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MANAGING ORGANIZATIONAL CHANGE IN THE AGE OF ARTIFICIAL INTELLIGENCE: LEADERSHIP CHALLENGES AND OPPORTUNITIES THE CASE OF ETHIO TELECOM

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DECLARATION

I hereby declare that the work is own original work of mine and has not been presented, in whole or in part for any degree of any other university. All sources used or referenced in this document have been properly and duly acknowledged .

Kemal Mohammed

Date : June 2026

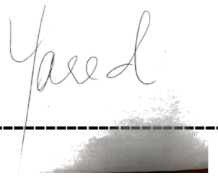
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CERTIFICATION

This is to certify that the thesis prepared by Kemal Mohammed entitled "Managing Organizational Change In The Age Of Artificial Intelligence : Leadership Challenges and Opportunities The Case Of Ethio Telecom (S.C.)" submitted to Addis Ababa University College Of Business And Economics In Partial Fulfillment Of The Requirements For The Masters Degree In Business Administration aligns with the regulation of the university and accepted standard in respect to originality and quality.

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ABSTRACT

Artificial intelligence is reshaping how large organizations work and Ethio Telecom which is Ethiopia's main telecom operator is moving through this change at an early stage and in an emerging economy environment . By the first half of the 2025/2026 fiscal year it served about 87.1 million subscribers and 49 million mobile data users and had introduced AI-based and digital services such as Telebirr, Ardi chatbot and biometric registration. Because adopting AI is as much a leadership and human task as a technical one, this study explores how that change is led and how employees and customers experience and accept it. It used an exploratory mixed methods and qualitative dominant design with 70 participants which is made up of 25 employees 15 managers and 30 customers. Data was from semi structured interviews and open-ended questions, Likert-scale questionnaires and six non-participant observations and secondary resources. The questionnaire answers were analyzed in SPSS using descriptive statistics while the open-ended answers, the observation and the secondary sources were analyzed thematically and brought together with the numbers through a joint display.

The central finding is that the technical side of the change largely succeeded while the human side was undermanaged. communication weakened as it moved down the organizational hierarchy and the weakest link was between senior management and middle managers. Employee fear was real as a psychological experience, but not based on actual local job displacement. Formal training was the weakest support so staff gained competence primarily through peer learning and self learning. Employees were left out of decisions but accepted the change because the tools were useful. Customer experience split in two ways: routine tasks like payments worked well while problem resolution was the lowest rated part of the study and connected urban users were served well while regional and older customers were left behind by a clear digital divide. The one clear human-side gain was that leading this imperfect change built real leadership confidence in managers. The study recommends briefing managers properly before each roll out, communicating honestly about AI and jobs, involving employees in decisions, redesigning training around real job tasks with follow-up support and keeping the branch and USSD channels open while improving the chatbot so complex problems can be solved without a call or a branch visit. Its contribution is a locally grounded account of the human process behind AI-driven change in a large Ethiopian organization complementing earlier work that measured performance gains but did not explain how they were achieved.

Keywords: *Artificial intelligence; organizational change; change management; leadership; digital transformation; Ethio Telecom; Ethiopia*

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ACRONYM

AI :	Artificial Intelligence
API	Application Programming Interface
CBE	Commercial bank of ethiopia
CEO	Chief Executive Officer
ETB	Ethiopian Birr
ET	Ethio Telecom
GSMA	Global System for Mobile Communications Association
HR	Human Resources
ICT	Information and Communications Technology
IT	Information Technology
MBA	Master of Business Administration
ML	Machine Learning
MTN	Mobile telephone network
NPS	Net promoter score
SPSS	Statistical Package for Social science
TOE	Technology Organization Environment
USSD	Unstructured Supplementary service data

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Artificial intelligence (AI) is the ability of computer systems to conduct tasks that require human expertise to do such as recognizing repeated patterns, understanding the language used, reasoning and also decision-making (Russell & Norvig, 2021). As a discipline, it dates back to mid-1950s when first systems were created based on hand-coded rules aimed to simulate human judgment. Unlike them, current AI works in a completely different way as it learns from massive amounts of data through a process called machine learning, thus improving itself constantly. Its most powerful area is deep learning which is capable of interpreting images, sound and text, and its latest incarnation – generative AI is able to create written language, images, and computer code (Wang & Siau, 2019). Thus, the plain meaning of AI is not a certain device or software but rather a group of data-driven technologies that allows machines to conduct cognitive activities and constantly improve at them and it is relevant to all modern organizations.

In organizations, this ability is usually applied in three areas: conducting routine, rule-based tasks which were conducted before manually; gaining insights by identifying patterns in data, predicting demand and assessing risks; and interacting with people through chat bots, virtual assistants and recommendations (Davenport & Ronanki, 2018). The economic importance of this trend is significant since according to PwC (2017), AI can generate up to US$15.7 trillion added value to global GDP by 2030, thus becoming one of the biggest commercial opportunities of this era. The telecommunication industry is one of those industries that use these technologies most actively by applying them in managing and optimizing networks, prediction and reduction of customer churn, detection of fraud, automation of customer service and verification of subscriber identity (Dwivedi et al., 2021; Mhlanga, 2022). In case of operator which serves millions of subscribers, AI becomes an inseparable part of the organization affecting almost all its parts from network to services provided to customers.

However, implementation of such technology is far from being purely technical. AI changes the way tasks are being done, the distribution of tasks between humans and machines and the way

services are delivered, therefore it is best seen as organizational change which involves leadership and people and not just technology (Abbu et al., 2022; Singh & Sharma, 2021; Danaher & Tchouaket, 2024). The challenges which are faced during its implementation, therefore, are mostly human and organizational, not technical. Such challenges include poor quality or unprepared data, lack of necessary skills for creation and operation of intelligent systems, difficulties in integration of new technologies into existing processes, fear of employees regarding potential impact of automation on their job and customers' hesitation to trusting new services (Dwivedi et al., 2021; Rajanala et al., 2024). Therefore, whether implementation of AI technology will be successful usually depends on the management of human factors, which puts leadership, employees and customers (three groups which are studied in this paper) at the center of the process.

There are two theoretical frameworks which explain the process of such change. The first framework covers the topic of organizational change management. Lewin (1947) described the process of change as unfreezing old practices, adopting new ones and then stabilizing them which shows from the very beginning that the human side of change is as important as the structural side; Kotter (1996) said that the major reason of failure of change efforts is not technical issues but ineffective communication, insufficient training and lack of management of resistances. The second framework covers the adoption of new technology by people. Rogers (2003) explained the process of diffusion of innovations within a community whereas Davis (1989) in his Technology Acceptance Model suggested that people will adopt the technology only if they consider it useful and easy to use – this approach was developed further by adding such factors as social influences and conditions (Venkatesh et al., 2003). Thus, we see from these theories that there are two interconnected sides of AI adoption: inside the company, employees need to be taken through the change process by their leaders, and outside the company, customers should consider the services valuable enough. Failure of any of them can jeopardize the whole process regardless of the level of technology involved.

This issue becomes especially important in countries which are rapidly digitized and AI technology finds its place in organizations and reaches customers who have never been exposed to it before. Most of the international studies were conducted in better resourced environments with more advanced digital experience and cannot be considered applicable to Africa automatically (GSMA, 2024; Mhlanga, 2022). Ethiopia is such rapidly digitizing country which placed the

digital transformation at the top of its agenda. The Digital Ethiopia 2025 strategy which has been succeeded by Digital Ethiopia 2030 vision aims at moving from simple connectivity to provision of digital services, an aim supported by establishment of the Ethiopian Artificial Intelligence Institute in 2022 (Council of Ministers Regulation No. 510/2022) and the first National Artificial Intelligence Policy in 2024 (FDRE, 2024). Ethio Telecom is the main company implementing national ambitions of the country.

With the help of its 2022-2025 digital transformation programme, Ethio Telecom introduced 838 new or upgraded products or services, and achieved a mobile-data growth of 446.2 percent (Ethio Telecom, 2025); by the end of the first half of the 2025/2026 fiscal year, it had reached 87.1 million subscribers, with 49 million mobile-data users, and a total employment of 44,031 (Ethio Telecom, 2026). Among Ethio Telecom's AI-based products or services are Telebirr mobile money service, Ardi customer-service chatbot, and biometric SIM registration, along with data-analytics dashboards for managing operations. But beyond the numbers and statistics, there is another question to ask: Are people adapting? Leaders are expected to lead their teams through systems that even they do not yet understand, employees need to adopt technologies before even understanding them as they keep changing, and customers are nudged to opt for technologies that are new to them. In an environment where AI adoption in Ethiopia is in its nascent stages, the perceptions that both employees and customers will have from the start would be harder to correct in the future. That is why it is essential to manage the beginning of this process carefully.

It is against this background that the current study investigates how leaders at Ethio Telecom manage AI-based organizational changes and how such management affects employees' adaptation and customers' adoption of it, based on the experiences of managers, employees, and customers. Given that this issue is hardly researched in the context of Ethiopia, the study follows a predominantly exploratory approach and employs a mixed-methods, predominantly qualitative case study design, in which open-ended responses, observations, and secondary sources form the core qualitative method, while the descriptive questionnaire data complement the core methods. As an exploratory study, this research sets out research questions and not hypotheses. The current research is expected to give locally-relevant insights on a transformation that is of national importance, and contribute both to the research of AI-enabled change in emerging economies and

the practice of Ethio Telecom and other similar firms. The specific problem addressed by the study is articulated in the following section.

1.2 Statement of the Problem

It is easy to treat AI adoption as a technology project. Section 1.1 explained why it is not. When AI enters an organization, it moves work from people to machines and changes how both staff and customers deal with the company. This is organizational change and the research on change is consistent about what drives it. The technology is rarely the deciding factor. Change fails when it is communicated poorly, when people are not trained and when their resistance is ignored (Kotter, 1996). Work on AI reaches the same conclusion: success depends on whether people are ready and whether leaders support them, not on how advanced the system is (Booyse & Scheepers, 2024; Soulami et al., 2024). One of the central challenges in adopting AI is a challenge of leadership and change management.

This human side has two parts and they pull on each other. Inside the company, employees have to take on unfamiliar systems and new routines. Whether they manage it turns on how the change is explained to them, on the training they get and on whether they are involved or simply told what to do (Kotter, 1996). Outside the company, customers have to be willing to use the new services, which depends on whether the services feel useful and easy and on whether customers can get online to use them at all (Davis, 1989; Venkatesh et al., 2003). Neither part stands alone. Staff who are uneasy with a system cannot help customers through it and customers who give up on the service take away the gains that paid for the change. A failure on either side can sink the whole effort, however good the technology. Leading AI adoption means running both transitions at once.

Where this happens changes the picture. Almost everything known about leading technological change comes from places with deep digital experience and well-resourced firms, where customers are already comfortable online. Those conditions do not hold in a country that is digitizing quickly, where AI reaches organizations and customers that have barely met it before (Ferede & Negash, 2025; Mhlanga, 2022; GSMA, 2024). Advice built for one setting may not carry to another. Borrowing it without checking risks treating a local problem as though it had already been solved

elsewhere. How AI change is led and how people receive it, has to be studied where the change is actually taking place.

This is the understanding that is missing for Ethio Telecom. The company is in the middle of the large transformation described in Section 1.1, yet no study has looked at how its leaders are managing that change, or at how its employees and customers are living through it. The closest study Kassa and Worku (2025) used structural equation modeling on 172 Ethio Telecom employees and found that AI performance is linked to higher productivity and better organizational performance. That finding is useful, but it marks the edge of the gap rather than closing it. It shows that AI lifts performance. It does not show how the leaders brought the change about, how employees accepted or resisted it, or how customers adjusted to the new services. The difference is partly one of method. A study like that one measures variables and reports how they move together, which answers the question of how much. It cannot reach the questions this study asks, which are how the change unfolded and what it meant to the people in it. Those questions need a mainly qualitative approach. Past the Kassa and Worku study, no research has examined the things that actually move this kind of change in an Ethiopian telecom: how clearly leaders communicate, how far employees are trained and involved and what helps or stops customers from adapting. Studies from other telecoms in Africa and similar markets show these things matter (Singh & Sharma, 2021; Mhlanga, 2022), but none has tested them here. Ethio Telecom is running an intensive, nationally important change with little to guide it.

Leaving this unstudied is costly. The company is early in its adoption relative to the global telecom sector and first impressions are hard to undo. If employees and customers lose confidence in these services during the early stages of implementation, rebuilding trust may become difficult and costly. There is also no ready-made answer to rely on, since the evidence from richer settings cannot simply be transferred and acting on guesswork invites failures that could have been avoided. The case also reaches past one firm. Ethio Telecom carries much of Ethiopia's digital plan and other organizations in the same position face the same task, so a clear account of how this change is led and received would help researchers and managers elsewhere. For Ethio Telecom, getting the human side right is what the whole transformation depends on.

This study takes up that gap. It looks at how Ethio Telecom's leaders manage AI-driven change and at how that management shapes the way employees adapt and customers accept it, drawing

on what managers, employees and customers say about their own experience. Because so little is known here. The objectives and questions follow below.

1.3 Research Objectives

1.3.1 General Objective

To investigate how AI-driven change is managed at Ethio Telecom and shapes the acceptance of employees and customers based on managers', employees', and customers' experiences

1.3.2 Specific Objectives

The research aims to achieve four specific objectives, all being analyzed qualitatively and supplemented with descriptive data from questionnaires:

1. To examine how managers at Ethio Telecom lead the introduction and implementation of AI-driven change, and how leading it develops them as leaders.
2. To examine how employees at Ethio Telecom experience and adapt to AI-driven change, and what helps or hinders their acceptance of it.
3. To examine how customers adopt and use Ethio Telecom's AI-enabled digital services, and what fosters or hinders their acceptance of them.
4. To develop evidence-based recommendations to help Ethio Telecom's management lead future AI-driven change.

1.4 Research Questions

Since this is an exploratory and mostly qualitative study, it is guided by research questions rather than hypotheses as it intends to explore how the participants make sense of their experiences related to AI-driven change and not to test any predetermined relationships between variables (Creswell & Creswell, 2018).

1. How do managers at Ethio Telecom lead the introduction and implementation of AI-driven change and how does leading it develop them as leaders?

2. How do employees at Ethio Telecom experience and adapt to AI-driven change and what helps or hinders their acceptance of it?

3. How do customers adopt and use Ethio Telecom's AI-enabled digital services, and what pushes them toward or away from accepting them?

4. What can Ethio Telecom's management do to lead future AI-driven change more effectively?

1.5 Significance of Study

This study makes both academic and practical contributions. Academically, it provides locally grounded, qualitative evidence on how AI-driven change is led and experienced at a large Ethiopian organization — a setting that remains largely unstudied, since existing work is concentrated in better-resourced contexts and tends to measure performance rather than explain the human process behind it. By examining the experiences of managers, employees, and customers within a single case, it offers an integrated account that single-group studies cannot.

Practically, the findings give Ethio Telecom and similar firms evidence-based guidance for leading future AI-driven change, showing where current approaches to communication, training, involvement, and customer support are working and where they are not. Because the study is exploratory, it also surfaces specific questions that future quantitative research could test at scale.

1.6 Scope and Limitations of the Study

The research is limited to the leadership of the change process through AI at Ethio Telecom and also to the experiences of three stakeholders who are affected by the change: managers and team leaders, employees in the departments affected, and customers using the services provided by Ethio Telecom including Telebirr, Ardi Chatbot and biometrics registration. The data collection took place mostly in Addis Ababa and few participants among the customers came from a regional (Sheger) city. The study does not assess the technical performance of AI systems, nor does it seek to generalize statistically to all of Ethio Telecom's staff or customers; consistent with its

exploratory, qualitative dominant design, the questionnaire data are used descriptively to support the qualitative findings.

Limitations of this study is the focus was only on the operations of ethio telecom in Addis Ababa, with a few customer respondent drawn from regional city (sheger city) also the sample 70 samples 25 employees 15 managers and 30 customers suits a mixed method study but are too small of sample to generalize to all of Ethio Telecom's staff or to its customers in all of Ethiopia. Purposive sampling is when participants are chosen for their relevance and experience than their representation in numbers.

When data was collected it was made the high intent to make the data collected to represent all groups but people responded based on how they feel or what they were doing or the matter the accepted to participate in this interview with a good intention or otherwise but we cant exclude the fact that their maybe unfair responses.

Another restriction is the pace of movement in the ai world that findings and observation might not hold true for another time so the change and how fast paced the change is going to limit if the study is going to be the same several years from now.

1.7 Organization of Thesis

There are 5 chapters in this study where the first chapter starts out by introducing the over all study and the limitation scope and also objectives and significance then the next chapter literature review is on the second chapter, the methodology is on the third chapter where the methods and ways the research was conducted are explained and also how the research was planned out ,where it was done and similar things are mentioned in the third chapter then chapter 4 explain the findings of the data collected and analyze them and on the last chapter conclusions and recommendations are presented.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This research finds the explanation of the AI and organizational performance in the main focus of the study it explores the performance in the leadership and employee performance also the effect in the customer responses it also reviews academic and professional studies relevant to the research's main themes. This also covers how leadership is in the employee and customer responses to AI related changes within the telecommunications sector and the specific African context.

