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Digital Transformation and Change Management: Challenges for Traditional Businesses

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ABSTRACT

In this study, we are exploring and analyzing the challenges faced by traditional businesses in terms of organizational and human aspects in regard to digital transformation, in particular, Artificial Intelligence (AI) integration. A mixed-methods sequential explanatory design was used, based on change management theory, with a survey of 300 managers and employees and 25 semi-structured interviews. Structural Equation Modeling (SEM) was used for quantitative data and Thematic Analysis for qualitative data. Results indicate that being ready for digital transformation positively impacts change management practices (ß = 0.52, $p < .001$) which in turn positively impacts organizational outcomes (ß = 0.45, $p < .001$). Adoption of AI has a negative relationship with outcomes in the organization ($\beta = -0.38$, $p < .001$). Importantly, change management practices mediate the relationship between readiness and outcomes (indirect effect = 0.31, $p < .001$) and moderate the negative impact of AI adoption challenges on outcomes ($\beta = 0.22$, $p < .001$). Leadership commitment, employee engagement, skills development, communication, and buffering effect of change management were found as critical success factors within the qualitative findings. This study has theoretical implications as it proposes change management as a mediation and buffering process in digital transformation and also has practical implications when it comes to the leaders' role in digital transformation in traditional business settings.

Keywords: *Digital Transformation, Change Management, Artificial Intelligence, Traditional Businesses, Organizational Outcomes, AI Adoption Challenges, Structural Equation Modeling*

INTRODUCTION

In today's business world, a revolution is afoot, and advanced digital technologies are making a lasting impact. Of these, Artificial Intelligence (AI) has not only become a significant driver of incremental improvement but a transformative force that is reshaping the nature of competition, operations and value creation (Rajapaksha et al., 2025). This change is paradoxical for traditional businesses that have long-term legacy structures, ingrained cultural norms, and entrenched operating routines. As much as digital transformation can be a massive opportunity to create efficiencies, personalise customer experience, and gain new insights for strategic decision-making, it's a significant challenge to execute (Sheikh, 2022). The failure rate of digital transformation programs is so high around 70% of digital transformation programs fail because of lack of organizational support and commitment – that understanding and managing the human and structural aspects of the journey becomes of paramount importance, particularly for organizations dealing with the complexities of integrating AI (Bidhendi et al., 2025). According to this

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paper, the essence of this challenge lies not in the technology itself but in the dynamic organizational aspect it is a strategic and structured challenge of change management (Rajapaksha et al., 2025).

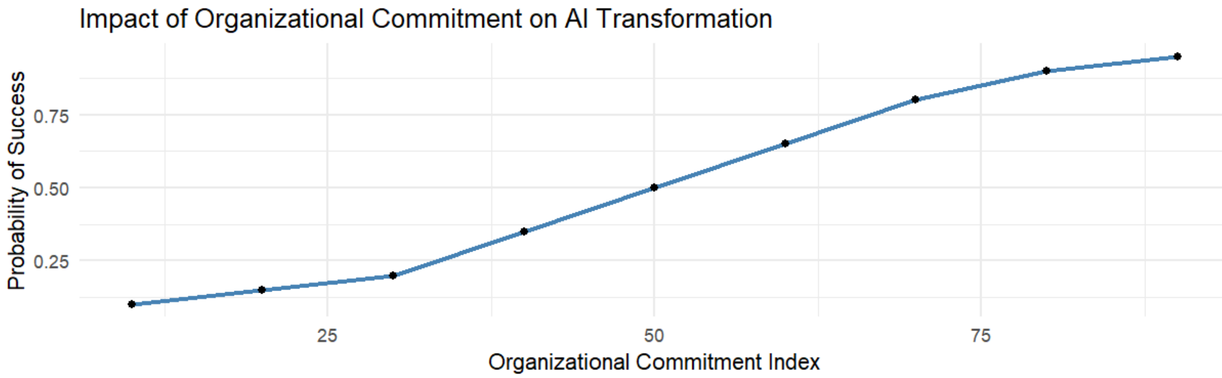


Figure 1 *The Relationship Between Organizational Commitment and AI Transformation Success*

Digital transformation is not just about converting information and automating tasks; it's about a change in working methods.Digital transformation isn't about digitizing information and automating the same things; it's about changing how things work. It is a comprehensive and strategic process that involves comprehensive changes to the properties, structures, practices and values of an entity by integrating information, computer, communication and connectivity technology (Chen, 2024). It is not just an IT project for a traditional enterprise, but a strategic must to consider the enterprise's identity and market position comprehensively (Sheikh, 2022). Sheikh (2022) notes that the shift from standard operation to digital systems can also involve considerable organisational resistance, cultural inertia and knowledge gaps, and can be especially challenging for existing organizations. The absence of digital culture and leadership commitment are also key impediments to digital transformation in traditional organizations, as identified by scholars (Panotogomo, 2025; Bidhendi et al., 2025).

Artificial Intelligence (AI) is a powerful enabler of this change. AI has transformed business operations, such as machine learning, NLP, and predictive analytics, which have streamlined decision-making, boosted data analytics, and automated processes (Panotogomo, 2025). But, using AI in a traditional business environment comes with its own set of challenges. There is a huge gap between the deployment of a technology and its implementation in businesses as the technology moves forward but the businesses are not able to catch up (Malik, 2026). However, the employees often lack the necessary skills to adapt to new technology, and the uncertainty surrounding change can also make employees feel unready to do so (Bari et al., 2025). In addition, it is often difficult for organisations to adopt new technologies within existing 'legacy' systems, which can be time consuming and financially expensive (Chen, 2024). Some studies have shown that lack of digitally proficient employees and employee resistance to automation are among the most common barriers to the uptake of AI (Panotogomo, 2025; Bidhendi et al., 2025).

Change Management (CM) is the well recognised practice that facilitates organisations to prepare, equip and support people to successfully embrace change and is an essential skill in the technology to organisational success relationship, which is often overlooked.Change Management (CM) is a well recognized practice that guides the way to prepare, equip and support individuals to successfully embrace change and is a critical skill in the relationship between the technology and the organisation's success, albeit one that is often overlooked. It aims to put the human component of change (Bidhendi et al., 2025) in focus, to ensure the desired outcomes of a transformation are realized. The traditional CM models, like the Three-Step Model (Unfreeze-Change-Refreeze) by Kurt Lewin and the 8-Step Process by John Kotter, have been around for decades, but their relevance to the dynamic and non-linear environment of digital transformation is beginning to be doubted (Bidhendi et al., 2025). Today's digital era requires a more flexible, incremental and culture-aware approach to change management (Sheikh, 2022). The implementation of AI is not just a technical change but also social, and involves a trust-building, learning, and adaptability process for employees that must rely on structured frameworks that are adapted to the context of the organization and the needs of the employees. (Vuorenheimo, 2025) In the current era, a focus on employee engagement and psychological safety has become a critical aspect of change management during technological shifts (Bidhendi et al., 2025; Rajapaksha et al., 2025).

