suggesting a saturation level had been achieved in the collection of data [20]. The outcome was thus an exhaustive capture of participant experiences and insights in implementing AI technologies.
This study is anchored in qualitative methods aimed at generating data through purposeful sampling of respondents who are knowledgeable about and personally involved in the adoption of AI processes from end to end. Hence, the emphasis is on inductive reasoning, where themes and constructs emerge through systematic coding and constant comparison. Hence, quantitative validation was not sought by the authors.

4. Data analysis

From the transcripts of the semi-structured interviews and FGD, themes emerged, and these themes provided inputs to the constructs of the data framework, technology enablers, leadership, employee skills, and compliance with regulatory matters. Many dimensions were identified in each construct from the transcripts, which acted as challenges to adopting AI technologies in the immediate term, and the participants demonstrated how each one of the challenges was overcome. The themes, constructs, and dimensions were coded to associate each dimension with a construct and aggregate similar items, but stated in different semantics. The validation of this process has been ensured by citing published literature, thereby providing validity and reliability of the findings [21]. NNN
Based on the researcher's four decades of experience, the purposeful selection of participants and the ensuing discussions provided deep and meaningful insights into the adoption process of AI technologies in the telephony and devices manufacturing businesses. As all the participants had a high degree of specialisation in one or more disciplines within the AI technologies, the data gathered was rich regarding real-life experiences [18]. The cross-pollination of ideas in the FGD enabled the listing of the challenges and, at the same time, provided solutions as to what can be done to overcome them [22]. It is imperative to take account of the significant investments made by these organisations in creating a large and robust infrastructure such as, data lakes, stack of technologies, use of system integrators (SI), education and training of employees, induction of mid-career recruits from global organisations who have had a successful track record of achievements and that led to development of more than one hundred and fifty AI applications that are being used in daily functioning in the data centres and the field. This is the main reason for selecting these organisations, as it explains how AI technologies have supported growth, productivity, profitability, and customer experience [2].

Whilst the data about adopting AI applications within the two organisations has been exhaustive and comprehensive, the question of generalisation remains open, especially whether the same would apply equally to other industry segments, such as manufacturing, retail, or the services sector. This can be considered a limitation of the study. Nonetheless, the findings can be transposed to organisations with similar issues in adopting AI technologies.

5. Results

A conceptual model for adopting AI technologies emerged based on the analysis of transcripts of the semi-structured interviews and FGD. The model is in Fig. 1.

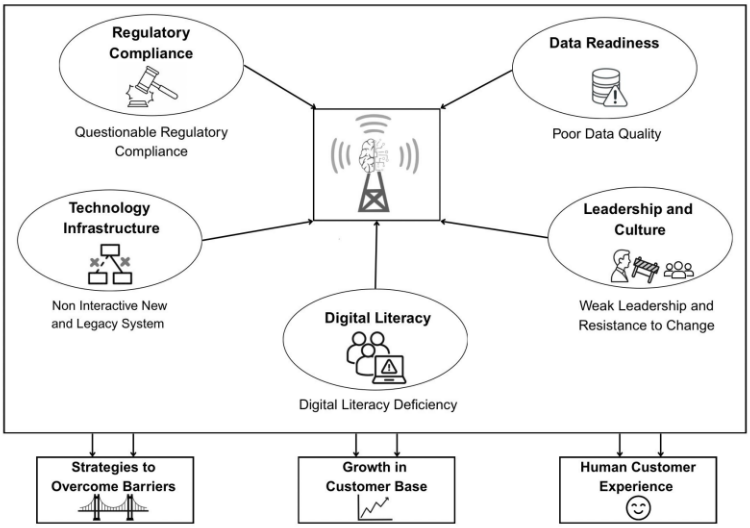

Fig. 1: Conceptual Framework for Adoption of AI Technologies.

Source: Author.

Fig. 1 depicts the conceptual model for identifying the challenges to adopting AI technologies in the Telecom industry. Data Readiness is the first and most significant challenge, as data comes from multiple sources, including manually entered customer data, which often does not meet the functional and technical requirements and needs to be cleaned. The second is creating data readiness and technology enablers for the network performance that determines the customer experience. Data readiness encompasses not only the availability and accessibility of data, but also its quality, consistency, completeness, and governance. There can be several infirmities that need to be corrected, such as missing values, data quality issues, outliers, and completeness of data. Missing values often result in biased models, reduced accuracy, and unreliable predictions. Several techniques are available, including data imputation, the creation of robust algorithms, and redesigning data collection processes, all of which are necessary to address this issue. Data quality relates to missing values, inconsistencies, and outliers. Missing values can lead to biased models, reduced accuracy, and unreliable predictions. AI models become confused with inconsistent data, resulting in a deficiency in understanding correlations or patterns. Outliers impact generalisation and often lead to overfitting due to the model's skewed training. Outliers are significant in the BFSI sector, where a transaction may be mistaken for fraud, thereby affecting the model. Completeness of each record is the extent to which all required data attributes are present. Incomplete data prevents AI models from learning important relationships. A case in point is that of a missing customer demographic field, which can severely impact the effectiveness of personalisation algorithms in retail or BFSI. Suppose the AI model cannot access the full context and content of the data because it is only available in silos. In that case, it dramatically reduces the effectiveness of data integration and the impact of data in silos. Platforms performing data integration and APIs are helpful in unifying data sources. Overall, the above infirmities in data can impact model accuracy, leading to false positives or false negatives, bias, and unfairness due to incomplete or inconsistent data, resulting in discriminatory outcomes. Models may perform unpredictably, creating operational risks, such as missed maintenance opportunities in manufacturing or incorrect credit or fraud decisions in BFSI.