This research was contextualized and known within the searches of Google Scholar also Emerald Insight and Research Gate website Priority was given to studies from 2018 to 2025 and to studies who also focus on the countries which have not been able to integrate the changes like other countries in terms of pace and acceptance rate. Because in many countries change range from active adoption to passive resistance which is why it better to categorize a study based on this.

2.2 Artificial Intelligence as Organizational Change

Section 1.1 established what AI is and why it is best treated as organizational change rather than a technical upgrade. This section develops that argument. Because AI redistributes tasks between people and machines and reshapes how work is done, adopting it is not simply installing a tool; it is a change in how an organization works, one that depends on leadership and people rather than on the technology alone (Abbu et al., 2022; Singh & Sharma, 2021). Within organizations, AI is applied to tasks such as customer-service automation, predictive analytics, fraud detection, and the optimization of networks and supply chains, and the value of these applications still rests on how well the surrounding change is managed.

The relationship between AI adoption and organization performance has been investigated by researchers within several sectors. According to findings, companies adopting AI technologies become more efficient, produce higher-quality output and even become more profitable due to their efforts to minimize costs but only if there is an appropriate organizational environment. Without proper infrastructure; workforce readiness and management support; AI may underperform (Wang and Siau 2019).

In telecommunications sector studies revealed that AI systems had already improved many services provided by companies including both creating new services sectors and improving existing ones. Automated wait time has decreased significantly and expenses on those services had changed (Enhancing Customer Service Efficiency, 2024). The reason is that AI systems help organizations reduce costs and improve operational efficiency. These systems also optimize routing and traffic as well as decrease power outages. In addition, using predictive analytics helps improve maintenance scheduling and reduces service disruptions (Verhoef et al. , 2021).

One example of study relevant to the present research is that conducted by Kassa and Worku (2025).Using structural equation modelling with 172 Ethio Telecom employees, the authors report that AI adoption is associated with higher organizational performance and employee productivity. Their study is directly relevant here because it documents that AI-related change at Ethio Telecom yields measurable results, yet it does not examine how that change was led or how employees and customers experienced it the very question this study takes up. This study is relevant because it demonstrates that AI-related changes at Ethio Telecom lead to tangible performance results which raises a question of how these changes were managed.

According to Kassa and Worku (2025), performance outcome depends on how AI implementation is managed. Any new technology should be treated carefully and every mistake such as skipping or rushing any of the steps can cause resistance and other outcomes of change.

2.3 Leadership and Organizational Change in the Digital Era

The modern study of planned change begins with Lewin (1947), who described it as a three-stage process unfreezing established practices, moving to new ones, and refreezing them establishing from the outset that the human side of change matters as much as the structural side. Building on this foundation, Kotter (1996) set out an eight-step change process.

It argues that successful change requires a clear sense of urgency,a guiding coalition, a compelling vision, broad communication, the removal of obstacles, short-term wins, sustained effort and the embedding of the change in organizational culture. Each step carries a direct leadership responsibility and when any of them is skipped or rushed, particularly the communication and vision steps, resistance tends to grow and change outcomes suffer.

This body of work informs the study's first objective, which examines how managers at Ethio Telecom lead AI-driven change.



Figure 2.1: Kotter's 8 Step Change Model (Source: Kotter, J. P. (1996).

The McKinsey 7 S Framework offers a complementary perspective. It identifies seven elements that must be aligned for organizational change to succeed : strategy, structure, systems, staff, skills, style and shared values (Waterman et al., 1980, as cited in Northouse, 2022). In AI driven change, the framework suggests that technology alone (systems) is insufficient leadership

must simultaneously attend to skills development, structural adaptation and changes in organizational values and style.

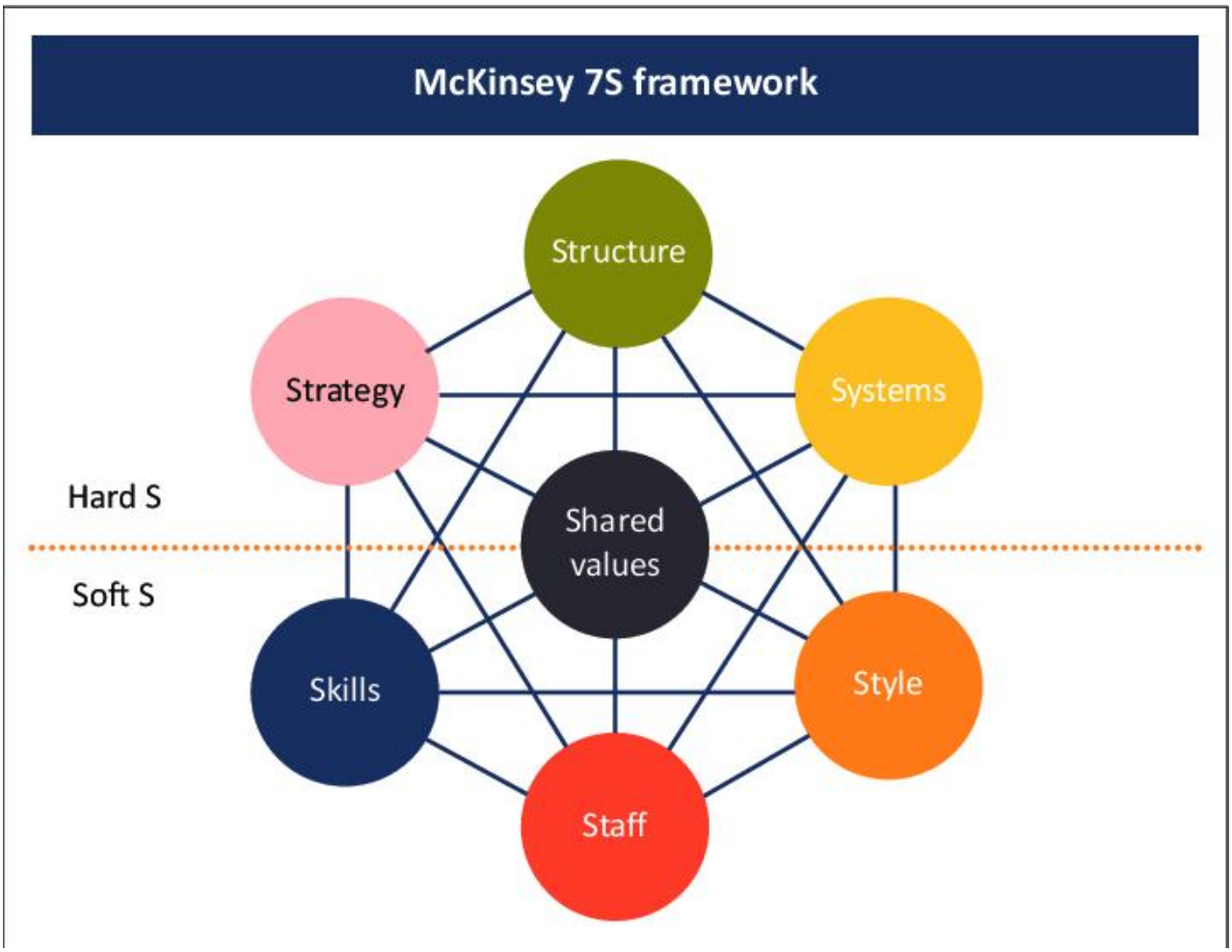


Figure 2.2: McKinsey 7 S Framework Applied to AI Driven Change (Source: Adapted from Northouse, P. G. (2022). Leadership: Theory and Practice (9th ed.). Sage Publications.)

Transformational leadership theory has attracted particular attention in the digital transformation literature. Transformational leaders inspire rather than direct they build trust, communicate a compelling vision, stimulate intellectual engagement and provide individualized support to team members (Northouse, 2022). Collectively these studies suggest that transformational leadership behaviors are particularly important during AI driven organizational change because they promote trust, communication and employee involvement.

A study by Singh and Sharma (2021) in Indian telecom firm from leaders that only followed orders and just try the top to down approach on every decision are much worse at leading rather than those who let employees have a say in the decisions and make them more involved in their adoption of ai related systems. This suggests that not only the change but how well its adopted matter to see a more beneficial technology change.

Digital vision and leadership capability were the strongest predictors of employee acceptance of AI systems Mhlanga (2022) a problem that is directly relevant to this study , middle managers who lacked clear direction from above often improvised their own communication strategies , leading to inconsistent employee experiences across the same organization. Mhlanga (2022) This middle manager pattern is a recognized feature of top down technological transformations (Abbu et al , 2022).

Abbu et al. (2022) study measure something called- the 'human dimensions of digital leadership' the combination of digital vision, digital agility, empathy and follower orientation that distinguishes effective digital leaders from less effective ones. All together the literatures indicate that effective digital leadership extend beyond communicating information. Successful AI driven change needs leaders to communicate a clear vision , actively involve employees , respond to concerns and provide continuous support throughout the change process. These findings were important in the analysis of the leadership practices at Ethio Telecom

Table 2.1 : Theoretical Frameworks on Change Management

Framework	Key Contribution	Relevance to This Study
Kotter's 8 Step Model (1996)	Provides a sequential road map for leading change; emphasizes urgency, vision and communication	Explains why skipped communication steps produce resistance
Lewin's Three-Stage Model (1947)	Frames change as unfreeze–change–refreeze; foundational emphasis on the human side	Anchors the study's view of AI adoption as a managed human process
McKinsey 7 S Framework	Requires alignment of seven organizational elements for change to succeed	Shows why technology change alone is insufficient without skill and staff changes

Transformational Leadership (Northouse, 2022)	Leaders inspire through vision, trust and individualized support	Explains the gap between information push communication and genuine engagement
Technology Acceptance Model (Davis, 1989)	Perceived usefulness and ease of use drive technology adoption	Explains customer and employee acceptance patterns in the data
Change Equation (Beckhard and Harris, 1987)	Change succeeds when dissatisfaction × vision × first steps > resistance	Explains why practical tool benefits overcame process level dissatisfaction

2.4 Employee Responses to AI Driven Change

Employee responses to AI driven change range from active adoption to passive resistance to outright refusal. The literature consistently identifies four main factors that shape which response predominates : the quality of communication about the change, the availability and relevance of training, the degree of employee involvement in the change process and individual characteristics such as age, education level and prior technical experience (Rajanala et al., 2024; Danaher and Tchouaket, 2024).

Fear of job displacement is one of the most studied employee responses to AI adoption. Rajanala et al. (2024) used an extended ordered probit model on data from 3,682 full time workers across multiple industries and found that job displacement fear is strongly predicted by worker age, sector and media exposure with older workers, senior service sector employees and those with higher internet use expressing the greatest concern. Their study found that this fear is largely perception based : it is driven by what people read and hear about AI's effects elsewhere, not by direct experience of job loss.

This differentiation between perceived and real risks is highly applicable in the context of Ethiopia. In its current state, AI introduction at Ethio Telecom is at its very beginning automation of the jobs is far from being started on a substantial scale. This fear, which employees show, is not produced locally, but is rather imported from foreign stories and tales about AI-driven disruptions in companies. Thus, handling this particular kind of perception is a special challenge faced by leaders in Ethiopia, which is not necessarily covered in standard change management literature.

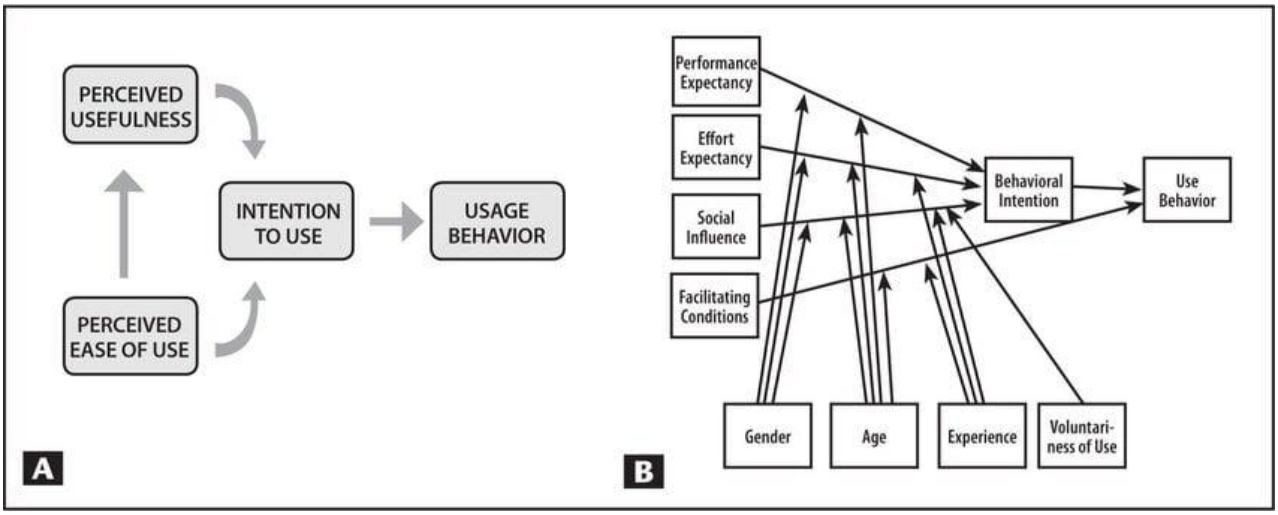


Figure 2.3: Technology Acceptance Model (TAM) (Source: Davis, F. D. (1989) MIS Quarterly, 13(3), 319–340.)

As already mentioned, the Technology Acceptance Model (TAM) proposed by Davis (1989) can explain the decisions made by employees regarding adopting new technologies. According to TAM, there are two basic variables that determine whether or not the technology will be accepted by its users. These variables include perceived usefulness (does this tool make me more efficient at work?) and perceived ease of use (is it easy to operate this thing?). Adoption occurs naturally if both variables are positive; otherwise especially, when ease of use is low employees' resistance can be expected.

One of such mechanisms of overcoming barriers is informal peer-based learning, which is often mentioned in digital workplaces learning literature. As shown by Lemmetty et al. (2023) in their two-year-long digital ethnography performed in a public sector workplace, peer-based informal knowledge exchange proved to be a much more adaptive strategy compared to formal training, especially in rapidly evolving environment. Colleagues can share tips, workarounds and explanations of certain things, which formal training cannot provide since it is prepared prior to the process.

Another important factor of successful technology adoption is employees' participation in technology roll-out decision-making processes, which has been examined extensively by researchers. Danaher and Tchouaket (2024) have analyzed organizational changes in Cote d'Ivoire telecom companies and showed that lack of employee participation in technology introduction decisions is the most stable reason preventing smooth adaptation. Even small participatory mechanisms e.g., filling out surveys, conducting feedback sessions or pilots reduce employees' resistance.

This literature informs the study's second objective, concerning how employees experience and adapt to AI-driven change

2.5 Customer Acceptance of Digital Services

The existing literature on consumer adoption of digital services in developing economies builds on the expanded Technology Acceptance Model. In their analysis of mobile payments adoption, Chandra et al. (2010) demonstrate that perceived ease of use, usefulness and trust in system security explain the largest proportion of variation. Trust in security of personal information becomes a key factor in countries where consumer experiences with fintech applications are limited; one bad experience may cause complete withdrawal from digital services.

The research builds on the general technology acceptance approach. The Unified Theory of Acceptance and Use of Technology (UTAUT) model expands on the theory of Davis by integrating such constructs as social influence and facilitating conditions into usefulness and ease of use variables whereas Rogers (2003) explains how innovations diffuse within the population based on their attributes and the readiness of adoption among various groups of people. Taken together, both frameworks help view customer acceptance in terms of not only characteristics of the service but also factors of trust, social environment, and facilitating conditions.

The discrepancy in consumer experience between urban and regional populations appears to be one of the major themes in the literature on mobile payments. More literate and connected urban dwellers are more likely to accept innovations and have a better experience adopting new digital tools. The reasons why consumers living in regional areas, older consumers and less educated

people face difficulties include unreliable connectivity, software developed for high bandwidth connections and lack of human assistance (GSMA, 2024).

It is worth mentioning the contribution of the literature on artificial intelligence chatbots to this research. Mostafa and Kasamani (2022) find that satisfaction with artificial intelligence chatbots has nothing to do with the availability and speed of connection. Instead, it depends on the resolution of the issue by a consumer during the chat. If it fails to address the problem i.e., it loops or needs a follow-up human intervention consumers will perceive it negatively regardless of its speed. This observation helps explain the problem resolution score (M = 2.10) in the Ethio Telecom customer data set.

Finally, the example of the regional leader in the telecommunications industry, Safaricom, provides relevant insights into customer experience management in telecommunication. According to the company's 2024 Annual Report, Safaricom has implemented a comprehensive AI-based strategy that includes chatbot Zuri addressing all routine requests, 89% accurate AI-based fraud detection and cloud technology for personalized service. A comparison with the position of Telebirr relative to M-Pesa two competing platforms in East Africa will help determine the company's place in the market.

This literature informs the study's third objective, concerning how customers adopt and accept Ethio Telecom's AI-enabled services.