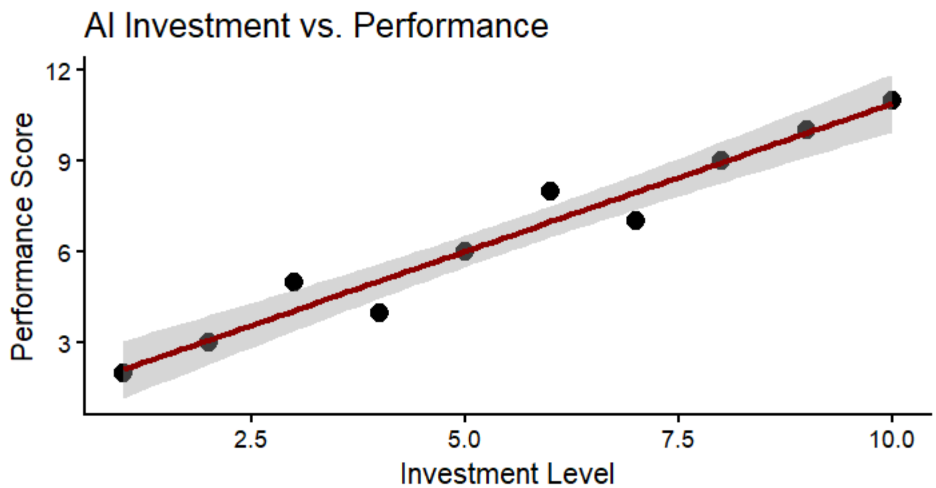


Figure 2 *The relationship between AI Investment and Organizational Performance.*

The current paper focuses on the central research question: How will traditional companies be able to effectively respond to the organizational and human aspects of digital transformation, particularly the application of AI, in order to sustainably succeed in the process? Although there is extensive literature on digital transformation and change management alone, there is a lack of literature on the integrated study of these phenomena, especially in the context of organizations that have legacy systems and are adopting AI (Bidhendi et al., 2025; Rajapaksha et al., 2025). This research study seeks to fill that void by examining the important relationship between technological initiatives and organizational preparedness (Sheikh, 2022).

For this, the paper will first draw on the literature to create an understanding of the essential elements of digital transformation and the integration of AI into traditional businesses, as well as the main challenges encountered. It will then examine change management models, theoretically, and practically, in the context. The main value of this study is the synthesized framework that highlights and organizes the distinctive change management actions and enablers to help overcome the complexities of the digital journey. The framework is designed to guide business leaders and change managers through minimizing resistance, developing digital skills, and ensuring technological advancements align with strategic objectives (Bidhendi et al., 2025). Finally, the paper concludes that the key to the success of traditional business in the future is not about technology, but is about adjusting their culture, leadership, and workforce to be more adaptive and competitive due to embracing AI.At the end of the day, the ability to evolve and adapt their culture, leadership, and workforce to take advantage of AI and become more adaptive and competitive versions themselves is the key to traditional businesses' success in the future (Sheikh, 2022; Rajapaksha et al., 2025).

LITERATURE REVIEW

Introduction

The existing literature on digital transformation, adoption of artificial intelligence and change management in traditional business is summarized in this chapter. The review draws together theoretical underpinning, empirical evidence and conceptual approaches to create a solid basis for appreciating the problems and opportunities that traditional organisations may face on their digital journey. The chapter has four major parts: Conceptuating DT, AI in DT of business, change management theories and models, and specific challenges of traditional businesses in DT projects.

Conceptualizing Digital Transformation

Defining Digital Transformation

Digital transformation is one of the key strategies that has come to prominence in all sectors. Despite the commonality of the term in both academic and practitioner settings, there is still a lot of discussion about the exact meaning and definition of it (Chen, 2024). Digital transformation is at the very heart of how organizations generate value from the intelligent use of digital technologies. A digital transformation is conceptualized as a holistic process where the four spheres of information, computing, communication and connectivity technologies (ICTs) bring about substantial changes to the properties, structures, practices, and values of an entity (Rajapaksha et al., 2025).

Digital transformation is not just about digitizing information or automating current processes, as pointed out by Sheikh (2022). Rather, it is a fundamental organizational shift that impacts business models, organizational culture, customer experience and processes. This is in keeping with the vision that digital transformation is not just about technology, but about reinventing the organization. Traditional ways of working and digitally enabled working sometimes involve significant cultural and organizational resistance and knowledge gaps, which can be a difficult journey for established companies (Sheikh, 2022).

The Strategic Imperative of Digital Transformation

In the modern business landscape, the significance of Digital transformation is undeniable. By successfully completing the digital transformation process, organizations can gain many competitive benefits, such as improved operational efficiency, better customer experiences, and the development of new revenue streams (Panotogomo, 2025). Yet, the journey toward digital transformation is riddled with obstacles, as studies show that only about 30% of digital transformation projects succeed, primarily because there is not enough commitment or support from the organization (Bidhendi et al., 2025).

The failure rate of digital transformations shows the critical need to understand and manage the human and structural aspects of organizational change (Bidhendi et al., 2025). They have pointed out that the technology investment is not enough for successful transformation, and that organizations have to take care of the cultural, behavioral and structural aspects that impact on change adoption. This is supported by Sheikh (2022) who argues that the shift from traditional to digital business models should not only be driven by technological infrastructure but also a shift in organizational mindsets and capabilities.

Artificial Intelligence in Business Transformation

The Role of AI as a Catalyst

The emergence of Artificial Intelligence (AI) has changed the manner in which organizations operate and conduct their activities and given them unmatched automation, data analysis and decision-making capabilities (Panotogomo, 2025). AI, machine learning, natural language processing, and predictive analytics are changing the way business works in a variety of industries. Applications of AI to automate repetitive work, personalize customer interactions, improve supply chain management, and extract insights about large volumes of data are underway (Rajapaksha et al., 2025).

Panotogomo (2025) highlights the fact that the adoption of AI is not just a technological advancement but a paradigm shift in organizational functioning and competition. AI is capable of converting reactive to predictive decision-making, standard to personalized customer experiences, and manual to automated operations. Nonetheless, in order to attain these advantages, organisations must go through numerous challenges that include the implementation of technology, skill development and change management.