In the case of this study, data readiness is closely related to the 'Core' in the transmission tower, which controls connectivity and traffic and has a specific capacity. With the help of AI and ML, the organisation has made it possible to vary the capacity of a single 'Core' in conjunction with other adjacent 'Cores' to absorb sudden increases or decreases in traffic. In addition, the early warning system enables the field engineer to attend to any fault likely to happen before such an event, thereby ensuring continuous and nonstop connectivity. Leadership drives in terms of constancy of purpose, frequent reviews that resolve any issues, allocation of resources, participation in digital literacy programs across the entire organisation, and walking the talk, enthuses a culture of risk-taking and entrepreneurship within the organisation that has accelerated the adoption of AI technologies. Telecom has access to immense personal data and preferences, especially in the hand phones and set-top-boxes that must be protected scrupulously. Here, adherence to regulatory norms and compliance with personal data protection laws are paramount. None of what is mentioned in the above paragraph is easy. Telecom organisations face these challenges in providing an outstanding customer experience and enhancing revenue. The paper addresses some key challenges in the discussion and conclusion sections.

The managerial implications are in terms of commitment of the leadership and empowerment of the staff creating the AI applications, widespread digital literacy programs, infusion of critical skills in the areas of data engineering and data sciences, hundred percent compliance to regulatory norms and personal data security, investment in creation of the required infrastructure in the form of technology platforms, network connectivity, ML usage in the devices manufacturing facilities, software integrity being maintained and demonstrating that adoption of AI / ML technologies does not mean loss of jobs but an upgradation of the work performed making the job easier and more productive through the availability of advance information and prescriptive actions by AI / ML models.

Some use cases relating to the conceptual framework, especially in Generative AI and Edge AI adoption, need to adapt towards addressing new opportunities and challenges such as data readiness, where Gen AI importance will increase with more unstructured text, images and real-time network data requiring stronger data governance and real-time data pipelines, particularly on edge computing deployed telecom networks. The edge AI reduces latency for applications like 5G optimisation and real-time data anomaly detection. The need is to ensure that the framework considers distributed computing architecture, model deployment at scale, and interoperability between cloud and edge devices. Everyone in the organisation will need upskilling in the areas of prompt engineering, model fine-tuning, and managing AI on edge computing. Perhaps the most important aspect is related to organisational structure and job design, wherein new roles and responsibilities will emerge because of Gen AI-powered automation and decision support. In terms of regulatory compliance, new technologies like Gen AI and Edge AI necessitate new privacy and security standards, given the substantial amount of personal data being collected, particularly when data storage occurs on third-party premises. This will require continuous compliance monitoring, and organisations need to be quick to comply with emerging governance and ethical regulations.
5G supports Gen AI to automate network planning, customer support, and personalisation of unique services as per individual needs. The framework supports quick experimentation and deployment of AI models for dynamic network management and prescriptive maintenance.

6. Discussion and conclusion

6.1. Building a robust data and technology framework

Develop a comprehensive data framework to guarantee the accuracy and completeness of technical and functional data, facilitating the integration of legacy and new data into a unified database. Special attention should be paid to 'outlier' data points, which require thorough analysis for contextual understanding. Additionally, it is vital to conduct a complete review of valid data points to identify best practices. Data sharing must follow a need-to-know model, enabling employees to effectively leverage their expertise [23], [24]. Moreover, not assembling a suitable technology stack can impede progress if hardware requirements—such as Central Processing Unit (CPU), Graphic Processing Unit (GPU), Field Programmable Gate Array (FPGA), and AI accelerators—are not adequately evaluated, alongside careful selection of domain-specific algorithms and software, including applications, models/frameworks, servers, data lakes, and other specialised infrastructure components. Lastly, the availability of SIs equipped with the necessary technologies and expertise presents a significant challenge, as no SI currently provides a fully integrated end-to-end solution [25], [26].