2.6 AI Adoption in the Telecom Sector

Adoption of artificial intelligence in telecommunications generally occurs in a relatively predictable manner across the globe, albeit in different paces, depending on maturity level of the market, as well as capabilities of organizations in question. Initial adoption is likely to involve AI for the purpose of network operations fault detection, traffic management, and prediction since such application areas demonstrate tangible ROI and lack of need for customer-facing engagement (Verhoef et al., 2021). Customer-facing use cases, such as chatbots, recommendation systems, and automated assistance with bill payments, occur later, as they necessitate higher AI and data quality.

Telecommunications firms in Africa have achieved notable success in developing mobile money solutions, where the implementation of AI is gaining momentum through the use of machine

learning in fraud detection, scoring, and personalization. For example, the platforms like MTN MoMo, M Pesa developed by Safaricom, as well as mobile money solutions offered by Airtel Africa, use machine learning algorithms for managing large transaction volumes. According to the GSMA's research, transaction volume in Sub-Saharan Africa's mobile money system is estimated to exceed USD 700 billion per year as of 2024.

Table 2.2 : AI Adoption Stages in African Telecommunications

Stage	Description	African Examples
Stage 1 : Network AI	Fault detection, traffic routing, predictive maintenance	MTN, Ethio Telecom network monitoring
Stage 2 : Operations AI	Automated billing, back office processing, workforce scheduling	Airtel Africa billing automation
Stage 3 : Basic Customer AI	Simple chatbot queries, USSD automation, balance inquiries	Ethio Telecom Ardi, M Pesa USSD
Stage 4 : Advanced Customer AI	Personalization, complex query resolution, proactive engagement	Safaricom Zuri, MTN MoMo assistant
Stage 5 : Predictive AI	Credit scoring, churn prediction, AI driven pricing	Safaricom credit services, partial MTN

Ethio Telecom currently functions mostly at the Stages 1 to 3 levels. Monitoring of networks and automation of operations is fairly advanced. Ardi, the chatbot, answers customers' basic questions, though it hasn't achieved the level of resolving such issues that one would see in Stage 4. Such a situation is not out of the ordinary for companies of this size in the given market environment Ethio Telecom actually does better than most other companies in Sub-Saharan Africa (outside South Africa and Kenya).

2.7 AI in Ethiopia and Sub Saharan Africa

While Sub-Saharan has been showing rapid growth of interest towards artificial intelligence technologies, problems related to underdeveloped infrastructure are still relevant. Thus, according to the data provided by GSMA (2024), the penetration rate of mobile internet among the Sub-Saharan population was 30 percent, which means that the region is significantly lagging behind the global average value, which was over 60 percent back in 2023. It can be said that AI-based services will be inherently more available to urban and educated populations rather than rural majorities due to infrastructure-related issues.

It is possible to state that Ethiopia serves as an example of similar issues. The country has one of the most young and rapidly developing populations across Africa and has managed to achieve tremendous progress in terms of mobile penetration. However, there are still serious infrastructure problems outside Addis Ababa and some secondary cities called sheger cities. Network failures occurring in afternoon and evening periods may hinder data-based services such as Telebirr.

In this regard, it should be noted that Digital Ethiopia 2025 served as a driving force that facilitated AI adoption and digital services implementation. The program established goals concerning connectivity, literacy and digitization of public services, which pushed Ethio Telecom to accelerate their development roadmap. The pace of acceleration forced by external forces constitutes one of the distinctive characteristics of the case in contrast to organically evolving transformations implemented in other countries. There have not been many academic works focusing on AI and Ethiopia yet; one of the latest is Kassa and Worku (2025). The literature on leadership and change management in the country is not abundant as well. Therefore, this study may be considered important due to the contribution of new empirical data to the field where existing knowledge is based mostly on theory imported from elsewhere.

2.8 Research Gap

There are a number of observations to be made from the review of literature presented in this chapter. First, AI implementation will increase the efficiency of an organization, and the success of the process will depend on the change management; second, the acceptance of the changes among employees will depend on communication, training, participation and individual characteristics;

third, the acceptance among customers will depend on usefulness, usability, trust and quality of problem resolution. The piece of information missing from the reviewed sources is the actual relationship between these elements within an Ethiopian organization based on local and qualitative research. Existing studies consider only one aspect at a time: results, the resistance of employees or the adoption of AI by the customers. Furthermore, most studies are quantitative in nature and are focused on outcomes rather than providing an insight into the process itself. To the best of the researcher's knowledge, no existing studies have dealt with this question in the context of the Ethiopian telecommunications industry, where AI adoption is in its early stages , fears of employees are mainly perception based rather than drawn from local experience, peer-to-peer learning compensates for training, and customers are transitioning from analogue to digital services.

This study addresses that gap by exploring the experiences of managers, employees and customers within a single case and integrating them to answer the research questions set out in Chapter One.

2.9 Conceptual Framework

This studies conceptual framework is shown in Figure 2.4 . As it follows the exploratory, mixed-methods and qualitative-dominant design, it is a conceptual map that defines the phenomenon under investigation, the concepts with which it is explored, three groups of whose experiences are examined, and how their narratives are combined into practical lessons. Its purpose is to organize the research process and to ensure alignment between the research questions, data and analysis (Creswell & Creswell, 2018).

The centre of the framework is AI-driven organizational change at Ethio Telecom, which is approached as the change process and context of this study, not as a variable. It follows the study premise, stated in Sections 1.1 and 1.2, that using AI is essentially an organizational and human process, not a purely technical one. Therefore, it focuses on the leadership and experience of the change, not on the extent to which adoption of AI leads to a certain performance level.

The conceptual framework is the researcher's own synthesis of two well-developed bodies of theory in relation to the research questions of the study. First of all, it is the literature on organizational change management – Lewin's (1947) unfreeze-change-refreeze process and Kotter's (1996) focus on communication, training, involvement and management of resistance.

Secondly, it is the literature on technology acceptance and diffusion – the Technology Acceptance Model of Davis (1989), its extension made by Venkatesh et al. (2003) and the diffusion of innovations approach of Rogers (2003). The choice is based on the dual human aspect of the problem: internally, the employees need to be managed through the change; externally, the customers have to adopt the new services. The conceptual framework was developed as the result of analyzing the research questions and extracting the corresponding concepts and expressing them as the elements of the relevant block; therefore, it differs from the previous model that is borrowed and tailored specifically to the questions and data of this study.

The framework goes from the context of the change, to the leadership practices, then to the experiences of the employees and customers, to the integration of evidence and finally to the recommendations. The leadership block (Research Question 1) is concerned with managing AI-driven change through communication, training and support, employee involvement and management of resistance (Lewin, 1947; Kotter, 1996); the understanding of leadership in this framework is that of creation of conditions for the change experience. The employee block (Research Question 2) is about the internal experience of the change – fears and concerns, training and peer learning, involvement (Kotter, 1996; Rogers, 2003). The customer block (Research Question 3) is about the external experience of the services – perceived usefulness and ease of use, trust and service quality (Davis, 1989; Venkatesh et al., 2003). Employee and customer acceptance are treated as parallel perspectives on the same change, not as a causal chain, because each experience is investigated on its own.

There is a developmental loop at the leadership block, which indicates that the leading AI-driven change is a formative experience, which shapes the managers leading it. It is linked to the second part of Research Question 1 and Objective 4 and relies on the reflective and adaptive approaches to leadership, which see leaders' development through managing uncertainty of others (Schön, 1983; Heifetz, 1994).

The integration of evidence is made explicit in the framework for a mixed-methods and qualitative-dominant study. Specifically, it includes the combination of narratives of the three groups of people at the integration stage, where the qualitative core – open-ended questions, observation and secondary sources is the key source of information and is supplemented by the

descriptive questionnaire data. It results in the formation of the last block, which is about the lessons learned in the leadership development and recommendations on leading AI-driven change in the future (Research Question 4). The framework is used consistently throughout the rest of the study, with every concept being associated with the research question, data collection instrument and analytical themes as summarized in Table 2.3.

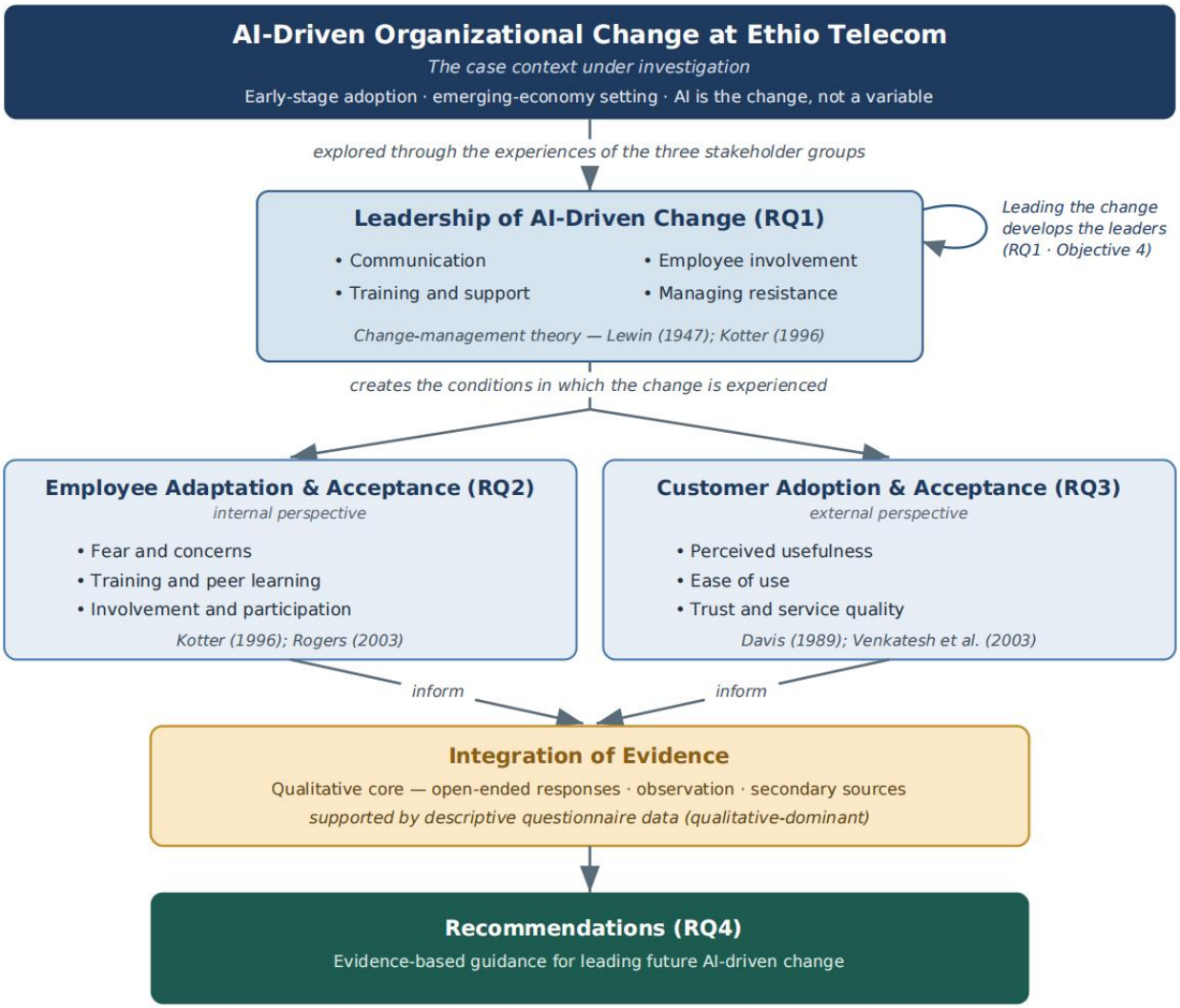


Figure 2.4. *Conceptual framework of the study.*

Source: Researcher's own synthesis, adapted from change-management theory (Lewin, 1947; Kotter, 1996) and technology acceptance and diffusion theory (Davis, 1989; Venkatesh et al., 2003; Rogers, 2003)

Table 2.3. Alignment of framework concepts, research questions, data sources and themes.

Framework concept	RQ	Main data sources	Corresponding theme(s)
Leadership of AI-driven change	RQ1	Manager interviews (open-ended); manager questionnaire; observation of supervisor–employee interaction; secondary sources	Theme 1: Communication gaps at multiple levels
Leadership development (the loop)	RQ1 / Obj. 4	Manager interviews; secondary sources	Theme 6: Leadership got stronger through the process
Employee adaptation and acceptance	RQ2	Employee interviews (open-ended); employee questionnaire; observation of employees using technology	Themes 2, 3, 4: fear from outside; peer learning filled the training gap; excluded from decisions but accepted the outcome
Customer adoption and acceptance	RQ3	Customer short-interview; customer questionnaire; observation of customers using self-service	Theme 5: Customer experience split by task and location
Integration and recommendations	RQ4 / Obj. 4	Integration of all of the above (qualitative core + descriptive support)	Central argument and recommendations (Chapters Four and Five)

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This Chapter describes the research methodology used to investigate how AI driven organizational change is managed at Ethio Telecom. It covers the research philosophy, design, study site, sampling strategy, data collection instruments, analysis procedures, validity and reliability considerations and ethical standards followed throughout the study.

3.2 Research Philosophy

This study adopts an interpretivism leaning pragmatic philosophy. Pragmatism is adopted because the study seeks practical understanding rather than allegiance to a single epistemology, and because it is the paradigm most consistent with combining qualitative and quantitative evidence in one design (Creswell & Creswell, 2018). The interpretivist lean follows from the study's priority: the central questions concern how participants understand and experience change, so meaning takes precedence and the numeric data play a supporting role. Interpretivism is appropriate because the study is concerned with meaning how managers, employees and customers understand and experience AI driven change rather than with measuring fixed objective quantities. On the other hand, pragmatic inquiry makes it possible to utilize qualitative and quantitative data in addressing the research questions, which is not limited by ontological principles either of pure interpretivism or positivism.

From the pragmatic perspective, research questions provide the point of departure when deciding on the methods to use. Because the research questions posed in this study call not only for descriptive patterns (for example, how many employees perceived the pace of change as too fast, or the mean rating for customer trust) but also, and primarily, for in-depth understanding (for example, why managers felt unsupported, or what peer learning looks like in practice), a mixed-methods design with a qualitative emphasis is appropriate.

3.3 Research Design

The design chosen for this study was a mixed-methods design with qualitative-dominant, exploratory single-case approach. This research is single case study research design , because of the uniqueness and boundedness of Ethio Telecom as an organization that undergoes transformation through the use of AI technologies. In the words of Yin (2018), a case study is appropriate when a researcher seeks an in depth understanding of a contemporary phenomenon within its real life context. Ethio Telecom was chosen as a critical case since it is among the few Ethiopian organizations implementing AI technologies. Multiple sources of evidence were utilized in this study in form of interviews, questionnaires, observations and documentation, thus enabling triangulation. The aim was not statistical generalization but analytic generalization where findings may provide insights relevant to similar organizations.Each of those labels is deliberate. Exploratory and not descriptive in nature because the phenomenon of interest – how AI-led change takes place at Ethio Telecom – has not been explored before in this specific setting and hence the aim of the research is to explore it, not to describe any pre defined variable or test any hypotheses (Section 1.4). It is a case study approach because the unit of analysis is one bounded system – Ethio Telecom – investigated thoroughly via multiple data sources, which is the proper design to analyze a phenomenon of the present day in its real-world organizational setting (Yin, 2018).It is qualitative-dominant because the questions posed are mainly about meanings and experiences, captured through qualitative instruments, namely open-ended interviews, non-participant observation, and secondary sources, which form the qualitative core of the study. The Likert-scale questionnaires make up a secondary, quantitative strand that provides descriptive support rather than the core material itself.

The data collection for the study is cross-sectional. Primary data was gathered in a single round during April–May 2026. Single round of data collection is usual and proper for such kind of case study as it is focused on giving an in-depth account of how participants view and experience change rather than measuring changes occurring over time. Depth of the investigation and the multiple simultaneous sources of data, not their repetition, constitute the foundation of claims made (Yin, 2018; Creswell & Creswell, 2018).

Qualitative and quantitative data is interpreted together in order to make descriptive findings illustrate the range of a pattern and qualitative findings explain the mechanism behind it. The process of the integration is outlined in Section 3.9.3.

3.4 Study Site

The study was conducted at Ethio Telecom, Ethiopia's only major telecom operator and one of the largest public enterprises in the country. The organization was selected because of its active and well documented implementation of AI technologies, including the Ardi chatbot, Telebirr, biometric registration systems and data analytics dashboards. It is also central to Ethiopia's Digital Ethiopia 2030 vision making its change management practices relevant beyond the organization itself.

Data were collected across multiple branches in Addis Ababa specifically Gofa, Shegole, Churchill Avenue, Bisrate Gebreal, Bole Michael and Mesalemiya well as at office departments. Some customer respondents were from regional city (sheger city) , providing partial geographic diversity in the customer data.

3.5 Target Population

The target population comprised three groups associated with AI-driven change at Ethio Telecom. The first was the organizations managerial staff — middle-level managers and team leaders with direct responsibility for leading teams through AI-related change. The second was employees working in departments directly affected by AI-enabled and digital systems; at the time of the study Ethio Telecom employed 44,031 staff (Ethio Telecom, 2026), of whom this group forms a subset. The third was the organizations customer base, which by the first half of the 2025/2026 fiscal year stood at approximately 87.1 million subscribers, including about 49 million mobile-data users (Ethio Telecom, 2026) the relevant sub population here was customers who actively use at least one AI-enabled digital service Telebirr, the Ardi chatbot, the self-service application or biometric registration.