Challenges in AI Adoption

While AI has the potential to revolutionize, its implementation in conventional business environments comes with its own set of intricacies. The technology gap is enormous as it moves at a much higher pace than the businesses' ability to effectively implement it (Malik, 2026). Malik (2026) pinpoints that over 80 per cent of AI tasks fail, which is two times the failure rate of non-AI technology tasks and provides a clear sign of the unique problems that come with using AI.

Among the major barriers to AI adoption in traditional companies, Bari et al. (2025) highlight employee resistance. Employees can feel ill-equipped to embrace new technologies either for a lack of relevant skills or because of the uncertainty that change impacts. This resistance is especially strong where there are well-established cultural norms and work practices within an organisation. Moreover, there are often challenges in the integration of new technology with existing legacy systems, which can be time-consuming and expensive (Chen, 2024).

In addition, Chen (2024) says that one of the most common obstacles to the adoption of AI is the lack of digitally literate workers, or the reluctance of workers to accept automation. Small and medium-sized enterprises (SMEs) may also face a shortage of digital talent to effectively implement and manage AI systems. The skills gap is exacerbated by the organizational structures and processes that might not support the adoption of AI, further complicating the successful implementation of these technologies.

The Human-Centric Perspective on AI Adoption

Vuorenheimo (2025) offers a more humanistic perspective of the implementation of AI, noting that it is not only a technical improvement, but an interpersonal process that requires trust, flexibility, and continuous learning. She emphasizes that structured frameworks should be designed to suit the context of the organization and the needs of its employees to help them successfully adopt AI. This view reinforces the importance of considering human factors in the implementation of AI, including the possible loss of jobs, changes in the working process, and the need to acquire new skills and competencies.

The necessity of change management to support the adoption of AI is also raised by Rajapaksa et al. (2025), because organizations have to educate, train, and empower their employees to effectively adopt the new technologies. Their results underline the significance of systematic approaches which address the technological and human side of AI implementation. This two-pronged strategy is particularly important in the case of legacy firms that have standardized work processes and cultural norms that may be a significant obstacle to change.

Change Management: Theoretical Foundations and Applications

Foundations of Change Management

Change management is a well-known discipline that helps organizations prepare, equip, and support their workforce to embrace change successfully (Rajapaksha et al., 2025). It is mainly aimed at ensuring that the desired outcomes of a transformation are realized by paying attention to the human side of change (Bidhendi et al., 2025). Over the last few decades, change management has developed a great deal and various models and frameworks have been developed to understand and facilitate change in an organization.

Change management practice has been guided by classical change management models like Kurt Lewin's Three-Step Model (Unfreeze-Change-Refreeze) and the 8-Step Process by John Kotter (Bidhendi et al., 2025). Creating readiness for change, implementing change, and stabilizing new practices are important elements of Lewin's model. A more detailed roadmap for the implementation of change is given by Kotter's model, which highlights the need for creating a sense of urgency, building coalitions, and installing change within the organizations culture.

Change Management in the Digital Age

Although classic change management models are still used as a guide to practice, there is growing doubt about their applicability in the dynamic and non-linear context of digital transformation (Bidhendi et al., 2025). Today, the digital era requires a more agile, iterative and culture-conscious way of managing change (Sheikh, 2022). Traditional change management models may be too linear and static to adapt to the complexity and rapid pace of digital change.

Sheikh (2022) believes that focusing on a gradual approach to implementation and fostering an attitude of innovation and adaptability can be considered more of a success factor than technology adoption alone. This view implies that organizations need to be capable of continuously adapting and learning, not thinking of change as having definite start and end points. The process of digital transformation is an iterative one, which means that organizations need to be agile and adaptable to new challenges and opportunities that arise.

A human-centric integrated change management framework is developed by Bidhendi et al. (2025), highlighting the importance of considering the human aspects of change in addition to technical aspects during the process of digital transformation. They emphasize employee participation, communication and engagement in change efforts. The human-centric approach is especially applicable to traditional businesses, where existing organizational culture and practices might result in massive resistance to change.

Integrating Change Management with Digital Transformation

As noted by Rajapaksha et al. (2025), change management is a key element in achieving effective digital transformation. Their research shows that organisations who master the human side of change have a higher probability of success in the outcomes of their digital transformation programmes. This result aligns with existing research that indicates that change management is one important factor in organizational changing.

In the context of digital transformation, organizations must focus on key areas such as leadership commitment, communication, employee engagement, skills development, and cultural change when integrating change management with digital transformation.There are several critical areas that organizations need to consider when integrating change management with digital transformation: leadership commitment, communication, employee engagement, skills development, and cultural change (Panotogomo, 2025). As Panotogomo (2025) points out, change management approaches need to be tailored to the particular situation of a digital transformation, which frequently is very uncertain and complex. Resistance to change, development of capacity, and a culture of ongoing learning and adaptation must be addressed.

Specifically, Bari et al. (2025) discuss leadership in pressure situations and the management of resistance in traditional organizations. Their research emphasizes the need for good leadership to help manage change, especially in organizations that have well established cultures and practices that might be resistant to change. The key in traditional organizations is that their leaders have to be willing to listen to employee fears and concerns, to establish trust, and provide a vision for the future.

Challenges for Traditional Businesses

Organizational and Cultural Barriers

There are specific challenges in digital transformation for traditional businesses, such as their existing structures, cultures, and practices (Chen, 2024). Organizational inertia, common in many traditional businesses, might present a challenge for change as workers and supervisors can be resistant to new methods of working. Traditional organizations can face significant challenges in overcoming cultural inertia, characterized by resistance to change, digital literacy issues, and the acceptance of new work practices, as identified by Chen (2024).

Many of the material shifts from traditional operational models to ones enabled by digital technologies come with significant organizational resistance, cultural immobility, and knowledge deficits, as Sheikh (2022) points out. The hindrances are especially significant in organizations that have been around for awhile and their cultural norms have been well established. However, deliberate action is needed to develop digital skills, change the culture of an organisation, and tackle employee concerns to overcome these.

Legacy Systems and Technological Challenges

One of the main issues that traditional businesses face is integrating new technologies into their legacy systems. Legacy IT systems are often not designed to allow for the introduction of more advanced digital capabilities, making it difficult to integrate the new capabilities into existing business architectures. Replacing or upgrading legacy systems can be costly and complex, making it a major hurdle for digital transformation.

According to Chen (2024), the integration of new technologies into legacy systems often poses challenges for organizations, making the process time-consuming and expensive. This challenge is especially great in traditional industries where the systems might have been in place for decades and are entrenched in organizations' processes. As companies work to keep their operations running while adopting new technology, the transformation process is further complicated.