6.2. Addressing people and regulatory challenges

People dimension, especially relating to digital literacy, acceptance that a machine can think better than a human, fear of job loss, resistance to change in the way of working, deficiency in data sharing, weak leadership, focus on individual KPIs rather than on collaborative and team KPIs, and fear of loss of control over the team can prove to be challenges [27 - 29]. Lack of specialised skills, especially relating to data science, data engineering, and platform engineers that are of recent origin, needs to be inculcated and/or infused in the organisation [30], [31]. Regulatory and personal data protection is increasingly gaining importance and cannot be overemphasised, especially considering several regulatory norms being established across countries and within the country. Failure to abide means a risk to business existence and often acts as a barrier, as organisations are wary of investing in this area. Regular and multiple audits of the algorithms and checks on data integrity can overcome the challenges presented by the regulatory and ethical factors [32], [33].

6.3. Critical success factors for AI/ML implementation

The important, critical and deciding factor in whether the AI / ML application will deliver the target with which it was designed will depend on the data quality, the extensiveness of technology infrastructure, the depth and understanding of digital technologies by the employees within the organisation at all levels and attention to detail when it concerns regulatory, ethical and security compliances. None of the five challenges mentioned above is insurmountable. However, the workforce's top leadership must drive and commit to making it happen. Collaboration, teamwork, knowledge acquisition, and the effective use of that knowledge in day-to-day work, as well as its transfer to colleagues, are crucial. Additionally, being open to ideas from anywhere and overcoming the fear of failure and job loss are essential for the successful implementation of AI technologies in the telecom industry. The study is restricted to two organisations in the telecom industry: the cellular service provider and the device manufacturer. However, the study can be extended to the manufacturing, BFSI, and service industries. Whilst this study relates to the telecom sector, it is equally applicable to manufacturing for energy optimisation, prescriptive maintenance, quality control, supply chain optimisation, and new product development. In the BFSI industry, the tenets of this study are applicable in the areas of fraud detection, customer services through Chatbots, personalised offerings, and credit risk assessment. In the service industry, the same conceptual framework can be used for demand forecasting, curating unstructured data, and compliance with regulatory norms such as HIPAA in Health Care, GDPR, and Central Bank Guidelines in the BFSI segment.

6.4. Adapting the framework for emerging technologies

Some use cases relating to the conceptual framework, especially in Generative AI and Edge AI adoption, need to adapt towards addressing new opportunities and challenges such as data readiness, where Gen AI importance will increase with more unstructured text, images and real-time network data requiring stronger data governance and real-time data pipelines, particularly on edge computing deployed telecom networks. The edge AI reduces latency for applications like 5G optimisation and real-time data anomaly detection. The need is to ensure that the framework considers distributed computing architecture, model deployment at scale, and interoperability between cloud and edge devices. Everyone in the organisation will need upskilling in the areas of prompt engineering, model fine-tuning, and managing AI on edge computing. Perhaps the most important aspect is related to organisational structure and job design, wherein new roles and responsibilities will emerge because of Gen AI-powered automation and decision support. In terms of regulatory compliance, new technologies like Gen AI and Edge AI necessitate new privacy and security standards, given the substantial amount of personal data being collected, particularly when data storage occurs on third-party premises. This will require continuous compliance monitoring, and organisations need to be quick to comply with emerging governance and ethical regulations.

6.5. Leveraging 5G

5G supports Gen AI to automate network planning, customer support and personalisation of unique services as per individual needs. The framework supports quick experimentation and deployment of AI models for dynamic network management and prescriptive maintenance.

6.6. Challenges in AI adoption

The study highlights critical enablers, such as leadership drive and employee upskilling. Simultaneously, it is important to acknowledge practical challenges that organisations would need to resolve. The cost of infrastructure is such a challenge that requires investment in sophisticated hardware, cloud services, and secure data storage facilities, which can be a challenge for smaller telecom organisations. Culture change is another area of concern where a lack of transparent and honest communication by leadership can lead to fear of job loss and resistance to new technology adoption. Hence, financial planning, appropriate resource allocation, and change management practices, including reward and recognition practices, need to be internalised by the organisation.

6.7. Future research

The Conceptual Framework mentioned in this study needs to be tested in both small and large organisations, as it would support identifying size-specific challenges, resource constraints, and best practices to create customised suggestions in different organisational contexts. Research on ethical implications in telecom, such as algorithmic bias, privacy issues, and responsible use of consumer data, requires developing sector-specific ethical guidelines and learning how organisations bring to life the ethical AI principles. To understand the long-term impact of AI adoption on performance and organisational culture, a longitudinal study is a felt need. Testing the generalizability of the conceptual framework by applying it to non-telecom sectors, such as financial services, banking, and manufacturing, will provide insights into industry-specific assimilation challenges. Also, a quantitative research opportunity exists to check the correlation between independent and dependent factors within the universe of challenges.

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This study is an original work by the author(s) and has not been published earlier in any other publication. The authors declare no potential conflicts of interest concerning this research, authorship, and/or publication of this article.

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