Because no public register lists individual employees, managers or service-using customers, a complete sampling frame was not available for any group. Consistent with the study's exploratory, qualitative-dominant design, participants were therefore not selected to be statistically representative of these populations but purposively for their direct experience of AI-driven change

(Section 3.6). The population figures are reported to situate the study and to make explicit the gap between the small purposive sample and the very large populations it is drawn from; this gap is acknowledged as a limitation on statistical generalization (Section 1.6) and is the reason the questionnaire data are used descriptively rather than inferentially (Section 3.9.1).

3.6 Sampling Technique and Sample Size

Purposive sampling was used for all three groups. Purposive sampling selects participants based on specific criteria relevant to the research questions in this case, direct experience with AI driven change at Ethio Telecom rather than random selection. This approach is standard in qualitative and mixed methods research where the goal is depth and relevance rather than statistical representative (Creswell and Creswell, 2018).

For employees, criteria included working in a department where new digital systems had been introduced and having at least six months of experience with those systems. For managers, criteria included direct supervisory responsibility for teams that had been through AI related changes. For customers, criteria included regular use of at least one Ethio Telecom digital service in the preceding three months.

Table 3.1 : Sample Size by Stakeholder Group

Stakeholder Group	Sample Size (n)	Sampling Criteria
Employees	25	Departments affected by AI/digital changes; min. 6 months experience
Managers / Team Leaders	15	Direct supervisory role; team went through AI related changes
Customers	30	Regular users of at least one ET digital service in past 3 months
Total	70	

The total sample of 70 participants is appropriate for an exploratory, qualitative dominant case study. The qualitative literature suggests that sample sizes in this range are sufficient for thematic analysis and pattern identification, particularly when data saturation is monitored meaning that new interviews and observations stop revealing genuinely new themes (Braun and Clarke,

2006). In this study, saturation in the employee and manager interviews was reached at approximately 20 and 12 interviews respectively a point judged to have been reached when the last few interviews in each group produced no new codes or themes during analysis; all participants were nonetheless retained in the analysis to maximize coverage across departments and seniority levels..

3.7 Data Collection Methods

Four data collection methods were used to ensure triangulation the use of multiple independent sources to confirm or challenge findings.

3.7.1 Semi Structured Interviews

Semi structured interviews were conducted with all 25 employees and all 15 managers. Each interview followed a prepared guide of open ended questions but allowed the researcher to probe interesting responses and follow unexpected directions. Employee interviews focused on their experience of the change process, what helped them adapt, what their leaders did well or poorly and how they felt about AI's long term role in their jobs. Manager interviews focused on their leadership challenges, how they handled resistance and uncertainty, what support they received from above and what they would do differently.

Interviews were conducted in person at Ethio Telecom offices and branches and were recorded with participant consent and transcribed for analysis. Average interview duration was approximately 10 to 20 minutes.Even though these interviews were relatively short, they were quite concentrated. They all adhered to a structured guide built around a single, bounded topic which was the experience of changes driven by artificial intelligence, and they were conducted with the respondents who were purposefully selected because of their participation in these changes. This information was also supplemented with the open-ended questionnaire data, non-participant observation, and secondary literature. Thus, depth in the current research is achieved through the focus of questions as well as convergence of several sources of information.

In addition, customers responded to a short set of open-ended interview questions administered alongside their questionnaire (the "Short Interview Questions" in the Appendix), covering their experience of Ethio Telecom's digital services, what helped or hindered their use of them, and their views on how the change was handled. Although briefer than the employee and manager

interviews, these open-ended responses form part of the qualitative core of the study and were analyzed thematically together with the interview transcripts (Section 3.9.2).

3.7.2 Questionnaires

Likert scale questionnaires were administered to all three stakeholder groups. The employee survey consisted of 13 questions in four parts: adaptation, difficulties, leadership roles, and change effect. The manager survey included 22 questions in four parts: vision and communication, resistance and management of adaptation, training and development and leadership impact. Finally, The customer questionnaire was administered with 15 items across three sections — accessibility and ease of use; trust and quality; and leadership-driven change and customer experience — of which 11 were retained for the descriptive analysis (see Section 3.9.1). All of the questions on all surveys used a five-point scale ranging from one (strongly disagree) to five (strongly agree).

3.7.3 Non Participant Observation

Six observations were carried out among different Ethio Telecom branches during April to May 2026. The observation was made on customers interacting with self-service technology, employees interacting with technology while providing services, and supervisors interacting with employees. The researcher acted as an observer without participating in any service activity. Structured observation notes were taken by the researcher based on the observation checklist designed for the research.

The checklist comprised twelve structured items grouped under four dimensions — customer engagement with digital services, employee use of digital and AI tools, leadership and supervision behaviour, and overall integration — each recorded as a binary (Yes/No) observation with an accompanying notes field (Section 3.8). The observation therefore produced two data types: binary counts across the six sessions and qualitative field notes, both of which were analyzed and integrated into the thematic findings (Section 3.9.2)

3.7.4 Secondary Data

Published articles, annual reports of Ethio Telecom, GSMA, and annual reports of Safaricom were used as secondary data sources. These sources were treated as data in their own right: they were

subjected to document analysis and read thematically against the same analytical framework as the primary data, so that they could corroborate, contextualize or challenge the interview, questionnaire and observation findings rather than serve merely as background (Section 3.9.2

Table 3.2 : Data Collection Instruments

Instrument	Group	Purpose	Format
Semi structured interview	Employees, Managers	Explore lived experience of change	In person, recorded
Likert questionnaire	Employees, Managers, Customers	Measure attitudes and perceptions	Paper / digital form
Observation form	Branch staff and customers	Document observable behaviors and interactions	Structured field notes
Secondary data review	N/A	Contextualize and compare findings	Document analysis

3.8 Research Instruments

Questionnaires for all three categories of respondents were created exclusively for this study based on the research questions formulated in the conceptual framework, including the literature review on change management and digital transformation, particularly TAM model (Davis, 1989), change management strategies by Kotter (1996), and digital leadership competencies of Abbu et al. (2022).

Alongside the questionnaires, semi-structured interview guides were prepared for employees and managers, and a short open-ended interview schedule for customers. These were likewise derived from the conceptual framework and the research questions, with each block of questions mapped to a framework concept (Table 2.3)

The form included four dimensions: customer engagement with digital and AI-based technologies; usage of digital technologies and automation by employees; leadership and supervision behaviors; assessment of overall integration level. There were three to four observation criteria per dimension using Yes/No questions with notes fields for researchers.

Two employees and one manager were interviewed in pilot interviews. Minor adjustments were made to question wording following the pilot.

3.9 Data Analysis Procedures

3.9.1 Quantitative Analysis

Quantitative data from the questionnaires was analyzed using SPSS Version 25. The analysis focused on descriptive statistics : frequencies, valid percentages, cumulative percentages, means and standard deviations. Inferential statistical tests, like independent samples t-tests and one way ANOVA, were also avoided in this analysis. It was a conscious decision and not an oversight because the samples were obtained through purposeful sampling (Section 3.6) and hence did not serve any representative purposes for inferential testing no matter how many there might have been.

This meant that the quantitative part of the research remained confined to descriptive statistics including frequencies, valid and cumulative percentages, means, and standard deviations.

The mean is calculated as the arithmetic average of all valid responses for an item. For a Likert item with responses coded 1 to 5, the mean indicates the central tendency of the group's attitude. A mean above 3.50 indicates general agreement; a mean below 2.50 indicates general disagreement; means between 2.50 and 3.50 indicate a neutral or mixed response.These means and standard deviations are read as indicative only. They show how widely a view was held within this sample and where opinion was divided, and the 2.50 to 3.50 band is a reading aid for whether a rating leans positive, neutral, or negative, not a threshold for any claim about the wider population. The formula for the mean is shown in Equation 3.1.

$$\text{Mean } (\bar{x}) = \Sigma x \,/\, N \tag{3.1}$$

where Σx is the sum of all response values and N is the number of valid responses.

The standard deviation measures the spread of responses around the mean. A low standard deviation indicates that most respondents have given similar answers; a high standard deviation indicates more variation in views. The formula for sample standard deviation is shown in Equation 3.2.

$$SD\ (s) = \sqrt{[\ \Sigma(x \quad \bar{x})^2 \,/\, (N \ \ 1)\ ]} \tag{3.2}$$

where x is each individual response value, $\bar{x}$ is the mean and N is the number of valid responses. SPSS uses N 1 in the denominator (Bessel's correction) for sample standard deviation, which is the convention used throughout this thesis.

The customer questionnaire data were measured using fifteen different Likert scale questions. While eleven questions out of these were used for description in the results part, the remaining four questions (Question numbers 12 to 15 from the Appendix) pertained to their attitudes toward AI services, prior notice of any changes made in the services offered, trust toward the management of the organization, and overall customer satisfaction with the digitization process. All these future-focused questions were very much linked with other aspects explored by customer interviews in detail. Consistent with the mixed-methods, qualitative-dominant design of this study, these four items were explored through the customers' open-ended responses rather than reported separately as descriptive statistics (N = 30)

3.9.2 Qualitative Analysis

The qualitative data — the open-ended responses from employees, managers and customers (employees' "Open Ended Questions" and managers' and customers' "Short Interview Questions"), the non-participant observation field notes, and the secondary sources — were analyzed using Braun and Clarke's (2006) six-phase thematic analysis: familiarization, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the report. The themes were therefore developed from the participants' own words in these open-ended responses, not derived from the Likert questionnaire scores; the questionnaire results were used afterwards only to indicate how widely each theme was reflected across respondents.

Initial coding was done by reading each interview transcript multiple times and noting recurring ideas, phrases and patterns. Similar codes were categorized under themes and validated for consistency with the entire database. Six themes were identified, each supported by multiple interview responses and consistent with the quantitative data patterns.

The observation data was analyzed descriptively. Each of the twelve binary observation items (Yes/No) was tallied across the six sessions and the researcher notes were reviewed for patterns and unexpected findings .and the resulting patterns were folded into the relevant themes rather than reported in isolation.The secondary sources were analyzed through the same thematic lens,

and the themes arising from them were integrated with those from the primary data

3.9.3 Integration of the Qualitative and Quantitative Strands

Because this is a mixed-methods study, the two strands were brought together explicitly rather than reported side by side. Integration took place at the interpretation stage and followed a consistent logic: the descriptive questionnaire results established how widespread a perception was, while the qualitative data explained the reasoning and experience behind it. Because the employee and manager questionnaires use different items and different respondent groups, any comparison between them is read as a directional contrast in perception rather than as a measured point difference. For example, employees rated their own involvement in change decisions low (mean = 2.20) while managers rated their involvement of staff high (mean = 4.40); this contrast signalled a pattern that the open-ended responses then explained, showing that managers and employees understood "involvement" differently. Where the strands converged, the finding was strengthened; where they diverged, the divergence itself became an analytical finding. The integrated account, organized around the study's central themes, is presented in Chapter Four.

3.10 Validity and Reliability

3.10.1 Quantitative Reliability

Internal consistency of the questionnaire scales was assessed using Cronbach's alpha. The formula for Cronbach's alpha is shown in Equation 3.3.

$$\alpha = (k/(k\ \ 1)) \times (1\ \ \ \ \Sigma\sigma^{2}{}_{i}/\sigma^{2}{}_{t}\ ) \qquad (3.3)$$

where k is the number of items in the scale, $\Sigma\sigma^2_i$ is the sum of item variances and σ^2_t is the variance of the total scale score. An alpha above 0.70 is generally considered acceptable for research purposes (Nunnally, 1978).Alpha was used here as a standard internal-consistency check on each block of items at the instrument stage, not as a basis for computing composite scores. Because Chapter Four reports each item on its own rather than through summed scales (Section 3.9.1), these coefficients describe the quality of the instrument and do not carry any finding. Alpha is also sensitive to the number of items: scales of only two or three items tend to return lower values even when their items are consistent (Tavakol & Dennick, 2011), so the borderline coefficients on the shortest blocks are read in that light rather than as weak items

Table 3.3 : Cronbach's Alpha Reliability Coefficients

Questionnaire Section	No. of Items	Cronbach's Alpha	Interpretation
Employee : Adaptation (A)	3	0.74	Acceptable
Employee : Struggles (B)	3	0.71	Acceptable
Employee : Leadership Roles (C)	5	0.78	Good
Employee : Effect of Change (D)	2	0.69	Borderline acceptable
Manager : Vision & Communication	5	0.81	Good
Manager : Resistance Management	6	0.76	Good
Manager : Training & Building	5	0.79	Good
Manager : Leadership Outcomes	6	0.88	Very Good
Customer : Accessibility & Ease of Use	4	0.72	Acceptable
Customer : Trust, Quality, Improvement	4	0.73	Acceptable
Customer : Leadership Driven Change	3	0.68	Borderline acceptable

Note: alpha's value is used to check the reliability score even though composite scale scores are not used in this test but since the value of alpha goes down with the number of items , the borderline values for the two and three item scales (0.68 – 0.74) should be considered accordingly to their few items and not as a weak reliability.

3.10.2 Qualitative Trustworthiness

The trustworthiness of the qualitative findings was addressed using Lincoln and Guba's (1985) four criteria. Credibility was supported through triangulation across interviews, questionnaires, observation and secondary sources, and through informal member checking, in which key themes were shared with two participants who confirmed that the interpretations resonated with their

experience. Transferability was supported by thick description, giving readers enough contextual detail to judge how far the findings apply elsewhere. Dependability was supported by documenting the analytical procedure (the six phases above) so that the route from data to themes is transparent. Confirmability was supported by grounding every theme in participants' own words and retaining an audit trail of codes and supporting extracts, so the findings trace back to the data rather than to the researcher's assumptions. As is expected in qualitative work, the researcher's own position was considered throughout. The researcher approached the study as an MBA student rather than as a member of Ethio Telecom's staff, and had no authority over any participant, which helped participants speak freely. To reduce the risk of the researcher's own views shaping the results, the themes were built only from what participants said, codes and supporting quotes were kept as an audit trail, and the questionnaire numbers were used as a separate check on how widely each theme was shared rather than as confirmation of what the researcher expected to find.

3.11 Ethical Considerations

This study followed the ethical standards required by Addis Ababa University for academic research. Participation was entirely voluntary. All participants were informed of the study's purpose, the type of data being collected, how it would be used and their right to withdraw at any point without consequence. Informed consent was obtained in writing from all interview participants.

Anonymity and confidentiality were maintained throughout. Interview transcripts were coded by participant number rather than name. No individual's responses are identifiable in the findings. Data were stored securely and will be deleted upon thesis completion in line with university requirements.

For customers, special care was taken to ensure that participation did not interfere with their service access or create any obligation or discomfort. Customer participants were approached only at times and in settings where they were not in the middle of a service transaction.

The use of secondary data from published studies and organizational reports was conducted in accordance with intellectual property norms. All sources are acknowledged with full citations.

CHAPTER FOUR

DATA ANALYSIS AND FINDINGS

4.1 Introduction and Analytical Approach

This chapter presents and analyzes the data collected for the study. Data were collected from three groups at Ethio Telecom – 25 employees, 15 managers and 30 customers. Three types of data were collected from them. The questionnaires yielded Likert-scale ratings; the open-ended questions in the same forms ("Open Ended Questions" of the employees and "Short Interview Questions" of the managers and customers) yielded verbal responses; and six observations in branch and back-office settings yielded a structured field report. A set of secondary data sources was reviewed too. Consistent with the mixed-methods, qualitative-dominant and exploratory research design described in Chapter Three, the verbal responses, the observation and the secondary data make up the qualitative core of the analysis, whereas the ratings serve as descriptive data.

The quantitative data analysis was limited to descriptive statistics: frequencies, valid and cumulative percentages, means and standard deviations, the latter using the $N-1$ (sample) denominator consistently, as discussed in Chapter Three. Inferential tests were not conducted because the sample was selected purposively, not randomly, and was not meant to be representative of the whole organization. As for the background variables of a nominal nature, only the frequencies and percentages are reported, since the average value of a category such as department or location does not have a meaning. The questionnaire results are interpreted here for one purpose: to see how wide a certain view was shared by each group. They are not the source of the themes.

The qualitative data analysis was conducted using the six-phase thematic analysis proposed by Braun and Clarke (2006). This methodology was chosen due to its neutrality in terms of theory and appropriateness to explore people's experience of a change. All six phases were followed consecutively. First, the verbal responses, the observation notes and the secondary sources were read several times to be familiar with the data. Then, initial codes were identified for the recurring concepts in the data, line by line. After that, similar codes were clustered to form potential themes. Next, the potential themes were cross-checked against the coded extracts and the complete set of

responses to verify their coherence and exclusivity. Finally, each theme was defined, named and paired with the extracts of participants' responses that illustrate it most clearly. The themes thus emerged from the participants' words, and the questionnaire numbers were added later only as an indicator of how common each pattern was.

The field report is binary data. Each of the twelve checklist items was a yes/no judgement, so the frequency of "yes" answers among all 12 checklist items was calculated separately for each of the six sessions, and then the written notes and any unexpected events were interpreted in the same way as the interview responses. The patterns emerging from them were included in the themes and not considered separately. The secondary sources were reviewed through the same thematic prism, and the issues emerging from them were incorporated into the findings in parallel with the primary ones.