Gaps in Skills and Capability

One of the vast challenges is the lack of digitally skilled professionals in traditional businesses (Panotogomo, 2025). Organizations tend to lack digital skills to use and manage digital technologies effectively. This skills gap is exacerbated by organisational structures and processes, which may not be favourable to digital working for successful transformation.

Panotogomo (2025) is able to pinpoint that one of the most common difficulties when engaging in digital transformation is the lack of digital skilled professionals and employee resistance to automation. To tackle these gaps, traditional businesses will have to invest in their skills development and talent acquisition, and set the ground for their organizations to thrive in the digital working environment. Bari et al. (2025) emphasise the fact that employees may fear change because of their lack of skills, or because they are scared of the change itself.

Change Management Challenges

The human dimensions of change are particularly challenging for traditional businesses (Bidhendi et al., 2025). Challenges are often employee resistance to change, lack of leadership commitment, and difficulties in building a digital culture. The authors Bidhendi et al. (2025) point out that these challenges need to be overcome through a structured approach to change management that involves employees, develops capabilities and establishes a supportive environment for change.

Rajapaksha et al. (2025) highlight the importance of organization preparations, capabilities, and supports to effectively implement new technologies. This will include an investment in training & development, clear communication of the reasons for the change and an opportunity for employees to be actively involved in change programmes. Leadership has a special role as those leading are expected to be good role models, to have a message to give and to provide a supportive environment for change.

Research Gap and Conceptual Framework

The literature review identified a lack of research in the area of digital transformation, the adoption of AI technologies, and change management in traditional businesses, highlighting a research gap in this field (Bidhendi et al., 2025; Rajapaksha et al., 2025). There is much research on each of these themes in isolation but little work that explores their interconnections and how these can be successful integrated to drive organizational change. This gap is even more critical considering how AI is emerging as a driver of digital transformation and the struggles that some traditional businesses are encountering when it comes to digital change and the human experience.

Sheikh (2022) calls for studies that explore the traditional businesses' challenges for digital transformation. This research should take into account the specific attributes of traditional organizations, such as their organizational culture, structure and way of working, as well as the impact of these attributes on the success of digital transformation initiatives. Also, research is needed which will explore how change management can facilitate successful digital transformation, especially related to AI adoption.

Drawing on the literature review, the paper offers a conceptual framework which combines the concepts of digital transformation, AI adoption and change management. The framework acknowledges that effective change management, as well as technological investment, is necessary for successful digital transformation, in order to consider the human aspects of change. The framework identifies key success factors: leadership commitment, employee engagement, skills development and cultural change and explores how these interact to impact upon the outcome of transformation.

Summary

The chapter has given an extensive literature review for the digital transformation, AI adoption and change management in traditional business. The review has identified the strategic nature of digital transformation, the transformative role of AI, change management theories, and the peculiarities of traditional organisations. From the literature it is seen that although some progress has been made in understanding the phenomena separately, there is a need for integrated research which would consider their interrelationships and practical implications for traditional businesses.

The review has also pointed to a gap in the research in integrated study of these phenomena, especially in the context of traditional businesses facing the challenges of AI adoption. This space is what motivated the creation of the current research with the objective of building a synthesized framework about the understanding and management of the challenges of digital transformation in traditional companies. The methodology will be presented in the next chapter, analysis will be discussed, and recommendations for practice will be presented.

The review has also identified a research gap in the integrated study of these phenomena, particularly in the context of traditional businesses facing the challenges of AI adoption. This gap provides the rationale for the present study, which aims to develop a synthesized framework for understanding and managing the challenges of digital transformation in traditional businesses. The next chapter will present the methodology for this research, followed by an analysis of findings and recommendations for practice.

METHODOLOGY

Introduction

In this chapter, the research methodology used to examine the organizational and human issues of digital transformation and the best ways for traditional businesses to handle them, particularly regarding Artificial Intelligence (AI) applications, is presented. The methodology aims to fill the research gap identified in the literature review, which is the lack of integrated research on digital transformation, AI adoption, and change management in traditional business settings (Bidhendi et al., 2025; Rajapaksha et al., 2025). The research philosophy, approach and design, data collection, sampling, data analysis, model specification and ethical considerations that underpin this investigation are outlined in this chapter. The methodological options are supported in the context of the research goals and phenomenon being examined.

Research Philosophy

The pragmatic research philosophy is used in this study because it does not limit research questions with specific philosophies but rather guides these with methodological choices (Creswell & Creswell, 2018). Pragmatism is especially suitable for this research because it enables the combination of qualitative and quantitative approaches to answer the complex and multifaceted nature of the digital transformation and change management (Saunders et al., 2019). The pragmatic approach assumes that organizational phenomena like digital transformation are complex and that they cannot be comprehended in one epistemology only.

The pragmatic philosophy is consistent with the research goals to understand both the objective problems confronted by traditional businesses and subjective experiences of organizational members in the process of digital transformation. This philosophical standpoint helps the researcher use many sources of knowledge and various methodological approaches to acquire a full picture of the phenomenon of study (Tashakkori & Teddlie, 2010). The emphasis on practical outcomes and actionable insights also underlines the need for a pragmatic approach, as the study seeks to create a framework that is applicable in traditional business contexts.

Research Approach

The research approach used in this study is mixed method research which is a research method that uses both quantitative and qualitative data collection and analysis techniques (Creswell & Plano Clark, 2017). The justification for the use of the mixed methods is that the research phenomenon is complex and the experiences associated to digital transformation and change management are both broad and in-depth (Bryman, 2016). Qualitative methods can give a rich, contextual description of the experience of the members of the organization while quantitative methods can identify patterns and relationships across a larger sample.

The use of a mixed methods approach is warranted to address the research gap identified in the literature, as it enables the use of a diversity of perspectives and sources of evidence (Fetters et al., 2013). This integration is crucial to gain a holistic view of the problems that traditional businesses face and the change management approaches that can tackle these problems. The strategy also allows the results of the various sources to be triangulated, thereby increasing the validity and reliability of the research conclusions.

Research Design

This study uses the sequential explanatory research design where two phases of data collection and analysis are done (Creswell & Plano Clark, 2017). The first phase is a quantitative survey of managers and employees in traditional companies with a digital transformation process in progress or recently completed. The second phase consists of qualitative semi-structured interviews with key informants, who were drawn from the survey respondents to elicit more detailed information on the survey results.

This research can be conducted by using sequential explanatory design because after quantitative research results on patterns and relationships are obtained, then qualitative research can be carried out, namely to explain and elaborate on the results of quantitative research (Ivankova et al, 2006). This design allows the researcher to capitalize on the merits of quantitative and qualitative approach, and after the quantitative phase, the qualitative phase can be used to give meaning and context to the quantitative findings. The design further supports the construction of a comprehensive framework which incorporates findings from both phases.

Theoretical Framework and Model Specification

Conceptual Model

The literature study results led to the development of a conceptual model which brings together digital transformation readiness, AI adoption challenges, change management practices and organizational outcomes. The model is based on the theoretical aspects of change management and digital transformation literature (Bidhendi et al., 2025; Rajapaksha et al., 2025; Sheikh, 2022). The conceptual model suggests that between the readiness for digital transformation and the organizational outcomes are mediated by the change management practices, and also moderates the negative effect of DT challenges of AI on DT success.

There are the following constructs in the conceptual model:

1. Digital Transformation Readiness (DTR): Organizational capabilities, leadership commitment and cultural readiness for digital transformation (Kane et al., 2015; Sheikh, 2022).

2. AI Adoption Challenges (AIC): Technical challenges, skills gaps, legacy system integration difficulties, and resistance to change (Malik, 2026; Chen, 2024; Bari et al., 2025).

3. Change Management Practices (CMP): Methodologies and techniques for addressing the human aspect of change such as communication, employee engagement, training, and leadership support (Bidhendi et al., 2025; Rajapaksha et al., 2025).

4. Organizational Outcomes (OO): It refers to perceived success of digital transformation initiatives and organizational performance improvements (Panotogomo, 2025; Vuorenheimo, 2025).

Structural Equation Model

The hypothesized relationships are tested using Structural Equation Modeling (SEM) with AMOS software. SEM is appropriate for this research as it allows for the simultaneous examination of complex relationships between multiple constructs, including mediation and moderation effects (Kline, 2016; Hair et al., 2019). The measurement model assesses the reliability and validity of the constructs, while the structural model tests the hypothesized relationships.

Measurement Model Equations:

For each latent construct, the measurement model is specified as:

$$\mathbf{X = \Lambda x\ \xi + \delta}$$

Where:

- X = vector of observed indicators for exogenous constructs
- Λx = matrix of factor loadings for exogenous constructs
- ξ = vector of exogenous latent constructs (DTR and AIC)
- δ = vector of measurement errors for exogenous indicators

$$\mathbf{Y = \Lambda y\ \eta + \varepsilon}$$

Where:

- Y = vector of observed indicators for endogenous constructs
- Λy = matrix of factor loadings for endogenous constructs
- η = vector of endogenous latent constructs (CMP and OO)
- ε = vector of measurement errors for endogenous indicators

Structural Model Equations:

The structural model specifies the relationships between the latent constructs as follows:

$$\eta_1 = \gamma_{11}\,\xi_1 + \gamma_{12}\,\xi_2 + \zeta_1$$

$$\eta_2 = \gamma_{21}\,\xi_1 + \gamma_{22}\,\xi_2 + \beta_{21}\,\eta_1 + \zeta_2$$

Where:

- η_1 = Change Management Practices (CMP)
- η_2 = Organizational Outcomes (OO)
- ξ_1 = Digital Transformation Readiness (DTR)
- ξ_2 = AI Adoption Challenges (AIC)
- γ = path coefficients for exogenous to endogenous relationships
- β = path coefficient for endogenous to endogenous relationship
- ζ = structural errors (disturbances)

Mediation Model:

To test the mediating role of change management practices, the following equations are specified:

Total Effect: OO = c(DTR) + e_1

Direct Effect: OO = c'(DTR) + b(CMP) + e_2

Indirect Effect (Mediation): CMP = a(DTR) + e_3

Where:

- c = total effect of DTR on OO
- c' = direct effect of DTR on OO after controlling for CMP
- a = effect of DTR on CMP
- b = effect of CMP on OO
- Indirect effect = a × b

The significance of the indirect effect is tested using bootstrapping procedures with 5000 resamples (Preacher & Hayes, 2008).

Moderation Model:

To test the moderating role of change management practices on the relationship between AI adoption challenges and organizational outcomes, the following equation is specified:

$$OO = \beta_0 + \beta_1(AIC) + \beta_2(CMP) + \beta_3(AIC \times CMP) + e$$

Where:

- AIC × CMP = interaction term
- β_3 = moderation effect

A significant β_3 indicates that change management practices moderate the negative relationship between AI adoption challenges and organizational outcomes.

Hypothesis Development

Based on the theoretical framework and conceptual model, the following hypotheses are proposed:

H1: Digital transformation readiness positively influences change management practices in traditional businesses.

H2: AI adoption challenges negatively influence organizational outcomes in traditional businesses.

H3: Change management practices positively influence organizational outcomes in traditional businesses.

H4: Change management practices mediate the relationship between digital transformation readiness and organizational outcomes.

H5: Change management practices moderate the negative relationship between AI adoption challenges and organizational outcomes.

Data Collection Methods

Quantitative Phase: Survey Questionnaire

The quantitative phase of the research involved a survey questionnaire.

The quantitative phase utilizes a structured survey questionnaire for obtaining data from the managers and employees of traditional businesses. The questionnaire will focus on the following key variables related to digital transformation, AI adoption, change management practices, and organizational outcomes (DeVellis, 2017): The survey instrument is created according to the existing validated scales and modified to suit this research context. All items are answered on a 5-point scale from 1 (strongly disagree) to 5 (strongly agree).

The survey questionnaire has five sections:

- Section A: Demographic Information – Age, gender, education, job role, years of experience, industry sector.

- Section B: Digital Transformation Readiness (DTR) – Nine items assessing organizational capabilities, leadership commitment and cultural readiness for digital transformation, adapted from Kane et al. (2015) and Sheikh (2022). Examples of those items are: "Our leadership is dedicated to digital transformation", and "Our organizational culture embraces innovation and change.

- Section C: AI Adoption Challenges (AIC) (Ten items adapted from Malik (2026) and Chen (2024) assessing technical challenges, skills, legacy system integration challenges, and resistance to change. Examples of sample items are "We are not knowledgeable on AI skills" and "We have a legacy system that is hard to integrate with AI.

- Section D: Change Management Practices (CMP) – 12 items adapted from Bidhendi et al. (2025) and Rajapaksha et al. (2025) that measure structured change management practices such as communication, employee engagement, training and leadership support. Sample items are: "Our organization clearly communicates the reasons for change" and "Employees are involved in change decision-making.

- Section E: Organizational Outcomes (OO) – Eight items of perceived success of digital transformation initiatives and organizational performance improvements adapted from Panotogomo (2025) and Vuorenheimo (2025). Items consist of statements such as: “Our digital transformation has increased operational efficiency” and “Our organization has reached its digital transformation goals.”