Trustworthiness was achieved through the application of the four criteria outlined by Lincoln and Guba (1985). The credibility is ensured by the triangulation of the questionnaires, the verbal responses, the observation and the secondary sources and the informal member checking in which the main themes were discussed with two participants, and they confirmed that their reading of the data was correct. Transferability is supported by a description of the setting in sufficient detail that would allow the reader to see where the findings could be applied. The dependability follows from the explanation of the above process of data analysis in sufficient detail. Confirmability stems from linking each theme to the participants' words only and keeping the audit trail of codes and supporting extracts.

Finally, the two sets of findings were combined rather than reported separately. Following the logic of the mixed-methods integration (Fetters, Curry and Creswell, 2013; Creswell and Creswell, 2018), the descriptive ratings show how wide a certain perception was spread, and the qualitative data explain the reasoning and experience behind it. When the two coincide, the finding is stronger; when they differ, the very difference is treated as a finding. Such integration is presented below in Section 4.6 in the joint display format. Throughout the analysis, the themes are interpreted within the change management and technology acceptance frameworks elaborated in Chapter Two: especially, the works of Lewin (1947), Kotter (1996), the McKinsey 7-S framework, transformational leadership (Northouse, 2022), the change equation (Beckhard and Harris, 1987), the Technology Acceptance Model (Davis, 1989) and the unified model derived from it.

One idea lies throughout the entire chapter and unites the themes. At Ethio Telecom the technical aspect of the change, namely the adoption of AI era digital systems and tools, largely succeeded: people use the systems and find them valuable. The human aspect of the same change was much less successfully managed. Staff and, to some extent, their managers gained their competence mostly by ad hoc, peer and self-directed learning rather than through proper preparation, communication and involvement. A consistent gap emerges between managers' positive account of how the change was managed and the critical accounts of both employees and customers; the gap is interpreted here not as dishonesty but as a methodological finding related to the social desirability bias. The only obvious success in managing the human aspect of the change is that leading a flawed change builds leadership competence. The following sections elaborate each aspect of the argument from the findings.

4.2 Profile of the Respondents

The following are the three groups mentioned above in terms of numbers and percentages. The profile is provided so that the findings to follow may be viewed within their proper context.

Table 4.1: Employee Respondent Profile (n = 25)

Characteristic	Freq.	%	Category group
Age – Under 25	2	8.0	Age group
Age – 25–34	7	28.0	
Age – 35–44	8	32.0	
Age – 45–54	7	28.0	
Age – 55 and above	1	4.0	
Education – Secondary certificate	1	4.0	Education
Education – Diploma	8	32.0	
Education – Bachelor’s degree	14	56.0	
Education – Postgraduate degree	2	8.0	
Tenure – Less than 2 years	4	16.0	Years at Ethio Telecom

Characteristic	Freq.	%	Category group
Tenure – 2–5 years	6	24.0	
Tenure – 6–10 years	7	28.0	
Tenure – More than 10 years	8	32.0	
Department – Customer Service	8	32.0	Department
Department – IT Technology Dev.	4	16.0	
Department – Network Operations	4	16.0	
Department – Finance	4	16.0	
Department – HR	2	8.0	
Department – Digital Services / Telebirr	2	8.0	
Department – Hardware Installation	1	4.0	
AI / digital tools introduced – Significantly	18	72.0	Reach of change
AI / digital tools introduced – In small ways	7	28.0	
Uses AI tools – Every day	5	20.0	Frequency of use
Uses AI tools – Sometimes	15	60.0	
Uses AI tools – Rarely	5	20.0	

The employee sample included seven different departments, with the biggest proportion belonging to Customer Service (32.0%), followed by IT, Network Operations and Finance with 16.0% each. The age group 35-44 constituted the largest (32.0%), over half the participants possessed a Bachelor's degree (56.0%), and a third were with the company for over ten years (32.0%). All employees agreed that AI/digital technologies had entered their departments, almost all of them on a substantial scale (72.0%), and all of them used those technologies sometimes.

Table 4.2: Manager Respondent Profile (n = 15)

Characteristic	Freq.	%	Category group
Role – Team Leader	10	66.7	Role
Role – Middle Manager	4	26.7	
Role – Senior Manager	1	6.7	

Characteristic	Freq.	%	Category group
Department – Customer Service	5	33.3	Department
Department – Hardware Installation	3	20.0	
Department – IT Technologies Dev.	2	13.3	
Department – HR	2	13.3	
Department – Network Operations	1	6.7	
Department – Finance	1	6.7	
Department – Digital Services / Telebirr	1	6.7	
Tenure – 2–5 years	10	66.7	Years of experience
Tenure – 6–10 years	4	26.7	
Tenure – More than 10 years	1	6.7	
Education – Bachelor's degree	8	53.3	Education
Education – Postgraduate degree	7	46.7	
Team affected by AI – Significantly	5	33.3	Reach of change
Team affected by AI – Somewhat	7	46.7	
Team affected by AI – Not yet	3	20.0	

Two thirds of the managers were Team Leaders (66.7%), with four Middle Managers and one Senior Manager. Customer Service was again the most represented unit (33.3%). All managers held at least a bachelor's degree, and the group split fairly evenly between bachelor's (53.3%) and postgraduate (46.7%) holders. Most had two to five years of experience (66.7%). On the reach of the change, four in five managers said their team had been affected to some degree, while three said it had not yet reached them.

Table 4.3: Customer Respondent Profile (n = 30)

Characteristic	Freq.	%	Category group
Use of Ethio Telecom – Less than 1 year	2	6.7	Duration of use
Use of Ethio Telecom – 1–3 years	4	13.3	

Characteristic	Freq.	%	Category group
Use of Ethio Telecom – 4–7 years	12	40.0	
Use of Ethio Telecom – More than 7 years	12	40.0	
Age – Under 25	4	13.3	Age group
Age – 25–34	8	26.7	
Age – 35–44	11	36.7	
Age – 45–54	4	13.3	
Age – 55 and above	3	10.0	
Education – No formal education	1	3.3	Education
Education – Primary or secondary	5	16.7	
Education – Diploma	12	40.0	
Education – Degree or above	12	40.0	
Location – Addis Ababa	21	70.0	Location
Location – Regional city or town	9	30.0	
Digital service – Used	30	100	Service used
First action on a problem – Ardi chatbot / app	9	30.0	First point of contact
First action on a problem – Call hotline (994)	10	33.3	
First action on a problem – Visit a branch	11	36.7	

The customers were mostly long-standing users: four in five had been with Ethio Telecom for more than four years. The largest age band was 35–44 (36.7%), and education split evenly between diploma holders and those with a degree or above (40.0% each). Seven in ten were in Addis Ababa and the rest in regional towns, a split that matters for the customer findings later. When a problem arises, the three routes, the app, the hotline and the branch, were used in almost equal measure, which already hints that the digital channel had not replaced the human one.

4.3 Descriptive Findings from the Questionnaires

The results of the questionnaires for each group are presented here as descriptive evidence for the themes discussed below. Statistics for all items for each group are presented in a combined table

but the discussion will be confined only to those items relevant to the analysis and not all of the items included in the table will be discussed. The rating scale ranges from 1 (strongly disagree) to 5 (strongly agree). A mean greater than 3.50 will indicate broad agreement, less than 2.50 broad disagreement and a mean between 2.50 to 3.50 indicates neutrality.

Table 4.4: Employee Questionnaire – All Items (n = 25)

Item	Statement	Mean	SD
Q1	I can use the new digital tools at work without trouble	4.16	0.688
Q2	I know why Ethio Telecom is making these technology changes	3.72	0.843
Q3	The training I received helped me use the new systems	2.96	0.676
Q4	I am worried that machines or AI might take away my job	3.08	1.152
Q5	Changes have been happening too fast to keep up	3.92	0.759
Q6	I was told about the changes before they happened	3.00	0.866
Q7	My supervisor explained why the technology changes were happening	3.72	0.678
Q8	My manager gave me the help and tools I needed	3.60	0.866
Q9	When I share my worries or ideas, my leaders listen	2.92	0.812
Q10	Employees like me took part in deciding how technology was introduced	2.20	0.645
Q11	Senior leaders had a clear plan for managing the change	3.80	0.764
Q12	Technology changes have made my daily work easier and faster	4.00	0.707
Q13	Because of these changes I learned new skills or gained opportunities	3.76	0.831

Note. SD computed with the N–1 (sample) denominator. Scale: 1 = strongly disagree to 5 = strongly agree.

Two patterns stand out for the employees. The first is competence and practical benefit. Confidence in using the tools is the highest-rated item (Q1 = 4.16), and the sense that the change

made daily work easier is close behind (Q12 = 4.00), with no one disagreeing on either. The second is a weak support structure around that competence. Training is the lowest item in the adaptation section (Q3 = 2.96), advance notice of change was uneven (Q6 = 3.00), and taking part in the decisions about how technology was introduced is the lowest-rated item on the whole employee form (Q10 = 2.20), where the highest single answer was a neutral 3 and not one employee agreed. Between these two poles sit the human strains: the pace of change was felt as too fast (Q5 = 3.92), and worry about AI replacing jobs was divided, with the widest spread of any item (Q4 = 3.08, SD = 1.152), which signals that the group disagreed sharply rather than sat in the middle. Finally, the leadership items show communication running one way: employees agreed that managers explained the change (Q7 = 3.72) far more than they felt managers listened to them (Q9 = 2.92).

Table 4.5: Manager Questionnaire – All Items (n = 15)

Item	Statement	Mean	SD
Q1	I explained the changes clearly to my team	4.33	0.724
Q2	Senior management explained the changes clearly to me	3.33	0.617
Q3	My team understood the purpose and direction of the changes	4.27	0.594
Q4	I used more than one way to communicate	4.07	0.458
Q5	There was a clear aim and vision from the top	4.47	0.516
Q6	I ran into real resistance from employees †	2.40	0.632
Q7	I had good ways to deal with team concerns	4.20	0.561
Q8	My team got enough time and preparation	3.80	0.561
Q9	The pace was too rapid for employees to settle †	2.20	0.862
Q10	Adaptation was connected with age, tenure or education	4.20	0.414
Q11	I involved my team in decisions about how technology was introduced	4.40	0.632
Q12	My team had enough training and resources	4.27	0.594

Item	Statement	Mean	SD
Q13	Training came before or during rollout	4.07	0.594
Q14	Training was practical and relevant	4.27	0.594
Q15	I got enough support and guidance from senior leadership	4.53	0.516
Q16	I had to work out my own way without support †	3.67	0.617
Q17	New AI tools made me better as a leader	4.67	0.488
Q18	The changes made my team more productive and efficient	4.67	0.488
Q19	The changes brought real development, not just extra effort	4.67	0.488
Q20	My team can give better service than before	4.60	0.507
Q21	I feel confident leading future technology changes	4.87	0.352
Q22	Overall, the changes at Ethio Telecom have been handled well	4.40	0.737

Note. SD computed with the N–1 denominator. Scale: 1 = strongly disagree to 5 = strongly agree. † Reverse-worded items: a low mean means managers disagreed with the statement (so a low Q6 means little resistance was reported, and a low Q9 means the pace was not seen as too fast).

The managers rate the change far more favourably than the employees do, and that contrast is itself important. Managers are confident that they explained the change well (Q1 = 4.33), that the aim from the top was clear (Q5 = 4.47), that they received enough support from senior leadership (Q15 = 4.53) and that they involved their teams in decisions (Q11 = 4.40). They report very strong outcomes, with feeling more capable as a leader, a more productive team and real development all at 4.67, and confidence in handling future changes the single highest score anywhere in the study (Q21 = 4.87). Two readings cut against this otherwise smooth picture. The first is internal: the one communication item that drops is the message managers themselves received from above (Q2 = 3.33), well below their rating of the message they passed on (Q1 = 4.33), and they also admit to having had to find their own way without support (Q16 = 3.67). The second is the contrast with their staff: on the reverse-worded items, managers largely disagreed that the pace was too rapid (Q9 = 2.20), exactly the strain employees rated highly (Q5 = 3.92). The managers, in short, report a well-run change that their employees experienced rather differently.

Table 4.6: Customer Questionnaire – All Items (n = 30)

Item	Statement	Mean	SD
Q1	I find digital services easy to use on my own	3.53	1.358
Q2	Most of the time I can sort my issue without visiting a branch	3.23	1.073
Q3	Ethio Telecom gives me enough guidance when I get stuck	3.80	0.714
Q4	Digital services are usually up and working when I need them	3.77	0.935
Q5	I trust Ethio Telecom to keep my information safe	3.33	0.547
Q6	Service quality has improved after the digital change	3.57	0.774
Q7	Automated services sort requests faster than a human agent	3.03	0.718
Q8	Digital services stay consistent and reliable over time	3.60	1.276
Q9	Service has become more consistent over the past two years	3.70	0.952
Q10	Ethio Telecom understands ordinary customers, not just tech-savvy ones	3.70	0.915
Q11	When something goes wrong I can get it fixed quickly and without hassle	2.10	0.845

Note. SD computed with the N–1 denominator. Scale: 1 = strongly disagree to 5 = strongly agree. The four future-facing items (12–15 on the form) were explored through the open-ended answers rather than reported here, as set out in Chapter Three.

The customers offer a predominantly positive yet varied set of responses. They believe that there is sufficient assistance when they are unable to do something (Q3 = 3.80), that the systems work most of the time (Q4 = 3.77), that the quality has become better (Q6 = 3.57), that the service became more reliable and reaches common users (Q9 and Q10 both = 3.70). The variability can be seen in two points: first, the items with the highest standard deviation are ease of use (Q1 = 3.53, SD = 1.358) and long-term reliability (Q8 = 3.60, SD = 1.276); a high standard deviation implies that customers had varying views on these points, they were not unanimous about their opinions. Second, there are two low-ranked items: confidence in the superiority of an automatic system over a human representative is low (Q7 = 3.03) and speedy problem solving is the lowest one in the

whole questionnaire (Q11 = 2.10). Thus, the general pattern is that routine digital use works, yet problem resolution does not, a distinction created in the customer theme below.

4.4 Non-Participant Observation

Six non-participant observation sessions were carried out between 4 and 28 April 2026 at six Addis Ababa sites that differed in size and customer traffic, ranging from small branches with a handful of staff and walk-in customers to a busy call-centre floor with around twenty agents and no walk-in public. At each session the researcher completed a structured checklist of twelve yes/no items covering customer behaviour, employee behaviour and supervisor behaviour, and recorded open field notes. Because the items are binary, they are tallied across the six sessions in Table 4.7, and the field notes are then read for patterns in the same way as the interview answers.

Table 4.7: Structured Observation Checklist Tallied Across Six Sessions

Observed item	S1	S2	S3	S4	S5	S6	Yes (of 6)
1. Customers use digital self-service without staff help	No	Yes	–	No	No	Yes	2 of 5*
2. Customers show confusion or frustration	Yes	No	–	Yes	No	Yes	3 of 5*
3. Staff guide customers toward digital options	Yes	Yes	No	Yes	Yes	Yes	5
4. Digital services work smoothly	Yes	Yes	Yes	No	Yes	No	4
5. Employees use digital systems while serving	Yes	Yes	Yes	Yes	Yes	Yes	6
6. Employees struggle with digital tools	Yes	No	Yes	Yes	Yes	Yes	5
7. Employees help each other with system problems	No	Yes	Yes	No	Yes	Yes	4
8. Employees explain AI services clearly	Yes	Yes	No	No	Yes	Yes	4
9. Supervisor / team leader present	Yes	Yes	Yes	No	Yes	Yes	5

Observed item	S1	S2	S3	S4	S5	S6	Yes (of 6)
10. Supervisor helps struggling employees	Yes	No	Yes	No	Yes	Yes	4
11. Supervisor coaches rather than takes over	No	Yes	Yes	No	Yes	No	3
12. Supportive atmosphere during technology problems	Yes	Yes	Yes	Yes	Yes	Yes	6

*Sessions: S1 Gofa (4 Apr), S2 Shegole (6 Apr), S3 Churchill Avenue call centre (10 Apr), S4 Bisrate Gabreal (13 Apr), S5 Bole Michael back office (14 Apr), S6 Mesalemiya (28 Apr). * Items 1 and 2 concern walk-in customers; S3 was a call centre with no walk-in public, so these are reported out of five applicable sessions. Integration level recorded by the researcher: largely integrated at S2, S3 and S5; partially integrated at S1, S4 and S6.*

The checklist points in one direction. Employees used the digital systems while serving in every session (6 of 6) and the atmosphere during technology problems was supportive throughout (6 of 6), yet some struggle with the tools was visible in five of the six sessions. The way that struggle was handled is the telling part. Supervisors were present in five sessions and stepped in to help in four, but they coached employees through a problem rather than taking it over in only three; in the two busiest or least-supported sites the supervisor solved the difficult case directly instead of using it to build the staff member's skill. Peer help between colleagues was visible in four sessions and, in the notes, was often the real mechanism by which problems were resolved.