Qualitative Phase: Semi-Structured Interviews

Semi-Structured interviews are a component of the qualitative phase of the research process.

In the qualitative phase semi-structured interviews are used with the key informants who have been identified in the survey phase (Kvale & Brinkmann, 2009). The interviews aim to gain more in-depth understanding of the survey results and to investigate the experiences, perceptions and approaches of the members of the organization in the process of digital transformation and change management (King & Horrocks, 2010). Semi-structured format enables flexibility in the identification of new themes and in keeping the theme or set of research questions.

Questions for interviews are created from literature review and survey results including, but not limited to: nature of Digital transformation challenges in the organization, any role of AI in the Digital transformation, change management strategy used, factors that helped or hindered with successful Digital transformation and lessons learnt from the Digital transformation experience (Rubin & Rubin, 2012). Probes are used to elicit detailed responses and to go into the participants' experience in depth. Interviews are either conducted in person or through video conferencing, depending on the preferences of the participants and the geographical barriers, and are recorded on audio tape with the agreement of the participants.

Sampling Strategy

Quantitative Sampling

The quantitative phase uses a stratified random sampling technique that allows for representation from varying sectors of the industry and organizational size (Saunders et al., 2019). The target population are managers and employees in traditional businesses who have already started the digital transformation process and those who are still in the process. Traditional businesses are those businesses where traditional structures are already in place, cultural norms are profound and long-standing operational routines are established (Sheikh, 2025).

The sampling frame is created using business directories and industry associations; then stratified by industry sector (manufacturing, retail, financial services, healthcare, etc.) and size of the organization (small, medium, large enterprises). The aim is to obtain a sample size of 300 respondents which is adequate for the statistical analysis and generalizability of the findings (Hair et al., 2019). The sample size is more than the recommended minimum of 10 cases per parameter of the structural equation model (Kline, 2016). Participants are recruited via email invitation and professional networks and follow-up reminders sent to ensure a high return rate.

Qualitative Sampling

Qualitative phase uses purposive sampling to determine key informants among the respondents of the survey who can give rich and detailed information about the phenomenon of the research (Patton, 2015). Selection of participants depends on their role in the digital transformation initiative, level of involvement, and willingness to participate in followup interviews. The sample consists of managers, change management specialists and staff that have gone through the process of digital transformation.

The number of interviews aimed for is 20-25, consistent with recommendations for qualitative research when aiming for saturation (Guest et al., 2006). Participants are carefully chosen to be diverse across industry sectors, organizational sizes and roles, allowing the emergence of different perspectives and experiences. The survey questionnaire is used as a recruitment tool, asking respondents if they would be willing to do a follow-up interview.

Data Analysis Techniques

Quantitative Data Analysis

The quantitative data analysis is done using SPSS (version 28) and AMOS (version 26) (Hair et al., 2019). The analysis takes place in three stages:

- **Stage 1**: Descriptive and Preliminary Analysis – Descriptive statistics are calculated to describe the sample and the data of the survey items. Multiple imputation (Little & Rubin, 2019) is used to deal with missing data. Skewness and kurtosis values are used to evaluate normality assumptions, both absolute values of less than 2 and 7 respectively are acceptable (Kline, 2016). Variance Inflation Factor (VIF) is used to check the multicollinearity with VIF< 10 is acceptable.

- **Stage 2:** Measurement Model Assessment - Confirmatory Factor Analysis (CFA) will be performed to check the validation of the measurement model and the reliability and validity of the scales (Anderson & Gerbing, 1988). Multiple fit indices are used to assess model fit: Chi-square/df ratio (< 3), Comparative Fit Index (CFI > .90), Tucker-Lewis Index (TLI > .90), Root Mean Square Error of Approximation (RMSEA < .08) and Standardized Root Mean Square Residual (SRMR < .08) (Hu & Bentler, 1999). Cronbach's alpha and Composite Reliability (CR) values are used to assess internal consistency reliability and generally values of .70 or higher are considered acceptable (Nunnally & Bernstein, 1994). For the convergent validity, Average Variance Extracted (AVE) is used, and the results above .50 are acceptable (Fornell & Larcker, 1981). To examine the discriminant validity, the square root of AVE is compared with inter-construct correlations, and the square root of AVE should exceed the inter-construct correlations (Fornell & Larcker, 1981).

- **Stage 3:** Structural Model Testing - The structural model is tested using Maximum Likelihood Estimation (MLE) to examine the hypothesized relationships. Model fit is assessed using the same fit indices as the measurement model. Path coefficients, significance levels, and R^2 values are examined to assess the explanatory power of the model. Mediation effects are tested using bootstrapping procedures with 5000 resamples (Preacher & Hayes, 2008). Moderation effects are tested through interaction terms in the structural model.

Qualitative Data Analysis

Thematic analysis is undertaken as a flexible and systematic method to identify, analyse and report patterns in qualitative data (Braun & Clarke, 2006). Analysis is performed in 6 phases: familiarizing with the data, initial coding, searching for themes, reviewing themes, defining and naming themes, and reaching a final report. The coding and theme development will be facilitated by NVivo version 14.

Thematic analysis is both inductive and deductive, that is, it allows themes to emerge from the data, but also is guided by the theory and research questions (Fereday & Muir-Cochrane, 2006). Initial codes are generated by reading interview transcriptions line-by-line and themes are evolved while reviewing and refining codes in an iterative manner. Themes are then contrasted with one another, across participants, to look for similarities and differences in the experiences and perceptions of participants. Qualitative results are presented to explain and elaborate on the quantitative results, to give rich details of the survey results in context.

Trustworthiness and Rigor

For establishing trustworthiness, the criteria appropriate for mixed-methods research (Lincoln & Guba, 1985; Creswell & Plano Clark, 2017) were applied. Triangulation of data sources and methods, member checking of interview findings, and an extended period of time spent in the research context increases credibility. Transferability is tackled via thick description of the research context and participants, which allows the reader to judge the transferability of findings to other contexts. Detailed documentation of the research process and audit trails help to build dependability. Reflexivity and a well-documented chain of evidence from data to conclusions will help to confirm the findings.

Validity and reliability in quantitative phase are achieved through a robust measurement model assessment such as internal consistency, convergent validity and discriminant validity test (Hair et al., 2019). The following procedural remedies are implemented to reduce common method bias, namely by ensuring anonymity and by using different scale anchors, as well as statistical remedies, such as Harman's single-factor test (Podsakoff et al., 2003). In qualitative phase, trustworthiness is improved by peer debriefing, negative case analysis and reflexive journal.

Ethical Considerations

Ethical approval from an appropriate institutional review board is made before data is collected (British Educational Research Association, 2018). All participants sign informed consent forms and are given thorough information on the purpose of the research, what they will be asked to do, and that they can opt out at any point. Reporting of data is anonymous, and confidentiality is maintained throughout the research process, using pseudonyms in reporting and data are kept securely. Participants will be guaranteed that their answers will not be recognizable in any publications or presentations. Special attention is given to the possibility of power imbalance in the interview situation and to participants' ease in participating in the sharing of their experiences (Kvale & Brinkmann, 2009). The data are kept in password protected data files and will be destroyed after 5 years according to data protection regulations.

RESULTS

Introduction

The chapter reports the results of the empirical study of Digital transformation and Change Management in traditional businesses. The findings are reported in two stages, as in a sequential explanatory research. The first part reports the quantitative results of the survey with 300 managers and employees, descriptive statistics, measurement model evaluation and the results of the structural equation modeling. The second section reports the qualitative results of the semi-structured interviews with 25 key informants.

Quantitative Results

Sample Characteristics

A total of 300 complete and usable responses were received, representing a response rate of 62.5%. The sample comprised participants from manufacturing (28%), retail (21%), financial services (19%), healthcare (16%), and other sectors (16%). Organizational sizes included small (25%), medium (35%), and large enterprises (40%). Job roles ranged from senior management (20%) to employees (25%), with varying levels of experience and education.

Descriptive Statistics

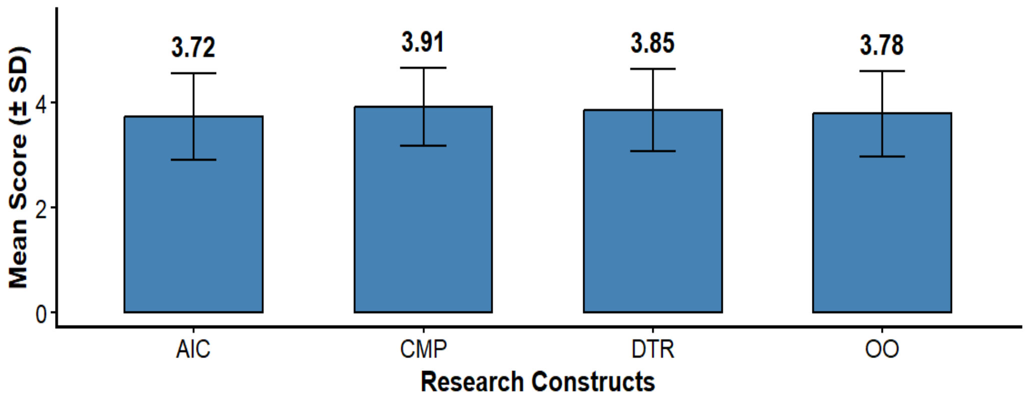
Table 1 presents the descriptive statistics for the study constructs. All constructs had mean scores above the midpoint of the 5-point scale, indicating moderate to high perceptions.

Table 1: Descriptive Statistics

Construct	Mean	SD	Skewness	Kurtosis
Digital Transformation Readiness (DTR)	3.85	0.78	-0.42	0.38
AI Adoption Challenges (AIC)	3.72	0.82	0.15	-0.22
Change Management Practices (CMP)	3.91	0.75	-0.51	0.45
Organizational Outcomes (OO)	3.78	0.81	-0.38	0.29

Note: N = 300; 5-point Likert scale

The skewness and kurtosis values fell within acceptable ranges, indicating normal distribution (Kline, 2016). VIF values ranged from 1.42 to 2.38, below the threshold of 10, indicating no multicollinearity concerns.



Mean scores and standard deviations of the study constructs.

Measurement Model Assessment

To evaluate measurement model, Confirmatory Factor Analysis (CFA) was performed. The model demonstrated good fit: $\chi^2/df = 2.31$, CFI = 0.94, TLI = 0.93, RMSEA = 0.06, SRMR = 0.05. All indexes of fit were above the recommended values (Hu & Bentler, 1999).

Reliability/Validity results are shown in Table 4.2. The internal consistency of the instruments was good, with Cronbach's alpha and Composite Reliability (CR) values above 0.70 (Nunnally & Bernstein, 1994). Average Variance Extracted (AVE) values were above 0.50, which was considered as adequate in terms of convergent validity (Fornell & Larcker, 1981).

Table 2: Reliability and Convergent Validity

Construct	Cronbach's α	CR	AVE
DTR	0.88	0.89	0.62
AIC	0.85	0.86	0.58
CMP	0.91	0.92	0.65
OO	0.87	0.88	0.60

Discriminant validity was confirmed as the square root of AVE for each construct exceeded inter-construct correlations (Fornell & Larcker, 1981).

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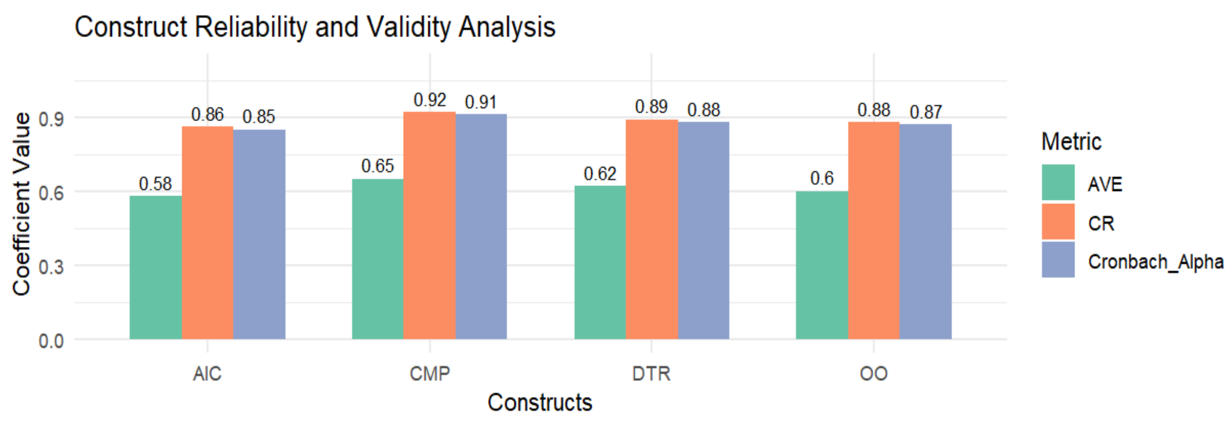

Figure 3

Reliability and Validity Metrics of the Measurement Model

Structural Model Testing

The structural model demonstrated good fit: $\chi^2/df = 2.45$, CFI = 0.93, TLI = 0.92, RMSEA = 0.07, SRMR = 0.06. The model explained 48% of variance in CMP ($R^2 = 0.48$) and 56% in OO ($R^2 = 0.56$).