The open notes reinforced this and added detail the checklist could not capture. At one back-office site the team leader opened the session with a short review of live digital performance figures, the most embedded use of data of any site observed. At a quieter branch two agents at adjacent desks were learning from each other informally, and staff were found to be sharing system-update notices through a phone group chat set up outside any official channel. At the call centre, one agent kept a handwritten shortcut guide for a system feature that the formal training had not fully covered. On the customer side, an elderly customer who had needed help completing a Telebirr transaction repeated it without help shortly afterwards once it had been demonstrated. These observations were folded into the relevant themes below, in particular peer and self-directed learning (Theme 3) and the growth of leadership capacity (Theme 6).

4.5 Thematic Analysis

The six themes were extracted from the written responses, observations and secondary sources through the six-step process outlined in section 4.1 above. They are listed below in the words of the participants, using excerpts of quotations from the interviewees coded according to their identity e.g. “Employee 16” or “Manager 3”. Each theme is then explained based on theory covered in Chapter Two and with comparison to similar empirical studies carried out in other organizations. Lastly, the results of questionnaire evaluation are presented to indicate the extent to which each theme was shared. The six themes include: communication gaps at various levels; fear of AI technology imported and not experienced locally; competence gained via peer and self-learning; being excluded from decisions while accepting the decision; the two-dimensional aspect of customer experience and leadership potential built during the process itself.

Theme 1: Communication Gaps at Multiple Levels

The information often came piecemeal or too late and the communication gap manifested itself on two levels: first, between senior management and the managers, and secondly, between the managers and their subordinates. According to the managers, they were provided with an unformed message and they should have delivered it further.

As a team leader put it bluntly: "I hadn't understood the system yet and I was explaining it to my team". (Manager 2, Customer Service) Another manager stated that the message he got from above was unformed and that he guessed about what he was going to tell his employees (Manager 3, IT). A manager from Hardware Installation department stressed that the managers below top-level managers had to guess too much (Manager 10).

Some employees experienced the gap on the second level: they faced a new system without warning. One of the finance officers explained it like this: "One day I sat down and saw the new interface". (Employee 16, Finance) Another one learned about the change from the colleague sitting next to him who did not know about it (Employee 20, Finance).

According to the change management literature, it is not a fault of individual managers. It is a breakdown in the process of communicating that is crucial in change management models. For example, in Kotter's model (1996) under-communication of the vision is one of the most common causes of change failure, and the breakdown took place one level higher than usual: the managers could not communicate the vision since they received it half-formed, thus, the weak link in the chain was not the manager-to-staff but senior-to-manager communication. This breakdown also

coincides with the difference Abbu et al. (2022) note in the digital leadership theory between the information-pushing approach that is only telling the audience what is happening and dialogic approach that makes staff members participants in the change process; in this case, managers communicated the message without two-sided communication characteristic of individualized consideration by transformational leaders (Northouse, 2022). When viewed within McKinsey 7-S framework, the message degraded as it went through the organization structure since the communication system and the leadership style were not compatible with each other.

The questionnaire confirmed two levels of the gap. Among managers, the only communication element that scored low was the message from senior management (Q2 = 3.33), well below the message managers passed to their subordinates (Q1 = 4.33), and among employees advanced notice of change average score was neutral (Q6 = 3.00). The same process was reported in the most similar studies. Mhlanga (2022), researching African telecommunications companies, found out that middle managers lacking clear direction from above improvised communication strategies leaving employees in one organization experiencing different change process, and Singh and Sharma (2021) found out that telecommunication leaders using only top-down communication conducted change less efficiently than the leaders opening it. The result of the communication breakdown in Ethio Telecom is exactly this unevenness: each manager bridged the gap in his own way, thus, the change experience of an employee depends on the team he works in. The same mechanism will become apparent in the support and listening items further.

Theme 2: AI Fear Comes From Outside, Not From Local Experience

Where employees were anxious about AI, the anxiety did not come from anything that had happened at Ethio Telecom. It came from what people had read and heard about AI elsewhere.

A customer-service team leader traced it directly to the news: “People saw on the news how AI takes jobs abroad, so my older agents got scared before anything even changed here.” (Manager 1, Customer Service)

An employee in HR captured how the idea weighed more than the reality: “The AI fear was harder than the actual system.” (Employee 13, HR) A finance officer said the worry about his position

came mostly from the stories read outside (Employee 4), and a long-serving agent observed that the outside stories make the change sound much bigger than what is actually present (Employee 15).

This finding is most interesting for what it reveals about the limits of the acceptance model the study uses. The Technology Acceptance Model (Davis, 1989) explains adoption through perceived usefulness and perceived ease of use, and on both counts the local tools scored well, with confidence in using them at 4.16 and the sense that they made work easier at 4.00. The fear therefore did not arise from the tools themselves; it sat outside the TAM variables altogether, as an imported threat narrative about AI in general. The construct that comes closest to capturing it is the social-influence element of the unified acceptance model, the effect of the surrounding discourse on how people feel about a technology, which is why employees could hold a real fear of AI and adopt the local systems at the same time. Managing that fear is thus a different task from managing adoption: it is the management of a perception rather than of an experience.

The questionnaire shows why this matters. Employees were divided on whether AI threatened their jobs, and that item had the widest spread on the whole form (Q4 = 3.08, SD = 1.152), yet the managers reported running into little real resistance (Q6 = 2.40 on the reverse-worded item). The split between a real but imported fear and a calm local reality is exactly what the wider literature predicts. Rajanala and colleagues (2024) find that worry about AI is driven by age, sector and media exposure rather than by actual job loss, and falls most heavily on older and more senior service staff, precisely the group the managers here named as the uneasiest. The global narrative that fuels such fear, typified by widely cited estimates that large shares of jobs are technically susceptible to automation (Frey and Osborne, 2017), describes a frontier that a late-adopting organization like Ethio Telecom is far from reaching, as Chapter Two notes; the fear consequently outruns the local reality. This is a leadership challenge specific to the Ethiopian setting and one that standard change-management advice, written for organizations where the threat is more immediate, does not fully address.

Theme 3: Peer and Self-Directed Learning Filled the Training Gap

Formal training was the least successful component of the transition process, and people managed to compensate for it themselves, relying mostly on colleagues and, in the case of younger employees, on digital tools and AI assistants.

One of the younger Telebirr employees stated: "I simply learned to use AI from AI". (Employee 23, Digital Services / Telebirr) Other employees learned from whoever was closest: one network technician asked for help from his colleague during the shift if the manual was confusing (Employee 12), another customer service representative combined YouTube video instructions with advice from the colleague sitting at the next desk (Employee 25). One of the finance officers noted she worked out the new system in collaboration with her colleague, who was quicker to understand it (Employee 10).

Peer assistance was the practical way of coping even for those who were struggling the most. One of the older network employees expressed this idea clearly: "A colleague explained to me the new features; without him, I would be completely lost". (Employee 19, Network Operations)

This is the most evident case in the data where the ease-of-use barrier was successfully overcome via informal mechanisms. The training indicator was the lowest among other indicators in the adaptation section (Q3 = 2.96), but employees became confident with the tool (Q1 = 4.16); and the path from the first one to the second was not formal training but social learning situated within the work process. Lave and Wenger (1991) described this exact process, when competence is acquired by participating in work process together with more experienced colleagues and not through the separate teaching activity. Bandura (1977) explains the same phenomenon as a form of learning through observation of the others' behaviour. According to the McKinsey 7-S model, in this case the skills necessary for changing were developed by the employees themselves and not provided by the organization, which paid attention to the systems and neglected the people. The observations confirm this interpretation: informal peer learning between the agents, the group chat used by agents for discussing system changes outside of any official channel, and handwritten guide for a certain feature missing in training materials were all observed on the shopfloor.

The finding is a double-edged one, and the analysis should encompass both sides of it. On one side, it demonstrates true organizational resilience, the same adaptive and peer-based learning which Lemmetty and colleagues (2023) discovered to be more efficient than formal training in constantly changing digital world, since it is immediate and contextual. On the other side, it represents a quiet managerial abdication: the organization ended up depending on the learning process that it did not design and resource, and such emergent processes are frail and uneven. An employee without the help of a supportive colleague or good access to the Internet does not have a fallback position, and

the people who are the most vulnerable are the older and less digitally literate employees, who, like Employee 19, noted that they would be completely lost without a colleague's help. Competence, in other words, was achieved despite of, not because of, the training provided by the organization, which is one of the clearest symptoms of the mismatch between human support and technical change.

Theme 4: Excluded From Decisions But Accepting of the Outcome

Employees did not feel part of the decisions about how the technology would be introduced, yet they accepted the result because the tools themselves were useful. The two sit together throughout the data and form one of the study's central tensions.

The exclusion was stated clearly. As one agent put it, "The plan from above was clear, but we were not part of making it." (Employee 1, Customer Service) A long-serving IT employee felt his experience went unused, saying that after ten years in the field he had expected to be asked something (Employee 9), and another agent described the whole experience in three words: he was not told, not prepared and not heard (Employee 18).

A manager openly named the approach as a mistake: "We decided too much at the top and told them after; that was wrong." (Manager 4, Customer Service)

The puzzle this theme poses, total exclusion alongside genuine acceptance, is best explained by the change equation of Beckhard and Harris (1987), which holds that change overcomes resistance when dissatisfaction with the present, a clear vision and concrete first steps together outweigh the cost of changing. At Ethio Telecom the first steps were strong: the tools worked and delivered an immediate, visible benefit, and that practical usefulness, the central driver in the Technology Acceptance Model (Davis, 1989), was enough to carry acceptance even though participation, which Lewin (1947) treats as the classic way of reducing resistance during the moving stage, was almost entirely absent. The tools did the persuading that involvement would normally do. The involvement gap itself, between the employees' score for taking part (Q10 = 2.20, with no one agreeing) and the managers' score for involving their teams (Q11 = 4.40), also reflects two different definitions of the word: managers counted informing and explaining as involving, while employees meant having a say in the decision, the difference between consultation and the genuine voice that transformational leadership calls for (Northouse, 2022).

The wider evidence makes clear what was lost. Danaher and Tchouaket (2024) identify weak employee involvement as the single most consistent source of friction in telecom change programmes, and Singh and Sharma (2021) show that participative leadership outperforms a top-down approach in telecom AI adoption specifically; Kotter and Schlesinger (2008) list participation among the most effective strategies for lowering resistance precisely because it surfaces the frontline knowledge that improves a rollout. Acceptance at Ethio Telecom was therefore real but shallow, closer to satisfaction with an outcome than to ownership of a change, and it leaves two costs. It is fragile, because it rests on the tools continuing to work, and it forgoes the practical insight that the excluded employees, several of whom said they could see problems from the ground, would have contributed. This is the human-side deficit in its sharpest form: the change succeeded on adoption while leaving a participation gap that is both a present risk and a missed opportunity.

Theme 5: Customer Experience Split by Task and by User

The accounts of the customers have been divided into two groups on the basis of certain criteria. The first criterion pertains to the nature of the job at hand; routine digital transactions go very smoothly, but solving a problem is a failure. The second criterion pertains to the kind of customers and the places where they live.

For routine tasks the outcome was positive. “It’s fast, simple and I haven’t needed to contact anyone yet.” (Customer 6) and “it has made my week easy” (Customer 10). The problem solving aspect of the technology received very negative feedback. One customer lost her money due to a failed transaction and had to recount the whole story over and over again (Customer 15). Another one complained about the bot: “It goes in circles on the chatbot for anything more than basic things.” (Customer 9). The split between users in different locations is as clear as above. The problem of connectivity was described by a regional customer: “The app crashes the second 4G disconnects and the whole process ends.” (Customer 14) and another regional customer asked for the USSD menu that would do everything the app does as not everyone in a regional area has stable data access (Customer 25). The old-age customer segment also felt being excluded from the design of the system; one customer said that the app was not designed for people his age who were not used to the technology (Customer 19), and another one, having been a long-term customer, simply asks to keep the branch working with good staff (Customer 30).

The division of tasks perfectly matches the stages of adoption of AI presented in Chapter Two. Ethio Telecom operates on the level of network, operations and customer AI performing routine queries, balance checking and payments but it has not yet developed to the advanced stage when the system solves the problem independently; hence, the chatbot performs efficiently in tasks it was designed to do and loops in others. According to Mostafa and Kasamani (2022), the reason is that satisfaction with an AI chatbot depends on whether the problem was solved, not how quickly, so the looping or queueing of a system makes the customer dissatisfied regardless of the speed of the system. This is exactly the experience that lies behind the lowest score in the whole research – the problem resolution score 2.10 and repeated experience of retelling stories to several representatives. Trust forms a second layer. Chandra et al. (2010) prove that trust in the safety of personal information is one of the leading drivers of digital service adoption in developing markets and the neutral group formed around the question of trust (Q5 = 3.33) indicates a group of customers that is not committed yet and may drop off after a single bad experience.

The second split, between user and location is the digital divide in its pure form. The broad dispersion of scores on the questions of ease of use (Q1, SD = 1.358) and reliability (Q8, SD = 1.276) is not a mediocre average but a truly divided customer base that divides along the lines predicted by the literature. Van Dijk (2020) describes the digital divide as the gap in access, skills and usage rather than interest and the GSMA (2024) reports on the existence of the urban-rural divide in the region caused by the coverage, data costs and digital literacy. In the unified acceptance model, these are facilitating conditions that the customer has to possess before the usefulness and ease of use become relevant. The regional and older respondents faced the obstacle at this very point, due to the design of the app targeted at the users with high bandwidth and high digital literacy. The Safaricom's report on its service (2024) proves that even the most advanced telecom AI in the region performs the routine tasks excellently but uses human channels for the complex ones which proves that the restriction at Ethio Telecom is caused by the lack of development of the technology and lack of access rather than intention. The story of the customer, therefore, perfectly reflects the story of the employee: the technology works efficiently in performing routine tasks of the connected majority of customers, while the need for human support, the branch and the hotline persists exactly where the automation is limited or access is low.

Theme 6: Leadership Capacity Built Through the Process

The one unequivocally good result on the human front is that the leading of this messy transformation built the managers into leaders. Their evaluation of the results for themselves and their teams is extremely high, and they also mention having to improvise, which is an essential component of the process of building capacity.

Senior customer service manager learned his lesson from his experience: "Changes that failed are the ones rushed without getting the people ready." (Manager 14, Customer Service) A network manager outlined the approach that worked for him by putting his engineers into the planning process, so once they owned the project, the resistance vanished automatically (Manager 6). A team leader from Hardware Installation looked at the same situation from the angle of preparation: it is easier to lead people who are ready in their mind (Manager 15).

The formation of this particular capacity is best described through the concept of the reflective practitioner. Schön (1983) states that most of the skills acquired by the professional come from his reflections during actions, rather than from advance instructions, and this is the case seen on the questionnaire, as managers agree they often had to figure things out themselves (Q16 = 3.67); therefore, the excellent results came from doing the job rather than from getting ready for it. Heifetz (1994) calls this kind of leadership adaptive, as it consists of moving people through the process of change where no advance script exists; that can happen in the environment where the pace is externally controlled and the directive is incompletely formulated from above. Of interest to note, the manager who outlined his way of putting his team inside the planning process (Manager 6) used the participative and transformational style of behaviour recommended in the general leadership literature (Northouse, 2022; Singh and Sharma, 2021) without any prior organizational requirements. In terms of Lewin's model, some of the newly created practices were already refreezing into routine, as it could be seen in the back-office team leader's behavior of starting each session with a review of the current performance.

The results obtained on the questionnaire demonstrate the scale of this achievement. The manager's sense of capability as a leader, increased productivity of the team, development and the ability to deliver better service scored 4.67 points, the latter one scoring 4.60. The manager's confidence in managing future technology changes reached its top with 4.87 points on Q21 – the single highest mark in the whole study. The importance of this development goes beyond managers as Mhlanga (2022) finds digital-leadership capability to be one of the biggest

determinants of employees' acceptance of AI systems, and Abbu et al. (2022) prove the fact that human dimensions of digital leadership emerge mostly as a result of transformation management experience. It should be noted, however, that these are the evaluations made by the managers about their development, and they should be read with the gap between the manager self-reports and employees' experiences mentioned in the integration below in mind. Nonetheless, the reflections and observations confirm the trend. It is the positive side of the argument presented in the study: managers became capable during the process of transformation, although the employees who experienced it got insufficiently supported, and that is the most significant achievement of the change.

4.6 Integration of the Findings

The two strands are then combined. In Table 4.8, the joint presentation of the two strands shows each theme paired with its corresponding questionnaire indicator, its qualitative data, and a synthesis involving relevant theoretical perspectives and literature, using the concept of joint presentation in the context of mixed methods (Fetters et al., 2013; Creswell and Creswell, 2018). If the two strands indicate a similar direction, the conclusion is validated, but if not, the difference is taken as a conclusion in itself.