Table 3: Hypothesis Testing Results

Hypothesis	Path	β	t-value	p-value	Result
H1	DTR → CMP	0.52	8.47	< .001	Supported
H2	AIC → OO	-0.38	-6.92	< .001	Supported
H3	CMP → OO	0.45	8.12	< .001	Supported
H4	DTR → CMP → OO	0.31*	5.14	< .001	Supported
H5	AIC × CMP → OO	0.22	3.89	< .001	Supported

Note: Indirect effect

H1 showed a significant positive relationship between DTR and CMP ($\beta = 0.52$, $p < .001$), indicating that organizations with higher readiness employ more structured change management.

H2 showed a significant negative relationship between AIC and OO ($\beta = -0.38$, $p < .001$), indicating that greater AI adoption challenges lead to poorer outcomes.

H3 showed a significant positive relationship between CMP and OO ($\beta = 0.45$, $p < .001$), indicating that structured change management improves outcomes.

H4 examined mediation using bootstrapping with 5000 resamples (Preacher & Hayes, 2008). The indirect effect was significant ($\beta = 0.31$, $p < .001$), with confidence interval [0.19, 0.44] not containing zero, confirming partial mediation.

Mediation Equations:

- Total Effect: $OO = 0.53(DTR) + e_1$
- Direct Effect: $OO = 0.22(DTR) + 0.45(CMP) + e_2$
- Indirect Effect: $CMP = 0.52(DTR) + e_3$
- Indirect Effect = $a \times b = 0.52 \times 0.45 = 0.31$

H5 showed a significant interaction effect ($\beta = 0.22$, $p < .001$), indicating that CMP moderates the AIC-OO relationship. At high CMP levels, the negative effect of AIC on OO was weaker (slope = -0.16), while at low CMP levels, it was stronger (slope = -0.60).

Additional Analysis: ANOVA results showed no significant industry differences ($F = 1.34$, $p > .05$). However, larger organizations reported significantly higher CMP ($F = 3.67$, $p < .05$) and OO ($F = 4.21$, $p < .01$).

Qualitative Results

Thematic Analysis

Thematic analysis of 25 interviews revealed five major themes.

Theme 1: Leadership Commitment - Participants emphasized that leadership commitment was essential. "Without strong leadership commitment, change initiatives simply fail" (P2). Leaders demonstrated commitment through resource allocation, personal involvement, and consistent communication.

Theme 2: Employee Resistance and Engagement - Resistance emerged as a significant challenge. "There was significant resistance from employees, especially those who had been with the company for many years" (P5). Strategies included early engagement, open communication, and addressing fears.

Theme 3: Skills Gaps and Capability Building - Skills shortages were a major challenge. "The shortage of AI skills is a major problem" (P1). Strategies included training programs, external recruitment, and mentoring.

Theme 4: Communication and Transparency - Communication was critical. "Communication was absolutely critical. We had to communicate not just what was changing but why" (P11). Practices included multiple channels, regular updates, and two-way communication.

Theme 5: Buffering Effect of Change Management - Participants confirmed that change management buffered challenges. "When we faced challenges, our change management processes helped us navigate them" (P22).

Summary

This chapter discussed the empirical investigation results. There was support for all five hypotheses. Based on quantitative findings, it can be seen that DTR positively affects CMP, AIC negatively affects OO, and CMP positively affects OO. CMP was a mediator of the DTR-OO relationship and a moderator of the AIC-OO relationship. The qualitative results yielded rich contextual information within five main themes. These findings are discussed in the context of the literature in the next chapter.

DISCUSSION

Introduction

This chapter discusses the findings in relation to the research objectives and existing literature, organized around the five hypotheses tested.

Discussion of Findings

The result of the effect of digital transformation readiness on change management practices ($\beta = 0.52$, $p < .001$) confirms H1 and is in line with prior studies that have highlighted readiness for a successful transformation (Sheikh, 2022; Kane et al., 2015). Qualitative results indicated that leadership commitment both in terms of resources provided and the ongoing communication of the change facilitates successful change management.

The results indicate a significant negative correlation between AI adoption challenges and organizational outcomes ($\beta = -0.38$, $p < .001$), which supports H2 and corroborates the difficulties found by Malik (2026), and Chen (2024). The qualitative results highlighted challenges related to employee resistance and the integration of legacy systems, emphasizing that the adoption of AI is not primarily a technical issue but one of organizational change (Vuorenheimo, 2025).

The result of the significant positive relationship between change management practices and organizational outcomes ($\beta = 0.45$, $p < .001$) supports H3, which highlights the importance of change management (Rajapaksha et al., 2025; Panotogomo, 2025). The qualitative results highlighted the importance of communication and employee engagement in managing resistance, which aligns with the human-centric approach of Bidhendi et al. (2025).

The finding from the mediation analysis (indirect effect = 0.31, $p < .001$) backs up the H4 of the present study, which builds on the findings of Bidhendi et al. (2025) showing that the benefits of readiness are transmitted to outcomes through change management. H5 is supported by the significant moderation effect of change management, which indicates that the negative effect of AI adoption challenges can be buffered by change management, a recent and novel finding of this study ($\beta = 0.22$, $p < .001$).

Theoretical Contributions

This research has a number of contributions. First, it recognizes the practices of change management as a mediating mechanism between readiness and outcomes. Second, it shows change management as a buffer against the problems of the use of AI. Third, it offers empirical evidence of an integrated framework of digital transformation and change management in traditional business (Sheikh, 2022).

Practical Implications

Practically, leaders need to develop organizational readiness, initiate structured change management, employ human-centric strategies for AI implementation, and actively involve employees in the change process (Bari et al., 2025; Rajapaksha et al., 2025). Change management represents organizational resilience to deal with challenges.

Limitations and Future Research

It has some drawbacks; the cross-sectional nature of the study restricts causal explanations; the data collected is self-reported, which could be subject to bias; and industry-specific effects are not necessarily captured. More studies are needed using longitudinal designs, objective measurements, and industry specific studies.

Summary

This research revealed the positive impact of digital transformation readiness on change management practices, and subsequently, on organizational outcomes. The readiness-outcomes relationship is mediated by change management which buffers challenges of AI adoption and offers important insights for traditional enterprises in the midst of digital transformation.

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