Table 4.8: Joint Display – Integration of Quantitative and Qualitative Findings

Theme	Questionnaire signal	Qualitative evidence	Integrated reading (theory and literature)
1. Communication gaps at multiple levels	Manager "explained to team" Q1 = 4.33 vs "senior explained to me" Q2 = 3.33; employee "told before change" Q6 = 3.00	Managers relayed a half-formed message and guessed; employees met changed systems with no notice	A broken communication step (Kotter) one level above the usual, leaving information-push without dialogue (Abbu et al., 2022). Mhlanga (2022): improvising managers create uneven staff experience.
2. AI fear from outside, not local experience	Job-loss worry the most divided item (Q4 = 3.08, SD = 1.152); managers	Fear traced to foreign news, not to events at Ethio Telecom; "harder than the actual system"	Fear sits outside the TAM variables, as a social-influence effect; Rajanala et al. (2024)

Theme	Questionnaire signal	Qualitative evidence	Integrated reading (theory and literature)
	report little real resistance (Q6 = 2.40, reverse)		and Frey and Osborne (2017) on perception running ahead of a frontier a late adopter has not reached.
3. Peer and self-directed learning	Training the weakest adaptation item (Q3 = 2.96) against high tool confidence (Q1 = 4.16)	Colleagues, YouTube and ChatGPT did the teaching; peer channels and a handwritten guide seen in observation	Situated, social learning (Lave and Wenger, 1991; Bandura, 1977) supplied the skills element the organization did not (7-S); resilient but fragile and unequal (Lemmetty et al., 2023).
4. Excluded from decisions but accepting	Involvement lowest on the form (Q10 = 2.20, none agreed) vs managers' Q11 = 4.40; yet work made easier (Q12 = 4.00)	"The plan was clear but we were not part of making it"; a manager concedes deciding at the top	Working tools and usefulness (TAM) carried acceptance without participation (Beckhard and Harris, 1987; Lewin, 1947). Low involvement is the steadiest source of friction (Danaher and Tchouaket, 2024).
5. Customer experience split by task and user	Routine items positive (Q3 = 3.80, Q4 = 3.77) but resolution the study's floor (Q11 = 2.10); ease and reliability widely split (SD 1.358; 1.276)	Telebirr smooth for payments; the chatbot loops on complex issues; regional and older users blocked by connectivity and design	Task split tracks the adoption-stage model; resolution drives chatbot dissatisfaction (Mostafa and Kasamani, 2022). User split is the digital divide (van Dijk, 2020; GSMA, 2024).
6. Leadership capacity built through the	Outcomes high (Q17–Q19 = 4.67; Q20 = 4.60; Q22 =	"Easier to lead people who are ready in their mind"; a team leader	Capacity built by reflecting in action (Schön, 1983) and

Theme	Questionnaire signal	Qualitative evidence	Integrated reading (theory and literature)
process	4.40); confidence the study's highest (Q21 = 4.87); managers improvised (Q16 = 3.67)	running on live data	adaptive leadership (Heifetz, 1994); a predictor of employee acceptance (Mhlanga, 2022), tempered by self-report.

Reading down the display, all the strands come together to the argument of the theory, and it accounts for the phenomenon. The technical adoption proved successful in terms of itself, since employees are comfortable with the tools (Q1 = 4.16) and see actual benefits from them (Q12 = 4.00), and the Technology Acceptance Model explains it perfectly as the perception of usefulness and ease of use were high in that case. Human aspect of the same change was managed poorly, and the theories find the weak spots exactly in the areas where it becomes evident from the data. Communication step of Kotter's process is broken at the top of the ladder; the participation that Lewin puts in the middle of the change process is hardly seen; and skills component of the McKinsey 7-S model was left up to the staff to take care of themselves. That the change took place despite these aspects being weak can be explained by the change equation of Beckhard and Harris (1987): the first concrete steps and the usefulness of the tools outweighed any resistance with these human aspects being absent. The best proof of the under-management is found exactly where the questionnaire and the interviews coincide: it is the poor training (Q3 = 2.96) versus self-learning, lack of communication (Q6 = 3.00) versus guesses, and complete exclusion from decision-making (Q10 = 2.20) versus silent acceptance.

The most telling outcomes of this study are the steady differences in how managers and employees describe the same change, and these form a pattern rather than scattered disagreements. The clearest contrast is over involvement: employees rated their own part in the technology decisions very low (Q10 = 2.20, with no one agreeing), while managers rated their involvement of the team highly (Q11 = 4.40). The two groups describe the same decisions in opposite terms. The same divergence appears over pace: employees felt the change was too fast (Q5 = 3.92), while managers largely did not see the pace as a problem (Q9 = 2.20, reverse-worded). Within the employee responses, staff also felt less listened to than informed (Q9 = 2.92 against Q7 = 3.72). Across communication, training and support, managers consistently rated the change more positively than

their staff did. It is this consistent direction, not the size of any one difference, that is the finding. To some extent, it is a question of the viewpoint and definition, the difference between the information-push perspective from above and the dialogic perspective from below that Abbu et al. (2022) discuss, and it is a well-known tendency of respondents to rate themselves and the support positively, the self-report bias that the methodological literature considers an inherent risk in this type of research (Podsakoff et al., 2003). The point is not that the managers were lying; it is that relying solely on their account would have resulted in the human-side gap remaining unseen, and triangulating the data brings the gap into the light. The gap is thus interpreted as analytically significant finding regarding how the change was perceived in different roles, rather than as noise to average out.

On the customer side, the integration is simpler but it tells the same story. The convergence is that basic transactions go smoothly and customers say so, while problem resolution is clearly the weakest point with the lowest score in the study (Q11 = 2.10), backed up with stories of looping chatbots and repeated conversations with several agents, explained by adoption stage model and Mostafa & Kasamani (2022). The gap in the customer base, the split by connectivity and age as mentioned by regional and older customers and reflected in wide spread on the easy and reliable items, is the digital divide working through the same change. Customer findings are echoes of the employee story: technology serves the connected and routine majority well, while human channel is still needed in places where automation is shallow or access is low.

Together, these findings provide a coherent answer to the research question and reveal this study's contribution. Kassa & Worku (2025) have already demonstrated, with the survey modelling at Ethio Telecom, that the AI adoption is associated with higher organizational performance and employee productivity. The present analysis reveals how this result was achieved and at what cost on the human side: the performance increase relies on tools that work and on the competence of staff developed by themselves in the process of the change with lacking communication, no participation of employees, poor training and stress of pace and imported AI fear put on managers. The only obvious human-side achievement is the leadership competence gained by managers in the process of the change, which is the most durable benefit of the process and the direct answer to the study's fourth objective. Technology adoption, in other words, was successful; the human side

of the process is the area where the job needs to be done and where the leadership competence gained in the process becomes the organization's main resource to do that better next time.

4.7 Chapter Summary

This chapter analyzed the questionnaire ratings, the open-ended answers, the structured observation and the secondary sources for 25 employees, 15 managers and 30 customers of Ethio Telecom. The questionnaire data were used descriptively to show how widely each view was held, the open-ended answers and observation were analyzed thematically using the six phases of Braun and Clarke (2006), trustworthiness was addressed through the criteria of Lincoln and Guba (1985), and the two strands were integrated through a joint display and interpreted with the change-management and technology-acceptance frameworks set out in Chapter Two.

Six themes emerged: communication that thinned at each level of the hierarchy; an AI fear that came from outside rather than from local events; peer and self-directed learning as the real route to competence; exclusion from decisions alongside acceptance of a useful outcome; a customer experience split both by task and by user; and leadership capacity built through leading the change itself. Across all six, one argument held, and the theory explained why it held: the technical adoption succeeded because the tools were useful and easy to use, while the human side of the change was under-managed at exactly the points the change frameworks treat as decisive, namely communication, participation and skills. Employees and managers became capable mainly by improvising, acceptance was carried by working tools rather than by involvement, and the steady gap between managers' favourable accounts and the more critical employee and customer accounts is a methodological finding consistent with social-desirability bias, treated here as analytically meaningful. The clearest gain on the human side was the leadership capacity built in the process. Chapter Five discusses these findings against the research questions and sets out the conclusions and recommendations that follow from them.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This marks the conclusion of this study. The research aimed to find out how AI-driven change is managed at Ethio Telecom and how such change affects the management involved in it and the adoption of the workers and customers who have to deal with the effects of the change. This was done through an exploratory research approach involving a single-case design where the data collection tools used included a qualitative dominant, but mixed methods approach which involved the analysis of the responses from 70 people comprising 25 workers, 15 managers and 30 customers, using thematic analysis and their integration in Chapter Four. This chapter provides a summary of the major findings concerning the four research questions, the conclusions drawn, the practical implications to the organization and its management, the contributions of the study, the limitations, the possible future directions for research and finally the conclusion.

5.2 Summary of Major Findings

The findings are summarized below in the order of the four research questions set out in Chapter One. Each summary states what the study found and points to the strongest supporting evidence; the full reasoning is in Chapter Four.

5.2.1 Research Question One: How do managers introduce and implement AI-driven change, and how does this shape them as leaders?

Managers led a largely top-down change in which the brief from senior management often reached them incomplete. They rated the message they passed on to their teams highly (Q1 = 4.33) but the message they themselves received from above much lower (Q2 = 3.33), so they frequently relayed, and sometimes improvised, a vision they had received only half-formed. Decisions about how the technology would be introduced were taken at the top, with managers confident they had involved their teams (Q11 = 4.40) while employees recorded almost no involvement at all. The two chief leadership challenges were therefore this cascade communication gap and the pace of change, which managers underestimated: on the reverse-worded item they largely disagreed that the pace was too fast (Q9 = 2.20), the very strain employees rated highly (Q5 = 3.92). Yet the experience of

leading the change developed the managers themselves. They report the strongest outcomes in the study, with feeling more capable as a leader, a more productive team and real development all at 4.67 and confidence in leading future change the single highest score anywhere (Q21 = 4.87), while also conceding that they had often had to find their own way without support (Q16 = 3.67). In short, the manager's role was demanding and under-supported, but it built genuine leadership capacity.

5.2.2 Research Question Two: How do employees experience and adapt to AI-driven change, and what facilitates and hinders their acceptance?

Employees adapted the tools easily and accepted the change as beneficial; the confidence level in operating the systems was high (Q1 = 4.16) and the perception of their utility in simplifying work was very high (Q12 = 4.00), with not a single dissenter. The acceptance of change, however, took place in spite of the poor support structure, not because of it. What helped employees to adapt to changes were the utility of the tools and, mostly, peer and self-directed learning, while colleagues, online manuals and artificial intelligence substitutes for the poorest element of the support in adapting to changes – formal training (Q3 = 2.96). What prevented employees from adaptation were insufficient and inconsistent information (Q6 = 3.00), total absence from decision-making process (Q10 = 2.20, with no dissenters at all), perceived rate of change (Q5 = 3.92) and fear of artificial intelligence, which was indeed present in employees but was foreign to them, coming from outside media sources rather than from Ethio Telecom and showing up in the most controversial item on the questionnaire (Q4 = 3.08). The acceptance of changes was thus real but superficial, more of a satisfaction with the result than with the change itself.

5.2.3 Research Question Three: How do customers adopt and use Ethio Telecom's AI-driven digital services, and what factors foster or hinder their acceptance?

Customer experience divided along two lines. By task, routine transactions worked well: making payments through Telebirr, checking balances and getting basic guidance were rated positively (guidance when stuck Q3 = 3.80; availability Q4 = 3.77), but the resolution of problems was the weakest point in the entire study (Q11 = 2.10), with customers describing failed transactions, a chatbot that loops on anything complex, and the same issue retold to several agents. By user and location, connected and digitally confident customers in Addis were served well, while regional customers facing weak connectivity and older or less digitally literate customers facing an app built for high-bandwidth, smart phone fluent users were not; the wide spread on ease of use (Q1,

SD = 1.358) and reliability (Q8, SD = 1.276) reflects this divided base. Acceptance was therefore fostered by the usefulness of the service for routine tasks, by digital literacy and by reliable connectivity, and hindered by shallow automation for complex issues, weak connectivity, age and literacy barriers, and a trust in data security that sat only at neutral (Q5 = 3.33) and could turn into withdrawal after a single bad experience.

5.2.4 Research Question Four: What practical lessons and recommendations follow for leading future AI-driven change?

The overall lesson is that Ethio Telecom had done very well with regard to managing the technology, but has badly managed the human aspect, and the same weaknesses can be seen repeated among all three groups with respect to communication, participation, training and skills development and the ongoing need for human support in areas that have yet to be automated. The specific evidence-based recommendations which answer this question are contained in section 5.4 below. The overall lesson behind these recommendations is that the technical aspect of any such change will pretty much take care of itself once the technology is effective, while it is good communication, participation and training that future change really needs.

5.3 Conclusions

The overall conclusion regarding the change at Ethio Telecom is that it was a technical success and a human-side failure simultaneously. The organization adopted the functional and valuable digital systems characteristic of the AI era; however, the process of changing has been poorly managed on the human side, so that employees and to some extent their managers have become competent through improvisation. One major achievement on the human side was building leadership skills by leading an imperfect change. The following six more specific conclusions can be drawn.

Firstly, the central leadership challenge lies in communication, and the communication fails at the top of the chain before reaching the front line. Managers are required to explain the change which they themselves receive in an incomplete form, and employees face a changed system without being forewarned. This is a known problem of top-down digital transformation, and it has brought concrete costs to adaptation and trust, resulting in a radically different experience of one change in various teams.

Secondly, the fear of AI at Ethio Telecom is real but imported. It is caused by what employees learn from sources other than the workplace, and there has been no local loss of jobs because of AI, placing it outside the usual drivers of technology acceptance and making it a manageable issue of honest communication.

Thirdly, competence has been acquired through informal learning rather than formal training. It demonstrates high resilience of the workforce, but the system of learning which has not been designed or resourced by the organization is vulnerable and unequal, leaving older and less-connected workers who do not have a helpful colleague exposed.

Fourthly, employees were excluded from the decision-making process, but they accepted the decision due to the usefulness of tools. Thus, acceptance is present-focused and shallow rather than sense of ownership, and the persistent difference between the favourable reports of managers and critical reports of employees and customers is one of the findings of the study and should be treated as analytically relevant and not an error caused by social desirability bias.

Fifthly, the customer experience is divided according to the task and the user. Digital services function well and are appreciated, but the solving of complicated problems and the needs of less-connected and older customers are not satisfied, making the human branches and hotlines a must exactly where automation is weak.

Sixthly, leading the change increased the leadership skills genuinely and durably. It is the clearest positive result of the study, it addresses the problem of how the change affected the managers, and it is the asset of the organization in managing the future changes better than the previous ones.

5.4 Recommendations

The following recommendations follow directly from the conclusions and are grouped by the people best placed to act on them. They are deliberately practical and low-cost, since the evidence suggests that the human-side gaps at Ethio Telecom are gaps of process and attention rather than of resources.

5.4.1 For Senior Leadership

Senior management should put in place a structured briefing for managers before any technology rollout is announced. At present, decisions are taken in strategic forums and reach managers late and incompletely. A short, standard brief covering what is changing, why, on what timeline, the

key messages to pass on and the questions to expect would close the gap between what managers receive (Q2 = 3.33) and what they are expected to deliver (Q1 = 4.33) at its source.

Senior leaders should also speak openly about AI and job security. The fear is legitimate and fuelled by international coverage, and it will not be eased by reassurances that AI simply makes the company better for customers, which carry little weight when staff have read about layoffs elsewhere. A direct account of where AI is and is not heading at Ethio Telecom, which roles are genuinely affected, and where human work remains essential is what reduces the fear without over-promising. More broadly, senior leadership should adopt a simple, repeatable change-management framework for technology launches, with mandatory advance notice, a feedback channel and post-launch support, so that the good practices some managers already improvise become routine rather than personal initiative.

5.4.2 For Middle Managers and Team Leaders

Managers should communicate earlier. Employees consistently learned of changes only as they arrived, and even a brief, timely signal in a team meeting or a group message that a change is coming, and why, would make people readier for it; the timing of the message matters more than its detail. Managers should also open at least one genuine channel for feedback during each rollout, a short discussion of likely problems that takes the team's concerns into account, moving from simply telling people what is happening towards a two-way exchange. The participative approach that worked for some managers, bringing the team into the planning so that they own the change and resistance fades, should be the model rather than the exception, because it both lowers resistance and surfaces the frontline knowledge that improves a rollout.

5.4.3 For Training and Skills Development

Training should be redesigned around the specific digital tasks each role performs rather than delivered as a general introduction to the technology, and it should be paired with follow-up support two to four weeks after rollout, when staff are using the system on real work and their questions are concrete. This will cost more than a single pre-launch session but should lift the training item that is currently the weakest point of the employee experience (Q3 = 2.96). In addition, the informal peer learning that already carries most adaptation should be formalised into a buddy or peer-mentor arrangement, so that it is supported and made equitable rather than left to chance, which would particularly protect the older and less-connected staff who at present depend

on a single willing colleague.

5.4.4 For Customer Service and Digital Inclusion

Ethio Telecom should treat the USSD service (*127#) and the branch as designed parts of its digital strategy rather than as afterthoughts to the app. A substantial share of customers are in regional areas where the app is unstable, and many older customers cannot use it independently beyond basic payments, so these channels carry real demand. The chatbot and the integration between channels should be deepened so that complex matters, failed transactions, billing disputes and account changes can be resolved end to end without forcing a call or a branch visit; the lowest score in the study (Q11 = 2.10) reflects a gap in resolution capability, not a rejection of digital service. Finally, an inclusive-design rule should apply: branches should not be reduced or closed until a digital alternative genuinely serves everyone the branch now serves, including older, remote and lower-literacy customers.

5.4.5 For Ethio Telecom as an organization

Beyond the individual groups, the organization should consolidate these measures into a standing change-management capability, so that advance notice, employee involvement, task-based training and post-launch support are expected of every technology launch rather than reinvented each time. It should also invest in digital-literacy support for both employees and customers, since widening the number of people who can participate confidently in the digital transition is the surest way to keep the human-side gaps documented here from reopening as adoption deepens.

5.5 Contribution of the Study

These contributions are related. Theoretically, the research tests and illustrates the use of two change management models, the Technology Acceptance Model, and a change equation and shows the strengths and weaknesses of each in a context they were not developed for. The Technology Acceptance Model predicts the good adoption because the tools proved to be useful and usable; Lewin's and Kotter's models explain why there were human side vulnerabilities precisely in terms of communication and participation; and Beckhard and Harris' change equation explains the puzzling combination of exclusion and acceptance in terms of useful tools carrying the change without participation. At the same time, the study highlights a gap in the literature, which focuses on contexts where the threat of automation is imminent and thus neglects the issue of managing the

imported fear. This study also contributes the insight into the reading of the manager-employee perception gap as a methodological artifact due to the social desirability bias and the elaboration on the model of building leadership capacity in action proposed by Schön and Heifetz.

Practically, the research provides Ethio Telecom and similar organizations with a map of where their current approach to AI-driven change succeeds and where it fails along with the practical recommendations listed in Section 5.4. Contextually and empirically, the study provides locally grounded qualitative insights into how such change is led and experienced in a large Ethiopian organization, a context where prior research, such as Kassa and Worku (2025), measures the performance gains from adopting AI and fails to explain the human process that produced those gains. Integrating the perspectives of managers, employees and customers in one case, this study explains that human process, namely how those performance gains were accomplished, and at what cost.

5.6 Limitations of the Study

There are several important limitations that must be taken into consideration when analyzing the results of this study, all of which are related to the explorative nature and high level of qualitative dominance of this research design. First of all, the sample of 25 employees, 15 managers and 30 customers used in this study is adequate for the analysis of patterns and themes, but it is not sufficient for the use of statistical generalization to the larger population of Ethio Telecom's employees or customers. The participants were recruited in a non-random way, so the presence of selection bias cannot be excluded since participants who agreed to take part in the study might have been more opinionated; in order to avoid this limitation, participants from various departments and positions were selected. There is a possibility of social-desirability bias in the case of manager's questionnaire data because managers had to evaluate their own communicational skills, training and leadership; the problem was handled by triangulation of data and treating the gap between the results of manager's evaluation and results obtained from other participants as the study's findings. Data were collected at a particular moment of time – early 2026 - in the process of organizational change, so some problems discussed in the study might have been resolved and new problems might have arisen. Finally, this research deals with one particular organization, so it is impossible to say to what extent the results can be generalized to other organizations in Ethiopia and other telecom companies in Africa based only on this study.A further limitation concerns the

design of the questionnaires. Two of the customer background questions asked respondents to tick all Ethio Telecom services they use. These are multiple response questions and are reported as services used in the profile table, with each service counted according to whether the customer uses it. The two questions were used only to confirm that each customer uses at least one service which was a condition for taking part and to give an overall profile of the sample. They were not used to calculate any result or to create any theme so they do not affect the findings.

5.7 Suggestions for Future Research

These four directions naturally follow from this research. First, in view of the limited scope of the research, which considered just one company and used qualitative methods of analysis, a broader quantitative study of the relationships discovered could be conducted, for instance, through structural equation modeling on the relationships between quality of communication, adequacy of training and speed of implementation on one side and adaptation of the employees and customer satisfaction on the other side. Second, a longitudinal study of the changes observed among the same managers, employees and customers in the period of two or three years is warranted as the initial dynamics of the process under study, such as the imported fear of AI, peer learning as the main way of achieving proficiency in using the technology and provision of basic rather than complex services due to lagging resolution, do not seem likely to persist. . Third, a comparative study across several large Ethiopian public organizations, such as Ethiopian Airlines, the Commercial Bank of Ethiopia and the revenue authority, would show whether the patterns identified here are specific to telecommunications and to this organization or are general features of AI-driven change in the Ethiopian public sector. Fourth, the customer findings raise a question worth pursuing in its own right: what is the minimum digital-service capability that should exist before physical branch alternatives are reduced, particularly for older and less digitally literate customers? This is at once a service-design and a social-inclusion question, and its relevance reaches beyond the telecom sector.

5.8 Concluding Remarks

The case of Ethio Telecom shows that adopting artificial intelligence is, in the end, less a technical problem than a human one. The systems were installed and they work, and employees and

customers use them and value them for what they do well. What proved harder was leading people through the change: communicating it in time, involving those affected, preparing them properly, and continuing to serve those the technology does not yet reach. The organization managed the first task and under-managed the second, and its people closed much of the gap themselves through improvisation and goodwill. The most valuable thing the change produced was not the technology but the leadership capacity built by steering it, imperfections and all. That capacity, used deliberately and applied to the human side of the next change, is what will allow Ethio Telecom to do better what it has already shown it can begin.

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APPENDICES

Questionnaire

Managers

Variable (Tick (✓) the appropriate box)

1. working role

❒ Team Leader

❒ Middle Manager

❒ Senior Manager

2. Working department

❒ Customer Service

❒ IT technologys development

❒ Network Operations

❒ Finance

❒ HR

❒ Digital Services / Telebirr

❒ Hardware Installation

3. Years worked

❒ < 2 years

❒ 2 – 5 years

❒ 6 – 10 years

❒ > 10 years

4. Highest Education achieved

❒ Diploma

❒ Bachelor's Degree

❒ Postgraduate Degree

5. Has your team been affected by the introduction of new AI systems or technology changes?

❒ Yes,significantly affected

❒ Yes,somewhat affected

❒ No ,not yet affected

❒ Doesn’t know

PART TWO: LEADERSHIP AND CHANGE MANAGEMENT

1: Vision and Communication

No.	Question	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
1	I explained clearly to my team changes in Ethio Telecom were happening.	❒	❒	❒	❒	❒
2	Senior management explained clearly to me so that I can explain to my team.	❒	❒	❒	❒	❒
3	After talking to my team they understood the purpose and direction of the changes.	❒	❒	❒	❒	❒
4	I used more than one means of communicating like meetings, written notices, one to one chats, and so on.	❒	❒	❒	❒	❒
5	There was a clear aim and vision from the top about how these changes go with the company's future goals.	❒	❒	❒	❒	❒

2: Resistance and Adaptation Management

No.	Question	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
6	When the changes came in, I ran into real resistance from employees.	❒	❒	❒	❒	❒
7	I had a good ways to deal with my team's concerns and resistance about the changes.	❒	❒	❒	❒	❒
8	My team got enough time and preparation	❒	❒	❒	❒	❒
9	the pace of changes at Ethio Telecom has been too rapid for employees to settle into.	❒	❒	❒	❒	❒

10	How well people adapted seemed to connect with things like their age, how long they'd been working, or their education level.	❒	❒	❒	❒	❒
11	I involved my team in decisions about how the new technology's and AI systems would actually be introduced out in our working environment.	❒	❒	❒	❒	❒

3: Training and Building

No.	Question	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
12	My team had gotten enough training and resources to help them understand the new digital systems.	❒	❒	❒	❒	❒
13	That training came before or during the roll out, not just after issues had already started to show up.	❒	❒	❒	❒	❒
14	The training was practical and relevant to the tools my team had to use.	❒	❒	❒	❒	❒
15	As a manager, I got enough support and guidance from senior leadership	❒	❒	❒	❒	❒
16	A lot of the time I had to work out my own way of guiding the change, without support from the organization.	❒	❒	❒	❒	❒

4: Leadership Opportunities and Outcomes

No.	Question	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
17	New AI tools dashboards, data analytics and monitoring system have made me more better as a leader.	❒	❒	❒	❒	❒
18	As time goes the changes have made my team more productive and efficient.	❒	❒			❒

				❒	❒	
19	This changes have made real development for my team not just extra effort and time.	❒	❒	❒	❒	❒
20	My team can give better service than before this systems.	❒	❒	❒	❒	❒
21	I feel confident leading for any next technology changes	❒	❒	❒	❒	❒
22	All together, the changes at Ethio Telecom have been handled well	❒	❒	❒	❒	❒

PART THREE: SHORT INTERVIEW QUESTIONS

1. what was you biggest challenge in the age of AI and what made you to better deal with it?

2. what do you think are the top things that managers should do differently for future technological changes?

EMPLOYEES QUESTIONNAIRE

Variable (Tick (✓) the appropriate box)

1. Age

- ❒ Under 25
- ❒ 25 – 34
- ❒ 35 – 44
- ❒ 45 – 54
- ❒ 55 and above

2. Highest Education Achieved

- ❒ Secondary Certificate
- ❒ Diploma
- ❒ Bachelor's Degree

❒ Postgraduate Degree

3. Years Worked

❒ < 2 years

❒ 2 – 5 years

❒ 6 – 10 years

❒ > 10 years

4. Working Department

❒ Customer Service

❒ IT Technology dev.

❒ Network Operation

❒ Finance

❒ Human Resources

❒ Digital Services likeTelebirr

❒ hardware installation

5. Have new digital systems or AI systems been introduced in your department?

❒ Yes a significant amount

❒ Yes small things

❒ No

❒ Not sure

6. Do you use AI or automated tools as part of your daily work?

❒ Yes every day

❒ Yes sometimes

❒ Rarely

❒ No

PART TWO: EXPERIENCE WITH AI

A: Adaptation

No.	Question	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
1	I can use the new digital tools at work without trouble.	❒	❒	❒	❒	❒
2	I know why Ethio Telecom is bringing all these new technology changes.	❒	❒	❒	❒	❒
3	The training I got helped me use new	❒	❒			❒

	systems.			❒	❒	

B: Struggles

No.	Questions	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
4	I am worried that machines or AI might take away my job in the future.	❒	❒	❒	❒	❒
5	The changes have been happening too fast making It too hard to keep up.	❒	❒	❒	❒	❒
6	I was told about the changes before they happened.	❒	❒	❒	❒	❒

C: Leaders roles

No.	Questions	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
7	My supervisor explained why the technology changes were happening.	❒	❒	❒	❒	❒
8	My manager gave me the help and tools	❒	❒	❒	❒	❒
9	When I share my worries or ideas, my leaders listened to me.	❒	❒	❒	❒	❒
10	Employees like me were part of deciding how the new technology was first introduced to the work environment.	❒	❒	❒	❒	❒
11	Senior leaders had clear plan for how all change would be managed.	❒	❒			❒

				❒	❒	

D: effect of change

No.	Questions	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
12	The technology changes have made my daily work easier also faster.	❒	❒	❒	❒	❒
13	Because of these new changes I have learned new skills or got new opportunities.	❒	❒	❒	❒	❒

PART THREE: OPEN ENDED QUESTIONS

1. What has been the hardest part of technology changes , and what or who helped you with it?

2. What is one thing your leaders could have done differently to make the technology change more easier for employees like you?

CUSTOMER QUESTIONNAIRE:

PART ONE: BACKGROUND

Variable **Please tick (✓) the appropriate box**

1. How long have you been using Ethio Telecom?

❒ Less than 1 year

❒ 1 –3 years

❒ 4 – 7 years

❒ More than 7 years

2. Which Ethio Telecom services do you use? (you can tick sevral)

❒ voice calls

❒ Internet mobile

❒ Telebirr

❒ Fixed broadband

❒ Ethio TV or other

3. Age Group

- ❒ Under 25
- ❒ 25 – 34
- ❒ 35 – 44
- ❒ 45 – 54
- ❒ 55 and above

4. Highest Education achieved

- ❒ No formal education
- ❒ Primary or Secondary
- ❒ Diploma
- ❒ Degree or above

5. Location

- ❒ Addis Ababa
- ❒ Regional city / town

6. Which of the following Ethio Telecom digital services have you used? (tick all that apply)

- ❒ Ardi chatbot (website / WhatsApp / Telegram / Facebook)
- ❒ Telebirr app or USSD (*127#)
- ❒ Ethio Telecom self service app
- ❒ Digital SIM or ID registration (fingerprint machine)
- ❒ None of the above

7. When you have a problem or question, what do you do first?

- ❒ Use the Ardi chatbot or self service app
- ❒ Call the customer service hotline (994)
- ❒ Visit a service branch in person
- ❒ Ask a family member or friend
- ❒ Other

PART TWO: YOUR EXPERIENCE LIKERT SCALE

Section A: Accessibility and Ease of Use

	Questions	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
1	I find Ethio Telecom's digital services the Ardi chatbot, telebirr app, USSD menus easy to use on my own.	❒	❒	❒	❒	❒

2	Most of the time I can sort out my issue without visiting a branch or talking to a person.	❒	❒	❒	❒	❒
3	When I get stuck on a digital service, Ethio Telecom gives me enough guidance or support.	❒	❒	❒	❒	❒
4	Ethio Telecom's digital services are usually up and working when I need them.	❒	❒	❒	❒	❒

Section B: Trust, Quality, and Service Improvement

	Question	**Strongly Disagree (1)**	**Disagree (2)**	**Neutral (3)**	**Agree (4)**	**Strongly Agree (5)**
5	I trust Ethio Telecom's digital systems to keep my information safe.	❒	❒	❒	❒	❒
6	Service quality has gotten better after the digital change.	❒	❒	❒	❒	❒
7	Digital or automated services like Ardi or telebirr sort my requests out faster than a human agent would.	❒	❒	❒	❒	❒
8	The digital services stay consistent and reliable, not just good for a while after a new launch.	❒	❒	❒	❒	❒

Section C: Impact of Leadership Driven Change on the Customer Experience

No.	**Statement**	**1**	**2**	**3**	**4**	**5**

		Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
9	Over the past year or two, I've noticed Ethio Telecom's service becoming more consistent and reliable.	❒	❒	❒	❒	❒
10	It feels like Ethio Telecom understands ordinary customers, not just the tech savvy ones.	❒	❒	❒	❒	❒
11	When something goes wrong with a digital service, I can get it fixed quickly and without too much hassle.	❒	❒	❒	❒	❒
12	I'm comfortable with more and more of my Ethio Telecom services being handled by automated or AI systems.	❒	❒	❒	❒	❒
13	Ethio Telecom tells me about service changes clearly, before or when they happen, not after the fact.	❒	❒	❒	❒	❒
14	The way Ethio Telecom brings in new technology gives me confidence in how the organization is led.	❒	❒	❒	❒	❒
15	On the whole, the move toward digital services at Ethio Telecom has made things better for me as a customer.	❒	❒	❒	❒	❒

Note: Questions 12 to 15 were used during data collection but were subjected to qualitative analysis using the interview responses (See Section 3.9.1).

1. Compared to two or three years ago, how is your overall experience as an Ethio Telecom customer today?

❒ Much better ❒ A little better ❒ About the same ❒ A little worse ❒ Much worse

2. What do Ethio Telecom's digital services do well, and what should they improve?

3. Is there anything you wish for management at Ethio Telecom to be aware of regarding how these digital changes impact you as a customer?

Observation Session Details

Variable **Tick (✓) the appropriate box**

Date of observation:

Location / Branch name:

Type of area observed:

- ❒ **Customer service counter**
- ❒ **Area for Digital/ Self-service Kiosks**
- ❒ **Floor space for call center employees**
- ❒ **Operational Area for back office**

Time

Number of employees present (approx):

Number of customers seen (approx):

1: Customer Interactions with Digital and Artificial Intelligence-based Services

No.	Observation Item	Yes	No	Researcher Notes
1	Customers make use of digital self-service technology, such as kiosks, chatbots, and apps, without requiring any assistance from staff members.	❒	❒	
2	Customers exhibit confusion or dissatisfaction in the use of digital services	❒	❒	
3	Staff guide customers toward digital options rather than handling everything manually.	❒	❒	
4	Digital services appear to work smoothly, without technical failures, during the visit.	❒	❒	

2: Employee Use of Digital and Automated Work Systems

No.	Observation Item	Yes	No	Researcher Notes
5	Employees use digital systems confidently and fluently while serving customers.	❒	❒	

6 Employees seem hesitant or struggle with certain digital tools. ❒ **Yes** ❒ **No**

7 Employees help each other with digital system problems (informal peer learning). ❒ **Yes** ❒ **No**

8 Employees are able to provide customers with an adequate explanation of their digital products. ❒ **Yes** ❒ **No**

3: Leadership and Supervisory Behavior

No.	Observation Item	Yes	No	Researcher Notes
9	A supervisor/team leader is physically present on the sales floor. ❒ **Yes** ❒ **No**			
10	A supervisor helps the employee with a digital system challenge or a demanding customer. ❒ **Yes** ❒ **No**			
11	In supporting others, the supervisor acts as a mentor for the employee and not as a controller who does everything for the employee. ❒ **Yes** ❒ **No**			
12	The work environment is characterized by support among colleagues in relation to IT issues ❒ **Yes** ❒ **No**			

4: Overall Integration and Researcher Notes

Summary of the integration of digital systems in this location (circle one):

Fully Integrated Largely Integrated Partially Integrated Early Stage Only Minimal / Not Yet Observed

Researcher notes Main observations, unexpected findings, or details wrath recording: