HELLENIC OPEN UNIVERSITY

School of Social Science

Master in Business Administration

Postgraduate Dissertation

“Leading the Digital Shift: Employee Perspectives on Leadership and Change Management in the Age of Artificial Intelligence”

Supervisor: Dr. Niki Glaveli

Patras, Greece, March 2026

Leading the Digital Shift: Employee Perspectives on Leadership and Change Management in the Age of Artificial Intelligence

Panagiotis Thodos

Supervising Committee

Supervisor*:*

Niki Glaveli

Department of Business Administration

University of the Aegean

Co-Supervisor:

Tsekos Theodoros

Department of Business Administration & Organizations

University of the Peloponnese

Patras, Greece, March 2026

"To those who stood by me,

and to the strength I found along the way."

Abstract

This dissertation explores the human and organizational dimensions of Artificial Intelligence (AI) adoption by examining employee perceptions of leadership behaviours and change management practices during digital transformation. The study focuses on employees working in the Fast-Moving Consumer Goods (FMCG) sector, a context characterized by rapid operational change and increasing reliance on data-driven technologies. Rather than approaching AI adoption as a purely technological initiative, the research adopts an employee-centered perspective that investigates how leadership and organizational practices shape readiness for change and trust in AI systems.

Grounded in leadership theory, change management literature, and research on digital transformation, the study develops a conceptual framework linking perceived leadership behaviours and change management effectiveness with employee readiness and trust. A quantitative research design was employed using an online survey distributed to employees exposed to AI or digital tools in their work environment. The final sample consisted of 148 respondents. Data were analysed through reliability testing, descriptive statistics, correlation analysis, and multiple regression modelling to examine relationships between the main constructs.

The findings indicate that employees generally demonstrate positive readiness toward AI-driven transformation, suggesting that resistance to technology may not be the primary barrier to adoption. Instead, organizational practices, particularly communication, participation, and support during change, appear to play a stronger role in shaping trust in AI. Leadership behaviours were closely associated with readiness for change, highlighting the importance of sensemaking and psychological support in periods of technological uncertainty. The results emphasize that AI adoption is not solely determined by technological capabilities but is strongly influenced by social and organizational dynamics.

Overall, the dissertation contributes to a more human-centered understanding of AI-enabled transformation by integrating leadership, change management, and employee perception perspectives. By highlighting the interplay between organizational practices and employee attitudes, the study provides theoretical insights and practical implications for organizations seeking to implement AI in a sustainable and responsible manner.

Keywords

Artificial Intelligence adoption, Leadership, Change Management, Employee Readiness, Trust in AI

Περίληψη

Η παρούσα διπλωματική εργασία εξετάζει τις ανθρώπινες και οργανωσιακές διαστάσεις της υιοθέτησης της Τεχνητής Νοημοσύνης (AI), διερευνώντας τις αντιλήψεις των εργαζομένων σχετικά με τις ηγετικές συμπεριφορές και τις πρακτικές διαχείρισης αλλαγής κατά τη διάρκεια ψηφιακών μετασχηματισμών. Η έρευνα εστιάζει στον κλάδο των ταχέως κινούμενων καταναλωτικών αγαθών (FMCG), ένα περιβάλλον που χαρακτηρίζεται από υψηλή λειτουργική ταχύτητα και αυξανόμενη ενσωμάτωση τεχνολογιών βασισμένων σε δεδομένα. Αντί να προσεγγίζει την υιοθέτηση της AI αποκλειστικά ως τεχνολογική διαδικασία, η μελέτη υιοθετεί μια ανθρωποκεντρική οπτική, εξετάζοντας πώς η ηγεσία και οι οργανωσιακές πρακτικές επηρεάζουν την ετοιμότητα για αλλαγή και την εμπιστοσύνη προς τα συστήματα AI.

Βασισμένη στη βιβλιογραφία της ηγεσίας, της οργανωσιακής αλλαγής και του ψηφιακού μετασχηματισμού, η εργασία αναπτύσσει ένα εννοιολογικό πλαίσιο που συνδέει τις αντιλήψεις για την ηγεσία και τη διαχείριση αλλαγής με την ετοιμότητα των εργαζομένων και την εμπιστοσύνη τους στην τεχνολογία. Ακολουθήθηκε ποσοτική μεθοδολογία μέσω διαδικτυακού ερωτηματολογίου, το οποίο απαντήθηκε από 148 εργαζομένους που εκτίθενται σε ψηφιακά εργαλεία ή εφαρμογές AI στον εργασιακό τους χώρο. Η ανάλυση δεδομένων περιλάμβανε ελέγχους αξιοπιστίας, περιγραφική στατιστική, συσχετίσεις και πολλαπλή παλινδρόμηση.

Τα αποτελέσματα δείχνουν ότι οι εργαζόμενοι εμφανίζονται σχετικά έτοιμοι να προσαρμοστούν σε αλλαγές που σχετίζονται με την AI, γεγονός που υποδηλώνει ότι η αντίσταση στην τεχνολογία δεν αποτελεί το βασικό εμπόδιο. Αντίθετα, οι οργανωσιακές πρακτικές διαχείρισης αλλαγής, όπως η επικοινωνία, η συμμετοχή και η υποστήριξη, φαίνεται να επηρεάζουν περισσότερο την ανάπτυξη εμπιστοσύνης προς τα συστήματα AI. Παράλληλα, οι ηγετικές συμπεριφορές συνδέονται στενά με την ψυχολογική ετοιμότητα των εργαζομένων, υπογραμμίζοντας τον ρόλο της ηγεσίας στη νοηματοδότηση της τεχνολογικής αλλαγής.

Συνοψίζοντας, η εργασία συμβάλλει στην κατανόηση της υιοθέτησης της AI ως κοινωνικο-τεχνικής διαδικασίας, αναδεικνύοντας τη σημασία των ανθρώπινων παραγόντων και

προσφέροντας θεωρητικές και πρακτικές προεκτάσεις για οργανισμούς που επιδιώκουν βιώσιμο ψηφιακό μετασχηματισμό.

Λέξεις – Κλειδιά

Τεχνητή Νοημοσύνη, Ηγεσία, Διαχείριση Αλλαγής, Ετοιμότητα Εργαζομένων, Εμπιστοσύνη στην ΤΝ

Table of Contents

List of Tables

List of Abbreviations & Acronyms

AI - Artificial Intelligence

CHAPTER 1 – INTRODUCTION

1.1 Background and Context

Across all sectors, organizations have been digitally transforming for over a decade now. The impact of digital technologies on company operations including big data analytics, automation and cloud computing. Artificial Intelligence (AI) does impact organizations nowadays. The process of enacting fundamental changes in how organizations function, by rethinking on the organization's structures, processes, and value-creating mechanisms, rather than merely the adoption of new technologies (Vial 2019; Verhoef et al. 2021). Of these technologies, AI has increasingly been the most powerful enabler of organisational change as AI allows machines to conduct verbal tasks similar to humans. These tasks include prediction, learning as well as decision-making (Dwivedi et al. 2021).

The nature of work and management are changing in organizations due to AI. Businesses are gradually implementing AI for better decision-making, optimizing processes, automation of repetitive tasks and improving efficiency. At the same time, the use of the AI has important implications for jobs design, skills required, performance assessment and worker autonomy (Raisch and Krakowski, 2021). Workers experience uncertainty and anxiety about their job security, algorithmic control, and transparency of algorithmic decision-making (Kellogg, Valentine and Christin, 2020). As a result, the transformation caused by AI is not only technological, it also involves organizational and social transformation, which involves a lot of complexities.

Leadership will play a key role in how, when and where changes will be introduced, communicated and experienced by staff. Previous research has shown leadership behaviours influence the employee's response to change. Shifting one's mindset affects one's ability to accept, resist and commit to change (Oreg et al. 2011). Leaders must build a common vision, inspire trust, and encourage learning and adaptability when there is digital disruption (Westerman, Bonnet and McAfee, 2014). Transformational leadership stresses the importance of inspiring and intellectually stimulating behaviours. Authentic leadership stresses transparency and ethics. The two leadership styles are transformational leadership and authentic leadership which are particularly relevant in uncertainty and technology-rich environments.

To adopt AI effectively requires leadership as well as management. According to change management frameworks, communication, staff involvement and ongoing support can mitigate resistance and enhance readiness for change (Kotter, 1996; Rafferty, Jimmieson and Armenakis, 2013). With the ongoing AI-oriented changes these practices take on high relevance, employees must get used to using new system, trust in algorithm-based instruments and acquire new digital skills (Jöhnk, Weißert and Wyrtki, 2021). If the human factors are not considered, they can lead to fatigue against change, lack of engagement and non-optimal use of AI tech (Tarafdar, Pullins and Ragu-Nathan, 2015).

Despite the increasing number of research papers on digital transformation and AI, the literature mostly emphasizes technological capabilities or organizational performance consequences, while smaller implicit attention has been devoted to employees' perceptions of leadership and change management in the case of AI (Vial, 2019; Verhoef et al., 2021) adoption. It is essential to understand how employees experience and make sense of leadership behaviours and processes of change since this will determine their trust and readiness for, as well as acceptance of change driven by AI. Accordingly, this study is positioned here to contribute to a more human-centered understanding of AI-enabled organizational transformation.

1.2 Research Rationale and Problem Statement

There is growing academic interest in the topic of digital transformation and its implications for work and management due to the increased use of AI in organizations. Existing studies have made significant progress in the understanding of AI issues focusing on technology, orientation strategy and performance for instance efficiency, data-driven decision making and competitive advantage (Bharadwaj et al., 2013; Dwivedi et al., 2021). Besides, there are streams of literature on leadership and change management as important enablers of change (Kotter, 1996; Rafferty, Jimmieson and Armenakis, 2013). For successful change management, vision, communication and engagement must be well channeled. Despite these developments, research in these areas remains disconnected, especially concerning employees lived experiences in organizational change involving AI.

A key downside of the existing literature is its treatment of the adoption of AI as a marketing and technical issue rather than as a social and human issue. Research about AI and automation often focuses on the capabilities of systems or the organizational outcomes with little attention paid to how employees view and respond to algorithmic systems introduced into their work life (Jarrahi, 2018; Kellogg, Valentine, and Christin, 2020). Simultaneously, research into leadership and change management has studied organisational change more widely without adapting their thinking towards the specifics of AI (e.g. opacity, perceived loss of control over AI, ethical issues over data sharing and algorithmic decision making) (Raisch and Krakowski, 2021).

There is a large gap this fragmentation creates. Even though it is known that leadership behaviours are an important determinant of employee responses to change (Oreg, Vakola and Armenakis, 2011), not much empirical evidence is available to determine the impact of leadership and change management practices on employee readiness, trust or acceptance in the context of AI adoption. AI stands to technology like anything we've never seen before by not only automating tasks but also increasingly replacing or supplementing human judgement. This contests employees' professional identities and sense of autonomy (Faraj, Pachidi and Sayegh, 2018). Because these traits are easy to notice, negative feelings about artificial intelligence could interfere with its successful use even when they are complex.

In addition, for AI-enabled transformation to succeed and be effective, employees must be willing to use the technology and trust the organisation and the contact intelligence itself. According to research, excessive trust or distrust on the part of tractor operator can impair performance and intention to act positively in case of malfunctions (Lee and See, 2004; Glikson and Woolley, 2020). The interaction between leadership behaviours and change management processes, as well as how this affects trust in AI at the employee level, is rarely considered in current research. Organizations lack evidence-based advice for navigating the human side of AI implementations.

Moreover, many empirical studies that have been conducted on AI adoption have taken place either at the organizational or the managerial level usually based on the perspectives of senior executives (Vial, 2019; Verhoef et al., 2021). There's a danger that this top-down focus will overlook those employees whose work and performance will be assessed through AI and related technology. Due to the importance of employees for both usage and deployment of AI systems, their perceptions are a critical but under-researched dimension of digital transformation.

In this context, the present study is motivated by the need to fulfil this gap by empirically studying the perceptions of employees about leadership and changing management in AI-led transformation of organization. With a focus on the views of employees, this study will contribute to the literature on leadership and digital transformation and facilitate an understanding of AI that is more holistic and human centric. Similarly, it will offer organisations a concrete understanding in making AI implementable in a sustainable and socially responsible manner.

1.3 Research Aim, Objectives and Questions

The purpose of this study is to determine the human and managerial aspects of Artificial Intelligence (AI) adoption in organizations with particular reference to employees' views on leadership and change management practices. As AI-driven transformation becomes increasingly common among organizations, it is actualizing newer roles, processes and changing organizational culture. Therefore, there is a need for systematic empirical research that observes how employees experience and make sense of the same.

Research Aim

The overarching aim of this study is:

- To explore how employees perceive leadership and change management practices during the adoption of Artificial Intelligence in organizations, and how these perceptions influence readiness, trust, and acceptance of AI-driven change.

This aim reflects the study's focus on the employee perspective and its intention to integrate leadership theory, change management frameworks, and research on AI adoption.

Research Objectives

To achieve this aim, the study pursues the following specific objectives:

- To identify the leadership styles and behaviours that employees associate with effective management of AI-driven organizational change.
- To examine employees' perceptions of change management practices, including communication, participation, and support, during the implementation of AI technologies.

- To assess employee readiness for organizational transformation and their level of trust in AI systems introduced in the workplace.
- To investigate the relationship between leadership behaviours, perceived effectiveness of change management, and employee acceptance of AI.
- To generate evidence-based recommendations for organizational leaders and HR professionals on managing AI-related change in a sustainable and employee-centered manner.

These objectives are aligned with the study's conceptual framework and guide the selection of research variables and measurement instruments.

Research Questions

Based on the research aim and objectives, the study addresses the following research questions:

- How do employees perceive their leaders' roles and behaviours during AI-driven organizational change?
- Which leadership behaviours are perceived as facilitating or hindering effective AI adoption?
- How do employees evaluate the change management processes associated with the implementation of AI technologies?
- To what extent do employee readiness for change and trust in AI influence acceptance of AI-driven transformation?
- How are leadership behaviours and change management practices related to employee perceptions of AI and organizational change outcomes?

Together, these research questions provide a coherent structure for the empirical investigation and ensure that the study systematically examines the key factors influencing the human side of AI-driven organizational transformation.

1.4 Significance and Contribution of the Study

The application of AI technology in organizations seems to have accelerated due to its convenience in use and implementation, but the consequences of this for digital transformation are not yet understood. Earlier studies have yielded helpful insights from scholars; however, the applicability of these findings seems more strategic and technological than operational or economic, perhaps. Thus, further integrated and empirical analysis of human and managerial impact of AI-driven change is needed (Vial, 2019; Dwivedi et al., 2021). The importance of the current study can be weighed in response to the need to examine the perceptions of the employees in regard to leadership and change management in light of AI adoption.

The study amounts to a significant contribution to theory to the extent that it brings together three streams, namely, leadership, change management and AI-enabled digital transformation. As the literature on leadership has established for quite some time, it is the behaviour of the leaders that shapes employee attitudes, trust, commitment during organizational changes (Bass, 1985; Oreg, Vakola and Armenakis, 2011). In similar fashion, the literature on change management stresses the importance of readiness, communication and participation for successful transformation (Rafferty et al., 2013). However, they have seldom been employed explicitly in relation to AI, which poses new challenges regarding algorithmic decision-making as well as transparency and perceived loss of control (Raisch and Krakowski, 2021). This study builds on existing literature by examining the impact of leadership and change management practices on employee readiness and trust in AI in a real organisation that is contemporary and technologised.

Moreover, the research highlights the employees' perspective thus adding AI adoption research. Studies concerning artificial intelligence have largely been limited to firm-level capabilities, managerial decision-making or performance outcomes (Bharadwaj et al., 2013; Verhoef et al., 2021) as per existing literature. Although these contributions matter, they may overlook the people who actually use AI systems as part of their job on a daily basis. According to research, employee perceptions of AI (trust, perceived usefulness, perceived threat, etc.) determine whether AI systems are integrated or resisted (Glikson and Woolley, 2020; Jarrahi, 2018). Through empirical capturing of perceptions, the present study enhances clarity on the societal implications of AI transformation.

This study's practical importance is equally weighty. Businesses investing in AI often encounter employee reluctance, skill gaps, and fatigue from change, which may result in lower returns to the technological innovation (Tarafdar, Pullins and Ragu-Nathan, 2015). This paper provides substantiated evidence for managers, human resource experts, and policymakers after discovering behaviours of leadership and practices of change management which continue to develop employee readiness and trust. Insights from these lessons learned can enhance the design of leadership development programs and other communication and training initiatives for a more human-centred AI.

Ultimately, this study embeds itself within a bigger story of responsible and sustainable digital transformation. There has arisen an academic and policy debate on the ethics of Artificial Intelligence (AI), including fairness, accountability and transparency as well as increased interest in the subject (Jobin, Ienca and Vayena 2019; Floridi et al. 2018). The paper specifically illuminates the impact of corporate practices pertaining to AI on the employee. In the course of the study, leadership, change management and the impact of AI at workplace on employees will be discussed. Consequently, it urges a shift to digital transformation strategies that properly aligned technology, people and legitimacy.

1.5 Structure of the Dissertation

The dissertation consists of five chapters, each of which serves a specific purpose that is related to the research aim and research questions of the study. The way this framework has been fashioned, a reader will move easily from theory to evidence to conclusion.

The study's first chapter provides a unique background and context of Artificial Intelligence adoption in organizations. It also provides the motivation and problem statement of the study. Additionally, the paper presents the aim, objectives, and research questions of the study. The paper shows worth and importance of research and its significance. It shows the relevance of the research worth on leadership, change management, and digital transformation.

Chapter Two presents a wide literature review. The study examines different concepts of Artificial Intelligence to organizations, leadership types fit for the digital, and previously developed techniques for change management. The chapter also discusses employee views on leadership, support for change, organizational change readiness, and trust in AI. This chapter would identify the gaps in literature by synthesizing research and thus help to develop a theoretical foundation for empirical study.

Chapter Three explains the process of research being undertaken. The proposed chapter outlines the research design and strategy, target population and sampling approach, data collection methods, and methods of analysis. The participant consent, confidentiality and data protection ethical concerns were also addressed.

Chapter Four examines and scrutinises the empirical findings. The results of descriptive and inferential statistics are reported and then interpreted. This is followed by discussion that links them back to the theory and findings in the literature.

Ultimately, chapter five closes the thesis with a summary of what has been done, followed by the theoretical and practical implications, limitations of research and recommendations for future research.

CHAPTER 2 – LITERATURE REVIEW

2.1 Introduction

The literature review seeks to systematically map, critically review and synthesise the existing and relevant body of academic literature, in order to examine leadership and change management regarding AI (artificial intelligence) adoption from an employee's perspective. This chapter seeks to provide a theoretical basis for empirical investigation by synthesizing literature from several research strands to deal with the complexity of AI-driven organizational transformation. In particular, the review combines insights from studies of organizational settings and AI, relevant leadership theories, change management frameworks, as well as studies on employee perceptions, readiness for change and trust in AI.

The growing interest in AI adoption has spurred a huge, rapidly growing literature. All in all, this literature has become quite severely fragmented as information systems, management, organizational behaviour, human resource management, and ethics. Research on AI in organizations has mostly concerned technological capabilities and strategic implications along with firm-level performance outcomes, mainly efficiency, innovation, and competitive advantage (Vial, 2019; Verhoef et al, 2021). While the aforementioned contributions have investigated organizational-level digital transformation, their frequent techno-centric stance diminishes the important human and social factors of change enabled by AI. In other words, employees seldom treated as the fitted agents of technology, whose perception and reaction are critical in determining the success of AI initiatives.

The leadership literature and change management literature have long stressed leadership behaviours, leadership communications, and employee engagement during change as important (Kotter, 1996; Oreg, Vakola and Armenakis, 2011). Nevertheless, these studies have generally examined change more abstractly and have only recently begun to engage explicitly with the characteristics of AI, such as algorithmic decision-making, opacity and ethical concerns (Raisch and Krakowski, 2021). This gap has restricted the development of comprehensive theoretical explanations of how a variety of leadership and change management practices affect employee readiness, trust and acceptance in AI-enabled changes.

In response to this fracturing, the present study will take a multidisciplinary approach that involves digital transformation research, leadership theory, change management literature, and employee perceptions of technology literature. To capture the multifaceted technological, organizational, and human-related aspects of AI adoption, such an approach is significant (Dwivedi et al., 2021). By concentrating explicitly on the employees' viewpoint, it manages to fill one of the large gaps in the literature. Moreover, it also responds to the urgent need for a more human-centric and socially responsible approach to digital transformation.

The organization of this chapter is as below. In Section 2.2 AI is defined in organizations and it describes some of the basic applications, advantages, and disadvantages of AI. Furthermore, human-centered concepts of AI such as AI literacy, trust, and so on were shared in this section. The sub-section 2.3 discusses the leadership styles in the digital environment, particularly the transformative and authentic leadership. Section 2.4 looks at old and new change management frameworks and how they apply to change due to AI. The research on employee perceptions, organizational readiness for change, and trust in AI is presented in section 2.5. Ultimately, Section 2.6 summarises the literature review, identifies gaps, and shows how these are relevant to the study's conceptual framework and research design.

2.2 Conceptualizing Artificial Intelligence in Organizations

Artificial Intelligence (AI) is becoming increasingly important for businesses undergoing transformation and helps influence the design of work, decision-making and control in organisations. Artificial Intelligence does not refer to just one technology. Rather it is a set of computational systems that can perform tasks that human beings would normally perform. AI systems can learn things, recognize patterns, make predictions, solve problems and so on. As such, in organizational contexts, AI should not be understood simply as a technical innovation but as a socio-organizational phenomenon that interacts with structures, routines, and human agency. This section conceptualizes AI in organizations through an examination of its definitions, applications, benefits, challenges, and the human-centered concepts that support its adoption.

2.2.1 Defining AI in Organizational Contexts

In contrast to technical descriptions, management and organizational research most commonly define AI in functional terms, that is what systems "do", rather than how they are engineered. According to Dwivedi et al. (2021), AI comprises a range of technologies that enable machines to sense, comprehend, act, and learn, in one way or another, to support or substitute human decision making and task execution. In an organizational context, this definition does not view AI as a substitute for humans, but rather as a tool to enhance managers and operators.

A principal difference in literature is the distinction between automation and augmentation. Automation is defined as a case of replacing human labour with a machine that can do the work. Unlike replacement, augmentation refers to artificial intelligence systems that support human behaviour and decision-making by providing insights, recommendations, and predictions, but not making the final decision, which is left to humans (Raisch and Krakowski, 2021). For organizations to meaningfully investigate any resistance they are seeing to AI implementations, they need to distinguish automation from augmentation. Automation approaches seek to substitute human labor and are much more likely to engender employee resistance. Moreover, augmentation approaches offer opportunities for other learning and skill development and lead to greater acceptance (Jarrahi, 2018).

Essentially, in organizations, AI is a socio-technical system. Taking social context away from the linguistic practices only strips the practice of meaning. According to Jarrahi (2018), power relations, domain norms, and institutional constraints shape the organisational context of AI systems. Consequently, using technology is not merely a technical matter, but indeed a highly social and political process. The perspective on AI raises issues of deterministic AI in the sense of providing leadership and problematizing change management in AI adoption (Shrestha et al. 2019).

2.2.2 AI Applications in Organizations

More and more organizations are using artificial intelligence (AI) in order to boost efficiency, consistency and quality of decision-making. One major area of application is decision support where knowledge or recommendation is generated for managers through a computer system which analyses the data flows in a large body of information. Such systems are being used for forecasting, risk assessment and resource allocation, enabling more data driven decision making (Jarrahi, 2018).

The second most common application is predictive analytics leverage AI for discovering patterns and predicting future events. Predictive analytics could be used in an organizational context for predicting customer behaviour, optimizing supply chain and employee turnover. Though the new algorithmic systems are often characterized by greater accuracy and speed, they may also lead to issues of opacity or black box as employees and managers do not fully understand how predictions are generated (Kellogg, Valentine and Christin, 2020).

One area of AI application that has been a field of much contention is algorithmic management. Above all, in human resource management (HRM). Artificial intelligence (AI) is increasingly being used for tasks such as recruitment, performance assessment, task allocation, and even monitoring of employees. Meijerink et al. (2021) argue that under algorithmic HRM, there is a major shift in managerial control as the authority to decide is partly taken from managers and given to algorithms. While these networks may enhance consistency and reduce some types of biases, they can also ramp up monitoring, remove employee autonomy, and change the employment relationship.

Existing literature more often than not considers these applications as neutral or enhancing efficiencies. However, it says little about how employees experience and make sense of algorithmic decision-making in their work. Accordingly, the convergence of AI with user perceptions and organizational change is important to assess in organizational settings.

2.2.3 Benefits and Organizational Challenges of AI

Often, it is the mention in literature that AI has potential to prove beneficial for the performance of the organizations. As per Brynjolfsson and McAfee (2014), these benefits result in an increase in operating productivity, consistent decision-making and the ability to study and analyze large datasets beyond human capability. AI systems are often seen as a tool for helping organizations be more objective and rational. This is due to the fact that they eliminate human error and bias on routine decisions.

Nonetheless, there is a new set of critical research that wishes to jam the upbeat AI story. Algorithmic opacity is one issue - referred to as the 'black box' problem, which describes how logic behind the output from AI is hard to explain (Raisch and Krakowski, 2021). When employees do not fully understand these algorithms, it makes it difficult for them to challenge or correct them.

A further challenge concerns the lessening of independence and de-skilling. The employees may observe a decrease in their discretion and the hindrance of the development of their skills when AI systems dictate a particular workflow or restrict their judgment (Faraj, Pachidi and Sayegh, 2018). Over time, this could lead to the dependence on algorithms and erosion of expertise especially in knowledge jobs.

Organizational hurdles are ethical risks too. Artificial Intelligence can lead to unfair results as data bias affects either the AI analysis and/or the training data. Moreover, there are serious concerns involved in using AI to monitor employees. Privacy concerns consent and the power imbalance of workers and employers are addressed. Many organizational studies focus only on the efficiency and performance outcomes of AI tools, ignoring their social and ethical dimensions, despite the harms discussed above. The existence of imbalance makes it necessary to have leadership and change management models that address imbalance rather than providing them as an afterthought.

Much of the literature continues to consider Artificial Intelligence as an opportunity, particularly to boost productivity and improve the rationality of decisions. There is some acknowledgment of these organizational problems. An example of this perspective could be Brynjolfsson and McAfee (2014) who view AI as a powerful tool that uses its neutrality to act as a complement to human effort, increasing efficiency and organization performance. Although some of these perspectives make a good case for investing in AI, they have an important downside: they can obscure the social and political issues behind organizations' uses of AI.

On the other hand, studies critical of AI technology clearly show that such systems are not neutral objects; rather, they can enhance the distribution of power, along with controls and jobs. In the view of Faraj, Pachidi and Sayegh (2018), algorithmic systems exert influence over workflows and impose constraints on experts' actions. Similarly, Kellogg, Valentine and Christin (2020) demonstrate how algorithmic management enhances scrutiny and reconfigures authority in management. The drawing of conclusions mentioned above shows that technology is an opportunity in the hands of the powerful and a mechanism for control, which poses serious concerns with respect to voice and agency of the employees. Opportunity-focused narratives are not just empirically undernourished but also theoretically debilitating in how AI is conceived in organization studies.

2.2.4 Human-Centered Concepts in AI Adoption

In light of techno-centric views limitations, recent studies adoption outcome has given greater attention to human-centered concepts. The phrase 'AI literacy' refers to a more general understanding of how AI systems work, what they can do, and what they cannot do. People with a higher level of AI literacy are likely to use AI more appropriately, trust AI more, and have reduced anxiety. Conversely, people with lower AI literacy may misunderstand the technology and resist it (Dwivedi et al., 2021).

The problem of automation anxiety refers to employees' fear of losing their jobs, being deskilled, or a general loss of control owing to AI and automation. When someone suffers from anxiety, it can affect their well-being and restrict their openness to technologies. Moreover, poorly communicating or framing the use of AI can contribute to anxiety (Brynjolfsson and McAfee, 2014). Through leadership and change management practices that present AI as an augmentor, we can mitigate or alleviate automation anxiety.

Another important factor for successful implementation is trust in AI. Research on trust towards automation suggests both under-trust and over-trust can be harmful. A lack of trust may cause rejection of valuable systems. Over-trust might lead to undue approval of incorrect results (Lee and See, 2004) Trust in AI resulting from experience is generally characterized by Glikson and Woolley (2020) performance of the system, the organization's situational context, communication, and leadership credibility all shape trust.

Finally, ethical issues are major concerns for AI adoption. When the rationale for the decision taken by the AI system is clear and intelligible to the employees, they are likely to accept it. In addition, ethical principles related to fairness and accountability should be maintained to legitimize the system for successful implementation (Shin, 2021). At a broader level, frameworks for ethical AI stress that organization must ensure that the deployment of the AI system respects human dignity and social values (Jobin, Ienca and Vayena, 2019; Floridi et al., 2018). Human-centered concepts reinforce the argument that an AI adoption is as much a managerial and leadership challenge as it is a technological challenge. Achieving a sustainable and responsible AI-led transformation in organizations requires a better understanding of AI perceptions in employees and how leadership and change management practices shape these.

2.3 Leadership Styles Relevant to the Digital Era

Organizational processes are more integrated with Artificial Intelligence (AI), which are changing the environment with which the leader operates. The transformation brought about by artificial intelligence amplifies uncertainty and accelerates alterations. Additionally, it makes ethical decisions less evident. Leadership styles are subjected to new demands from leaders. The section looks at leadership in the digital era with transformational and authentic leadership styles strongly linked to employee engagement, trust and adaptability to change. In this section, the relevance and limitations of these leadership models are discussed in terms of AI-enabled organisational transformation.

2.3.1 Leadership in Digital and AI-Driven Change

Leadership is generally viewed as an important component of the success and failure of digital transformation. Changes brought about by AI at the organizational level is unlike traditional changes in nature and degree. It affects not just workflows and technologies, but also decision authority, professional identities, and power relations. Consequently, as Westerman et al. (2014) have characterized, leadership is key to how organizational members understand, legitimize and enact AI.

Making sense of digital transformation is a key function of leadership. Employees are dependent on the leaders who are required to make sense out of complex technological changes to make meaning that makes sense to employees as to why the change is required and how it fits into the larger scheme. According to Kane et al. (2015), the success of digital transformation is more about leadership creating a shared vision using digital technologies than the use of any specific technology. It is about experimentation and learning. In AI, sensemaking takes center stage as the opacity and lack of explainability of algorithmic systems increases uncertainty and anxiety among employees.

In addition, the advent of AI-related change disrupts traditional views of leadership and authority. Consequently, being a leader means managing tensions between efficiency and human judgment, control and autonomy, and innovative and ethical. The command-and-control types of leadership will no longer be sufficient, as they will call for communication, trust, and involvement. Lack of leadership on AI initiatives can lead to their imposition, a threatening nature, or misalignment with employee values, leading to resistance or underutilization of AI (Weber and Krehl., 2022).

2.3.2 Transformational Leadership

Transformational leadership is one of the most analyzed leadership styles in the context of organizational change. As indicated by Bass (1985), transformational leadership is made up of four different dimensions which are idealized influence, inspirational motivation, intellectual stimulation, and individualized consideration. The components together speak to a leader's ability to articulate a compelling vision, to motivate one's followers, to encourage creative problem solving, and to attend to individual development needs.

There has been a growing body of research that connects transformational leadership with enhanced learning and innovation. Transformational leadership is also associated with increased readiness for change. These studies focused on digital technologies and artificial intelligence. Transformational leaders facilitate the development of new ideas from subordinates by encouraging them to question existing practices and experiment with new ways of working in a technologically disrupted environment. Research shows that transformational leadership is positively associated with employees' openness to change and reduced resistance in complex and uncertain change situations (Oreg and Berson 2011).

Moreover, transformational leadership creates psychological conditions for digital innovation, including intrinsic motivation and organizational commitment. Leaders who instill confidence and provide a clear vision can raise employees' readiness to change by increasing the perceived appropriateness and efficacy of the change initiatives (Rafferty, Jimmieson and Armenakis, 2013). In the context of adopting an AI, such readiness is important. Employees usually have to learn new skills and work with algorithms that have changing ideas.

Although transformational leadership can explain organizational change at scale, it has severe limitations when applied to an artificial intelligence transformation. Focusing on vision, inspiration, and performance-driven change may unintentionally neglect ethical issues stemming from adoption of AI. With high-speed data and innovation, as well as their ability to make algorithmic systems work to the advantage of the organization, business leaders often downplay the significance of algorithmic transparency, accountability and bias as merely technical issues.

Furthermore, the mobilizing capacity of transformational leadership can stir up compliant pressure as it creates a sense of discomfort and dilemma among the employees to voice doubts and question the decisions made by AI. A transformational leader may be able to achieve successful implementation of the AI system even if it does not contribute to its responsible or socially sustainable development. Although it is possible that transformational leadership is effective in stimulating readiness for change and willingness to adapt and commit to adopt AI, it still seems to be insufficiently able to tackle the ethical reflection space. Thus, it may not be sufficient to address moral and governance challenges with complexity and uncertainty, including adoption of AI.

2.3.3 Authentic Leadership

Perhaps the most appropriate leadership style in times of uncertainty and moral ambiguity, is authentic leadership. According to Avolio and Gardner (2005), authentic leadership refers to the phenomenon that is defined by self-awareness, relational transparency, balanced processing and an internalized moral perspective. The transformational leadership approach is differently focused on inspiration and change whereas the perspective of authentic leadership is focused more on trust, ethical and a genuine leader-follower relationship.

As algorithmic opacity and workforce unease grow in prominence as issues with AI-driven change at work, prescriptive advice of authentic-leadership principles has never been more important. AI systems often work as a black box where it becomes difficult for the employees to figure out how the decisions being taken affect their work and their lives. It can break trust and trigger perceptions of unfairness. Concerns regarding AI can be alleviated by authentic leaders through their transparency and authenticity regarding its limitations and capabilities. They accomplish this by being candid and conversing with each other.

Trust facilitates the influence of authentic leadership on employee attitudes. According to an integrative model of organizational trust developed by Davis and Schoorman (1995), trust is a function of ability, benevolence and integrity. Authentic leadership basically illustrates ethical consistency and external concern for employees' well-being. The acceptance of AI by stakeholders might not only extend towards the leader, but also towards the technology itself, which can be crucial for employees' willingness to use AI.

Research reveals that authentic leadership is important in technology-based areas. According to Glikson and Woolley (2020), trust in AI is determined not only by the performance of the system but also by social cues and the organizational context, including the credibility of leadership. The employees' interpretations of artificial intelligence as supporting or threatening can be shaped by leaders. Authentic leadership may better cope with the moral dilemmas and emotional reactions surrounding AI that include fear of surveillance and loss of job security, than transformational leadership. Authentic leadership is being advocated as a remedy for the relational and ethical limitations of transformational leadership and focuses on transparency and trust. Such qualities are needed in AI contexts that are uncertain, algorithmically opaque, and discomfiting to employees. To foster employees' trust and establish psychological safety, authentic leaders must engage in open communication to highlight AI system limitations and risks, during this technological shift.

Nevertheless, authentic leadership faces several challenges due to fast-changing tech environment. The focus on deliberation, thoughtfulness, and consensus might hamper responsiveness in cases that require quick decision-making and continuing technological adjustment. In rapidly evolving competitive environments that are essential to artificial intelligence, strictly authenticity-driven leadership may not hold up the pressure that a rapidly changing organization can exercise. As authentic leadership is crucial to enhancing trust and addressing ethical issues, adopting authentic leadership may not be sufficient to manage a large-scale and high-speed digital transformation.

2.3.4 Leadership Styles and Employee Perceptions

One of the assumptions in the paper is that the effectiveness of leadership for AI-driven change can be best measured from the lens of employee perception instead of through leader perception or formal leadership policy. Studies of organizational change show that the ways employees subjectively interpret the behaviours of leaders are stronger predictors of attitudes, trust and readiness for change than objective measures of leaders' intent (Oreg, Vakola and Armenakis, 2011). When it comes to AI adoption due to its informal communication and sensemaking culture, employee-rated leadership captures how leadership is actually felt in everyday interactions.

When one focuses on the perceptions of the employees, one will be on the right track with the socio-technical view of AI as well. Transformational and authentic leadership styles not only model strategic decisions but also shape employees' opinions regarding the meaning, fairness, and consequences of AI-driven change. Acceptance, resistance, or engagement with AI systems may be influenced by the expections.

In this regard, the present paper conceptualizes leadership as a perception and places employee-rated leadership behaviours as antecedents as in the research model. This study contributes to leadership theory and the digital transformation literature by linking leadership style to perceptions of change management effectiveness, change readiness and trust in AI. This method of leadership can effectively spearhead the human side of change as organizations adopt AI technologies.

2.4 Change Management Frameworks

Most organizations are not able to adopt the technology of Artificial Intelligence (AI) because of their change management process. A successful stratagem does not only include technological readiness but the organizational readiness for the adoption of AI. AI transformation will require a restructuring of work practices, decision-making structures and employee–organization relationships. This makes the need for structured approaches to managing change quite significant. This section will examine popular change management models and critique their fitness for purpose in the context of AI. Moreover, it highlights important change management activities and defends the focus on employees' views of change management effectiveness.

2.4.1 Overview of Classical Change Models

The theoretical foundation of change has focused on classical change management models for a long time. Lewin's (1947) three-step model was one of the earliest and most influential frameworks and it conceptualises change as unfreezing, changing and refreezing. Lewin is of the opinion that the destabilization of current behaviours and mindsets will be followed by new and institutionalization. Although the model is easy to understand and follow, it does assume a fairly stable organizational environment and that change occurs as discrete episodes. The first assumption is being questioned more and more as organizations undergo various forms of digital transformation, a phenomenon that is almost never stable.

Kotter's (1996) eight-step model builds on earlier work and outlines the steps that need to be followed to manage change. It emphasises the creation of urgency, continuous vision development, coalition building and dissemination. Kotter's framework identifies leadership and communication as instrumental in maintaining the sustainability of change; thus, it is greatly influential on managerial practice. Despite its popularity, many critics claim that the model is still a largely linear prescriptive model.

The ADKAR model (Hiatt, 2006) shifts the focus from organization-wide processes to individual change. Successful change is based on awareness, desire, knowledge, ability, and reinforcement on the five elements. The model helps in understanding how the employees react to a change as it is the most effective when it assumes that change takes place through people. Though there are benefits, ADKAR has been critiqued for ignoring larger structural and contextual issues – notably power relations and culture (Bourne, 2019).

Although classical change management models are influential, they generally assume that organisational change is temporary, and linear and can take place with a purpose in mind. Models such as Lewin's (1947), three-step model and Kotter's (1996) staged approach depending on the return to stability. Specifically, they require "refreezing" or institutionalizing new practices. Likewise, the ADKAR model (Hiatt, 2006) assumes that the change can be reinforced and stabilized once people go through the stages.

It is becoming increasingly difficult to hold on to such an assumption in the case. AI tools are continually upgraded and retrained, with plans for further enhancement. For that reason, they may not be considered complete. Because of this reason, it is perhaps more useful to think of such models as heuristic frameworks that highlight core principles of change and not as precise recipes for managing AI-driven change. In the context of AI, the explanatory power of these models is limited unless adapted to change that employees experience.

2.4.2 Relevance of Change Management in AI Contexts

Change driven by AI is fundamentally different from regular organizational change. Rather than a once-only shift from one stable state to another, AI adoption is typically continuous, incremental and evolving change. As time goes on, new algorithms will be updated, data sources will change and system capabilities will expand. Thus, there is continuous change and adaptation, not a linear one. This calls into question the assumptions that inform classical models of change which typically view change as a bounded process with a definite beginning and end.

As per the study of organizational change, employees' reactions depend upon their perceptions of uncertainty, fairness and impact (Rafferty, Jimmieson and Armenakis, 2013). The fears of automation, job loss, and opacity of algorithms sharpen the perceptions in the context of AI. Employee readiness for change refers to how employees interpret the change and its effects on them personally (Vakola, 2014). This means that it is not possible to manage this process of AI adoption without doing it.

To add to this, organisations have to create dynamic capabilities for an AI-driven transformation which enables them to constantly reconfigure their resources and core competencies (Warner and Wäger, 2019). As per this viewpoint, change management is not a one-off intervention but a repeating organizational capability (Teece, 2008). It is important to use the lessons derived from traditional models like Lewin's or Kotter's that emphasise the necessity of communication and leadership support. However, they should be adapted so that the model captures the non-linear and emergent nature of change brought about by AI.

When it comes to transformation, organizational transformation through AI may be best viewed not as a trip between stable equilibria but rather a permanent beta. The implementation of artificial intelligence, unlike ordinary change initiatives, does not possess a so-called “refreeze-phase”, which means organizations and employees have to continuously adjust. Frequent change has increased uncertainty among employees and requires a constant drain on their mental and emotional energy. This means that how a change is felt is much more important than how a change is made.

The adaptation of classical change models to employee-centered perspectives will determine their relevance for contexts involving AI. The essential principles of communication, participation, and leadership support are still significant. However, their effectiveness will depend on the ongoing employee assessment of justice, competence and support. As employees are the ones experiencing the change, their perspective is important to measure the perceived effectiveness of change management success. This will help determine if change is merely an organizational thing or if it has been meaningfully integrated at the employee level.

2.4.3 Key Change Management Practices

Across both classical and contemporary frameworks, change management practices refer to managerial practices for successful organisations that have remained consistently important. One of the more popular factors influencing employee reactions to change is communication. According to Armenakis, Harris and Mossholder (1993), communicating effectively enhances readiness for change when employees understand the need for change, the appropriateness of proposed solutions and will be able to adapt. In the context of AI, communication is essential in dealing with uncertainty and explaining the impacts of algorithmic systems on roles and decisions.

Another important practice is employee participation. When employees become involved in decisions regarding change, they feel more in control and respond less negatively (Lines, 2004). Employees are important agents in adopting AI and participative system design due to their contextual knowledge that enhances AI and participative system design. The reliance on technology in projects often discourages people's effective participation and involvement.

Emotional encouragement and offering of resources from the leadership and organization are important determinative factors for a successful change process. According to Kotter and Schlesinger (1979), the mechanisms of support can reduce the resistance to change by alleviating the fears of the employees and making it less threatening to them. Assistance can be reassurance around job security or assistance about how to interact with the new system.

It is essential to train staff members to use AI systems and get their skillset involved. Employees who do not have adequate training will generally feel overloaded or incompetent. Hence their performance and change acceptance goes undone. One of the benefits of training is that it can show employees that they are valued, and trust and commitment will build throughout the process.

2.4.4 Measuring Perceived Change Management

Though the success of change management is assessed using project completion and performance indicators, more and more literature emphasizes the necessity of measuring employees' perception of change management effectiveness. Employee perceptions have an impact on their attitude, behaviour, and engagement, and may differ widely from managerial perceptions of success. According to Oreg, Vakola and Armenakis (2011) perceptions of the change processes actually predict stronger resistance and acceptance than formal change.

The effectiveness of change management is deemed especially crucial in the context of an AI-enabled transformation because the employee's trust, readiness, and willingness to engage with an AI system is based on their personal experience of change. Researchers utilize perceptions to assess various dimensions, such as measuring communication quality, participation, support, and other factors that are difficult to measure**.** Consequently, the current research takes a perceptual approach to measure change management and leverages a validated survey instrument with which employees assess the change process related to AI adoption. This method matches with the greater focus of the research on employee centre analysis. It also provides a valuable connection between change management theory and empirical study.

2.5 Employee Perceptions, Readiness, and Trust in Artificial Intelligence

The perception of AI-driven change by employees essentially determines the implementation of Artificial Intelligence (AI) in organizations. While technological capabilities and strategic intent matters, a large body of research indicates that perceptions of employees are also a crucial consideration when assessing whether changes will be accepted, resisted or illusory in their application. This chapter critically assesses the literature on employee perceptions and reactions to change, readiness for change and trust in leadership and AI, before integrating these perspectives into a cohesive foundation for the conceptual framework of the present study.

2.5.1 Employee Perceptions and Reactions to Change

For several years, employee responses to organizational change have been viewed as taking the form of resistance to acceptance. According to Coch and French (1948), employees do not resist change. Rather, the way change is initiated and how they experience it, brings out resistance to change. This knowledge still holds sway even today, as scholars and researchers have increasingly turned their focus to the context or perception behind the issue.

Latest studies confirm the most important thing is how employees perceive the change and respond. According to Oreg, Vakola and Armenakis (2011), employees' cognitive appraisal of change is knowledge of perceived fairness, uncertainty and personal impact and emotional evaluation is negative emotional reaction such as demoralisation, anxiety and anger are stronger predictors of resistance or acceptance of change than objective characteristics of change. The resistance should not be portrayed as mere opposition. Instead, it should be depicted as a response to the perceived threats in this process.

In the context of AI-driven transformation, perceptions of employees are especially important. The implementation of AI could involve imperceptible, multifaceted, and abstract changes over time. Changes could occur in something like algorithmic decision-making or data-driven performance assessment. Such involvement can exacerbate uncertainty and raise risk perception, especially if employees have little awareness of how an AI system can affect them. Consequently, the reactions to AI-induced change will likely depend more on how employees understand AI in terms of its implications for autonomy, and job security and identity than on its technical properties (Dietvorst et al., 2015).

Both acceptance and resistance often take on different forms in states and countries instead of being rigid countries or state's inherent dynamism. While employees can recognize the advantages of AI, they can also note its problems. This duality demonstrates that it is essential to have a very relevant leadership and change management approach that relies on employee sentiment and does not take acceptance to be a linear process.

2.5.2 Readiness for Organizational Transformation

The idea of readiness for change has become an important construct for understanding how employees respond to change. As per the definition given by Armenakis, Harris, and Mossholder (1993), readiness refers to the employee's belief, attitude and intention about the change being necessary and possible. Readiness refers to beliefs about whether change is appropriate (cognitive), feelings about it (for example confidence or anxiety, affective) and behaviour (for example, support for change, behavioural).

The research on the framework has subsequently developed, indicating its multi cue dynamic nature. Rafferty and colleagues (2013) identify readiness at three key levels namely, individual, group, and organizational level. The behavior of leadership and other contextual factors like experience with previous transformations determine relationship change. In organizational contexts of AI, readiness is impacted not only by perceptions of organizational capability but also by employees' confidence in their own ability to work with AI.

Another related construct receiving increasing attention in change research is that of psychological safety. Psychological safety is a shared belief of a work environment, where the environment is safe for interpersonal risk-taking. When a workplace is psychologically safe, employees are free to air concerns, ask questions and try out new practices (Frazier et al., 2017). User interactions with AI systems, including voice assistants and chatbots, will change owing to the fear of being branded incompetent due to mistakes made by AI systems. This growing fear will bring about a negative perception of AI systems. Hence, there is a need for psychological safety in AI adoption.

AI-driven transformation readiness will not be reduced to individual attitudes alone. Although techniques like training and skill development help in technical readiness, the emotional and relational factors are as important. These factors include confidence in the leaders and feeling supported by the organization. Organizations that do not manage readiness may experience compliance without commitment, resulting in thin adoption and low use of AI.

2.5.3 Trust in Leadership and Trust in AI

The link from leadership to change management to how employees respond to changes in technology hinges in large part on trust. Mayer, Davis and Schoorman (1995) has conceptualized trust in terms of propensity to be vulnerable. Further, this propensity is based on the perception of a trustee's ability to, benevolence towards and integrity with the trustor. The willingness of employees to cope with uncertainty and engage with change in an organizational context greatly depends on their trust in leadership.

Trust in transformation pertains to two subjects in the AI era. Trust in leaders and trust in AI. How employees understand the motives behind AI adoption and believe that leaders will do what is in their best interests, trust in leadership matters. When leaders are seen as clear and honest, workers tend to regard AI as a helpful tool rather than a control mechanism.

In comparison, trust in AI refers to a worker's confidence in the dependability, predictability and appropriateness of algorithms. Studies on trust in automation show that the right degree of trust plays a key role in human–machine interaction. According to Lee and See (2004), people may have an "over-trust" or a "under-trust" problem, whereby defects in reliance may lead them to accept a wrong solution or reject a correct solution respectively. Hoff and Bashir (2015) illustrate system characteristics, user experience, and organizational context shape trust in automation.

Literature has increasingly recognized the importance of trust within AI-driven organizational change. However, there is often no clear differentiation between trust in leadership and trust in AI with the two treated as one in the same. This mistake in notion obscures critical variance in how trust is created, sustained and transferred within organizations. Trust in leadership is fundamentally relational and value-based whereby trust is grounded in perceptions of integrity, benevolence and fairness (Mayer, Davis and Schoorman, 1995). Whereas trust in AI is primarily cognitive and performance oriented and is shaped by perceptions of reliability, predictability and system competence (Lee and See, 2004; Hoff and Bashir, 2015). These two types of trust are different but dependent. According to the findings of the study, the strong trust employees have in their leaders can counterbalance their low trust in AI. Employees that feel that leaders have their best interests in mind and are credible will accept the limitations of AI. Furthermore, the study shows that employees will be more willing to try and engage with AI in a way that challenges its implementation.

On the contrary, high trust in AI systems will likely not compensate for low trust in leadership when AI adoption is seen as imposed or misaligned with employee interests. The uneven power dynamics show that what leaders trust sets the standard for employees' responses. Realizing this difference enhances the explanatory power of employee-focused models of AI adoption. This justifies including both leadership-related trust and technology-related trust constructs in the study, which emphasizes perceived leadership behaviours and change management effectiveness as important antecedents of employee readiness and acceptance of AI.

2.5.4 Integrating Leadership, Change, and AI Perceptions

According to the literature given in this section the readiness and trust of the employees are together with their perceptions. The way change is managed, leadership behaviours are perceived, and AI systems are framed shapes employee reactions toward AI. The outcomes of any change process are not only influenced directly by leadership behaviour but also indirectly through perceptions fuelled by leadership behaviors involving justice, support and openness. Including these perspectives shows that a holistic approach to AI is very vital. Leadership that encourages trust and psychological safety enhances readiness for change, while effective change management can reduce resistance to change and lower uncertainty. Simultaneously, employees' beliefs about AI, especially concerning trust and ethics, provide feedback on their evaluation of leadership and the organization's intention.

The elaboration presents a substantial theoretical basis for the conceptual framework of this researcher. With the addition of leadership behaviours and perceived change management effectiveness as antecedents of employee readiness and trust in AI, the study defines the human mechanisms that determine success and failure of AI-driven change. In doing so, it goes past techno-centric explanations and offers employee-centred understanding of digital transformation in organizations (Rai, 2020).

2.6 Theoretical Framework and Hypotheses Development

2.6.1 Theoretical Basis

The present study is based on the perspective that Artificial Intelligence adoption is more than just a technical or operational process, but a socio-technical and organizational change that is shaped by employee perceptions, leadership behaviours and change practices. Past research has revealed that a firm's employees can use powerful, even superior systems and may still reject them. Such rejection has many causes, including how the change is framed and enacted within the organization. In circumstances where friendliness and uncertainty prevail, sensory overload or lack of autonomy make AI-enabled situations stand out as extremely important. In such situations, employees' responses are affected by the kind of organisation that disrupts the AI. This study takes an employee-centric perspective and invalidates perceptions of leadership and change management as key antecedents of employee responses to AI-based transformation.

The theoretical framework are mainly drawn from literature transformation leadership and change management. The transformational change where a leader can generate a vision and explain it; the leaders can inspire followers or people; the leaders can offer the followers away of thinking that is new and the leader provide the help the employees need to cope with the anxiety of the changing environment (Bass, 1985). In a digital and AI context, these leadership behaviours become especially relevant as employees need to make sense of complex technological developments and adapt to new ways of working. Simultaneously, the theory of change management emphasizes that successful change in organization stem from communication, involvement, training and supportive approach of top management (Armenakis, Harris and Mossholder, 1993; Kotter, 1996; Rafferty, Jimmieson and Armenakis, 2013). These actions alleviate doubt and guide employees to see change as controllable, justified, and valuable.

For purposes of this study, we use the term digital transformational leadership to reflect the application of transformational leadership behaviours in the context of AI-enabled and digitally intensive organisations. It cannot be viewed as a separate theoretical proposal, but rather an extension of transformational leadership theory adapted for the specific challenges related to digital transformation and AI implementation, as highlighted in previous sources

(McCarthy et al., 2022; Müller et al., 2024; Weber et al., 2022). This accountability safeguards conceptual clarity with the expanded leadership literature and allows this research to remain alert to the uniqueness of AI-enabled organizational change.

Drawing from this theoretical framework, the current research seeks to put forward that Digital Transformational Leadership and perceived Change Management Effectiveness are two significant explanatory factors of employee response to AI-induced change. To be more specific, it is proposed that these two antecedents positively enhance employee Readiness to Change and Trust in AI. Readiness to change refers to the extent to which employees perceive the AI-related transformation as proper, manageable, and worth their support. Trust in AI refers to the extent to which employees feel confidence in the reliability, usefulness, and legitimacy of AI-based systems at work. The framework combines leadership theory, change management theory, and employee perception research in order to explain the human side of AI adoption in organizations.

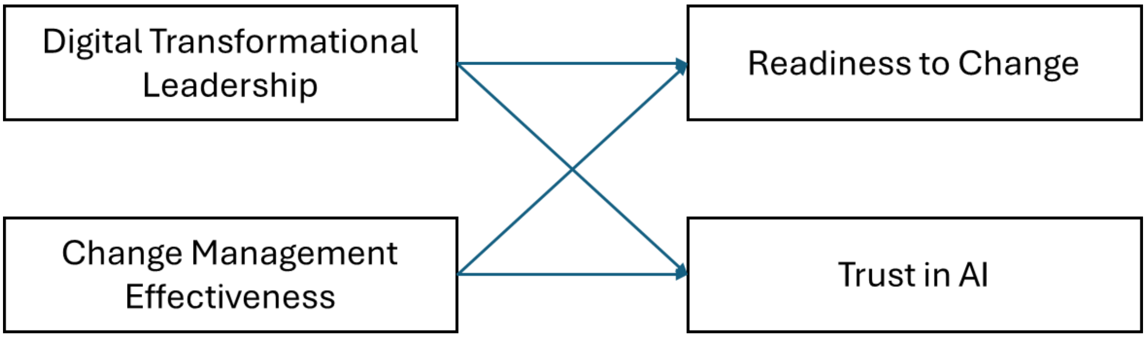

Figure 1: The conceptual diagram

2.6.2 Digital Transformational Leadership, Change Management Effectiveness & Readiness to Change

Readiness to change is considered very important attitudinal condition for organizational change. This term relates to how far employees regard change as necessary, appropriate and realistic and whether they feel psychologically ready to support it (Armenakis, Harris and Mossholder 1993; Rafferty, Jimmieson and Armenakis 2013). Readiness is particularly important in the adoption of AI in workplaces because employees often have to adapt to new systems, new routines and new forms of decision support under uncertainty. As job roles, skill requirements and perceptions of control may change due to AI, employees' acceptance of these socio-technical changes will depend not only on the technology but also on the social and organizational conditions surrounding its adoption.

It is envisaged that digital transformational leadership would have a favourable impact on readiness to change as it makes employees interpret AI-driven change meaningfully, and positively. Transformational leadership theory posits that leaders who articulate a clear vision, instil confidence in their followers, engage in intellectual stimulation of employees, and offer individualized support are likely to foster openness to change (Bass, 1985; Oreg and Berson, 2011). When technology becomes more complicated and rapidly evolving, especially in the digital environment, it is particularly imperative to observe such leader behaviours that allow employees to make sense. When leaders think of AI as a learning, improvement, and adaptation opportunity, employees are more likely to see the change as appropriate and manageable. Consequently, it is expected Digital Transformational Leadership will empower employees' readiness for AI-related transformation.

Perceived change management effectiveness is anticipated to positively influence readiness to change. As consistently demonstrated in existing literature on change management, communication, participation, training and support serve to reduce uncertainty and resistance while enhancing perceptions of efficacy and fairness (Kotter, 1996; Rafferty, Jimmieson and Armenakis, 2013). In the case of AI, where change tends to be continuous rather than episodic, these practices become even more important as employees need ongoing reassurance and guidance. Employees are easier to change their mind about change when it is perceived to be well managed. Employees are informed about the reason for AI adoption and supported extensibly. Employees are prepared and willing to adapt to change easily.

The following hypotheses are suggested on this basis:

H1a: Digital Transformational Leadership positively affects employee readiness to change.
H1b: Perceived Change Management Effectiveness positively affects employee readiness to change.

2.6.3 Digital Transformational Leadership, Change Management Effectiveness & Trust in AI

The current study also focuses on trust in AI as another central outcome as successful adoption of AI not only depends on technical performance but also whether employees will find AI systems to be reliable, understandable and appropriate for use in an organization. Earlier studies on trust in automation show that if AI is either less trusted or overly trusted, its use by employees will not be effective (Lee and See, 2004; Hoff and Bashir, 2015). In organizations, trust in AI is determined not only by the system's technical features but also by wider contextual and relational factors, such as the delivery of leadership credibility and how AI is presented in the organization. Consequently, faith in AI should be recognized as a socio-organizational process, not simply a technological one.

According to the argument, Digital Transformational Leadership will have a positive impact on trust in AI, since leaders act as important sensemaking agents in the context of technological transformation. In a digital environment, leaders' interpretation about the purpose, value, and impact of AI initiatives gets relied upon by the employees. Leaders who articulate a compelling vision, alleviate uncertainty, promote experimentation, and instill faith in technology can enhance employees’ views on AI in a more positive direction. Leaders who exhibit these behaviours increase the chances of employees viewing AI as a valuable resource that is legitimate rather than a threat to autonomy or job security. Within this framework, Digital Transformational Leadership can enhance trust in AI through the establishment of an environment that fosters confidence, openness and positive interpretation of this adoption.

Perceived change management effectiveness is likewise hypothesized to positively influence trust in AI According to research, the explanation of trust within technological systems or organisations occurs whenever the employees are adequately informed, how a system is used and involvement in it together with support mechanisms by the employer (Glikson and Woolley, 2020). Efficient change management can reduce opacity and uncertainty associated with AI by making the case for the adoption of AI clear, stating expected benefits and limitations, training and offering practical support. When workers believe that the transition process is just, wholesome, and caring, they tend to feel that the introduction of AI systems is responsible and their systems can be trusted.

The subsequent hypotheses have been proposed on this basis:

H2a: Digital Transformational Leadership positively affects employee trust in AI.
H2b: Perceived Change Management Effectiveness positively affects employee trust in AI.

2.7 Summary of the Literature Review

As indicated from the analysis of the literature in this chapter, Artificial Intelligence is increasingly being used as a key driver by modern organizations to transform themselves. Also, leadership and change management play a crucial role in influencing employee responses to AI and other transformations. According to existing literature, the adoption of AI is more than merely technical; it also affects decision-making power, job design, skills requirement, and power relations at the workplace (Jarrahi, 2018; Raisch and Krakowski, 2021). According to leadership studies, leadership behaviours affect how employees understand change and how they respond to it, especially in uncertain and complex environments (Bass, 1985; Avolio and Gardner, 2005). Conversely, change management literature argues that communication, participation, support, and readiness for change are the key determinants of success (Armenakis, Harris and Mossholder, 1993; Rafferty, Jimmieson and Armenakis, 2013). Studies have revealed that employees' acceptance of technology is influenced by their trust in management as well as their trust in the technology itself (Mayer, Davis and Schoorman, 1995; Lee and See, 2004).

Comprehending these well-established notions, however, severely restricts the literature and gaps. The focus of most organizational AI studies has remained techno-centric, privileging system capabilities, strategic outcomes and efficiency gains, with scant attention to employees lived experiences of AI-driven change (Nambisan et al., 2017). Leadership and change management theories have similarly seen little empirical research in the domain of AI adoption where issues such as algorithmic opacity, ethical issues and automation anxiety represent qualitatively different challenges. Consequently, there is hardly any integrated employee-focused research that systematically examines how leadership behaviours and change management practices determine employee readiness, trust and acceptance of AI. These changes are significant, especially in light of the fact that employees perceive the organization as responsible for the success or failure of organizational changes.

The current shortcomings offer a source of inspiration for the present study. On the basis of existing literature review, a conceptual model is proposed which suggests perceived leaders' behaviours and effective change management are key antecedents of employee readiness for AI-based transformation and trust in AI systems. The employees' insight is used here not as a peripheral outcome but as a central explanatory mechanism. The emphasis on leadership style and approach provides impetus for the selection of research variables. Such variables include perceived change management practices, readiness for change and trust in the AI domain. Literature provides methodological support for a quantitative, employee-centric approach utilizing validated perceptual measures that allow for the examination of relationships between leadership, change management and employee reactions to AI. Through this way literature review provides a coherent theoretical framework which integrated the fragmented research streams and lead logically to the empirical inquiry which is articulated in the next chapter.

CHAPTER 3 – METHODOLOGY

3.1 Introduction to Methodology

This chapter presents and justifies the methodological approach that has been followed to answer the research aim and questions. The methodology chapter primarily seeks to explain how the empirical study was designed and executed to assess the perceptions of employees regarding leadership and change management during the implementation of Artificial Intelligence or AI within the organization. The chapter gives findings and an overview of the research design and data collection and analysis procedures to ensure adherence to rigour and coherence of the methodology adopted.

The paper's ultimate purpose is to anticipate how employees are likely to perceive leadership behaviours and change management practices and coherence in transferable contents. Also, the way coherence is likely to anticipate their change and trust in AI. The questions in perspective of the research focus on how employees rate their leaders, how they have experienced change management processes and view on the use of AI in the workplace. In order to deal with these questions, it is necessary to have a methodology that can capture differences in interpretation, and patterns that are shared by groups of employees, rather than system performance or managerial intention.

Thus, the approach employed in this study is clearly employee-centered and perception-based. Organizational change and technology adoption are considered as socially constituted processes where final results are determined not only by deliberate strategic action but also by the way change and variation are experienced and construed by employees (Armenakis, Harris & Mossholder, 1993; Oreg, Vakola & Armenakis, 2011). This view fits well with literature, discussed in Chapter 2, which cites leadership credibility, perceived change management effectiveness, and trust in AI as factors influencing the adoption of AI (Rafferty, Jimmieson and Armenakis, 2013; Glikson and Woolley, 2020).

The study's research design and methodology are logically aligned with the theoretical framework. Moreover, the study focuses on employee perceptions. The research design and approach, population and sampling techniques, data collection tools, analytical tools and ethical issues are addressed in the following sections of this chapter thus providing a clear and systematic account of how the research questions are answered (Saunders, Lewis and Thornhill, 2019).

3.2 Research Design and Strategy

The design and strategy that guided this study are closely aligned with the research aim and research questions set out in Chapter 1 and the theoretical foundations established through literature. The quantitative research approach (survey) was chosen by the researcher to conduct a study that aims to explore perceptions of employees pertaining to leadership and change management and adoption of AI. Following Creswell (2014), the study employed a quantitative approach which would effectively answer the research question and examine the variables selected for the study. The present research does not aim at creating thick narratives about individuals, rather how, from an employee perspective, leadership behaviours, perceived effectiveness of change management, readiness for change and trust in AI are statistically related.

The quantitative nature of this research is supported by research questions that want to know the association and explanatory relationship, and not in-depth subjective meanings. Studies in organizational change and leadership have shown the relevance of quantitative tests for the theoretically derived relationships among perceptual constructs of readiness for change, trust and leadership perceptions (Armenakis et al., 1993; Harris and Mossholder, 1993; Oreg et al., 2011). In the study, standardized measurement instruments will be used to ensure objectivity and comparability along the respondents to produce reliable findings.

The philosophical perspective in which the study is placed is post-positivist. According to post-positivism social phenomena can be examined and measured systematically, albeit apart from the fact that observation restrictions in the form of imperfection will exist. Observations are guided and influenced by various contextual factors (Saunders, Lewis and Thornhill, 2019). This view seems particularly apt for studies on perceptions. After all, employees' responses reflect an interpretation not a second reflection of objective truth. They strive to achieve objectivity with the help of validated scales, standardized survey procedures, and established statistical techniques with the aim of minimizing researcher-bias (Bryman,2016).

A cross-sectional survey design was used in terms of research strategy. Cross-sectional surveys were carried out in which data were collected from a sample of respondents at a particular time are widely used in organizational and management research (Creswell, 2014). The rationale for this strategy is appropriate for the present study. To begin with, the researcher has accessibility to employees from varying roles in various types of organizations. As such, researchers will be able to gather perceptions about AI-driven change. In addition, given the constraints generally associated with postgraduate research, cross-sectional surveys are time-efficient and resource-efficient. Moreover, this design is particularly appropriate for measuring perceptual and attitudinal constructs. In other words, for constructs such as leadership evaluations and trust in AI which could be meaningfully assessed with self-reported questionnaire data (Rafferty et al. 2013).

As a result, the study has a one-shot time horizon, implying that data are gathered only once rather than overtime. This enables the assessment of current employee perceptions regarding AI-related changes currently or recently implemented. According to Bryman (2016), although longitudinal designs continuously measure the same subject over time, making it possible to get deeper insights into changes over time, they are often impractical for organizations, which may not have access to subjects over the long term or the capacity to collect data over longer periods. In this way, choosing a cross-sectional time horizon is a practical and theoretically justifiable way of responding to the study's research questions.

In addition, one should note the limitations inherent in a cross-sectional research design. As data is collected at a single point in time, certainty about causation cannot be inferred and the directional nature of relationships must be interpreted accordingly (Saunders, Lewis and Thornhill, 2019). Furthermore, cross-sectional surveys may extremely be sensitive to contextual effects such as temporary organizational conditions or external events affecting employee responses. The limitations acknowledged in this chapter will be discussed further in Chapter 5's discussion of research limitations, as they form part of the methodological compromises of the chosen design.

3.3 Population, Sampling, and Sample Size

The study covered employees working in organizations in the fast-moving consumer goods industry (FMCG) who are subjected to utilization of Artificial Intelligence (AI) or other digital tools in their day-to-day work. The FMCG industry has been chosen for the present study as it is characterized by a dynamic organization, a short life cycle, continuous creativity and increasing dependence on technology and/or data. In those scenarios, employees are usually faced with digital transformations that alter their workflows, decision-making and performance expectations. According to previous research, digital transformation provides opportunities and pressures for employees and requires them to adapt rapidly to new technologies and organizational practices (Günther et al., 2017). Furthermore, the increasing presence of digital applications and systems may create technostress and uncertainty which further emphasizes the need to study employee perceptions during technological change (Tarafdar et al. 2019). Through foreshadowing the employees operating within this context, the investigation aimed to capture authentic experiences of leadership, change management, readiness, and trust during adoption of AI.

The sampling procedure was non-probability, a combination of convenience sampling and purposive sampling. The limitations of access to material organizational participants and the voluntary nature of survey-based research led to the use of convenience sampling. Another logic which is purposive logic was followed while choosing the participants. It makes sure that the respondents are people and employees that have some knowledge and exposure to digital transformation or AI by the organization. Non-probability sampling methods are often used in behavioral and organizational research if the aim is to study people's perception and attitude rather than to provide statistically representative population estimates (Etikan, Musa and Alkassim, 2016). Bornstein et al. (2013) similarly note that sampling in applied settings is often influenced by practical considerations such as accessibility, organizational permission, and availability of participants. The accessibility of the questionnaire via the internet made it easy to obtain responses from participants across organizations and roles which made this beneficial as it is an employee-based study in the FMCG sector.

The final sample contained 148 valid responses, which is adequate for conducting multivariate statistics. As a rule of thumb, sample sizes above 100 are adequate for carrying out regression analyses and reliability tests, according to widely accepted standards (Tabachnick and Fidell, 2019). This is especially true when the number of predictors is small. In terms of statistical power, Cohen (1992) has apparently indicated that medium effect sizes can generally be detected with reasonable sample sizes in the social sciences. Thus, the sample described here is of an appropriate size to explore relationships among leadership perceptions, change management practices, readiness for change, and trust in AI. Although the sampling approach does not aspire to full representativeness of the larger FMCG workforce, it aims to provide sufficiently robust data for identifying patterns of association among employee perceptions. In summation, the selection of population, sampling choice, and sample size will be beneficial to the study objectives which centered on exploratory and employees. Moreover, quantitative analysis will be easier and practical in using a selected population.

3.4 Data Collection Methods

The current research analysis was carried out with the help of an online questionnaire developed to gauge the employees' perception towards leadership, change management practices, readiness for change and trust in AI. In this study, use of online survey method was considered as the most suitable for the collection of standardized responses from the respondents in different organizations of the FMCG sector. Online questionnaires enable researchers to efficiently gather responses from participants located in different geographical locations. Moreover, they ensure that the questions and format remain constant for all participants. Dillman, Smyth and Christian (2014) suggest that web-based surveys improve data quality through guided progression of survey questions and automated recording which goes a long way in eliminating manual coding errors. Moreover, data collection online allows for anonymity which may engender more honest responses when asking for evaluations of leadership behaviour or organizational practices. Wright (2005) further points out that internet surveys offer flexibility and accessibility, making them particularly suitable for research involving working professionals who can fill in the questionnaire at their convenience.

The questionnaire was designed in a manner which is clear, logical and aligned with the concepts of the study. A five-point Likert scale was used to measure the majority of items with strong disagreement to strong agreement, which enabled the respondents to show varying perceptions about Leadership, Change Management, Readiness for Change, and Trust in AI. Likert-type scales are commonly employed in organizational research as they allow for the measurement of attitudes and facilitate comparisons between different individuals (Joshi et al., 2015). The instrument also contained demographic questions, such as role and experience questions, to provide contextual information about the sample. The constructs were grouped into sections focused on leadership behaviours, perceived change management practices, readiness for change, and trust in AI. Moreover, the measurement validity can be supported by using clearly defined constructs when designing a questionnaire which would be useful for subsequent statistical analyses (DeVellis, 2017).

The development incorporated the principles for designing a measuring instrument.The questionnaire does not introduce entirely new measurement scales but is based on established instruments from prior research, which were adapted to reflect the employee-centred nature of AI-driven organizational change. The measures are presented in the next section (3.5). Using well-established measures enhance reliability and validity of constructs. Slight modifications were made to make them suitable for the FMCG context. According to Boateng et al. (2018), an important step involves adapting validated scales in order to make the scales relevant for the chosen setting while keeping the measurement quality.

According to Hinkin (1998), measuring errors may be minimized and content validity can be ensured, if constructs are carefully adapted to the theories. When necessary, the items were written in clear and simple language so as to not cause any ambiguity and assist with the correct interpretation of the questions by respondents. The selected data collection procedure along with the instrument design, which were reliable and employee-centric in nature, were employed to assess the perception of employees about AI adoption.

3.5 Measures

The scales used to measure the study variables were based on existing research but were modified to be more employee-centered in terms of AI-fueled organizational change. Leadership was translated mainly through transformational leadership dimensions, namely, vision, support, and development based on Bass (1985) and Rafferty and Griffin (2004) work. In relation to the objective of the study, the concept of digital transformational leadership is treated as a contextual extension of transformational leadership in the AI-enabled milieu, rather than a distinct construct. Recent literature is beginning to support sensemaking, ethical awareness, and support behaviours as important leadership behaviours in context of digital transformation (Weber, Krehl and Büttgen, 2022; McCarthy, Sammon and Alhassan, 2022; Müller et al., 2024). The leadership in technologically complex settings was captured by incorporating ethical considerations of transparency.

Effectiveness of change management was measured by using items from the earlier work done on organizational change processes (communication, participation and support) (Armenakis, Harris and Mossholder, 1993; Rafferty, Jimmieson and Armenakis, 2013). These dimensions indicate essential practices that influence the employees' view of the effective implementation of change. The readiness for change of employees was determined using items measuring their preparedness, confidence and willingness to change to AI-related changes. The items used were based on the framework used for measuring organizational readiness (Holt et al., 2007; Vakola, 2014). It represents the cognitive and behavioural components of acceptance of change. The final section of our questionnaire focused on one's trust in AI. This was measured using items from the literature on trust in automation as well as trust in algorithmic systems. More specifically, it measured the perceived reliability, understanding, and comfort in using AI (Lee and See, 2004; Hoff and

Bashir, 2015; Glikson and Woolley, 2020). In short, adapted, theory-based measures ensure validity and context-specificity.

3.6 Data Analysis Techniques

The data analysis process was carried out with quantitative structure to analyse the relationship between leadership perception, change management, readiness for change and trust in AI. The program is used for systematic data preparation, reliability test and inferential analysis. Multiple steps in this procedure were undertaken whereby the dataset is suitable for advanced statistical work and conforms to the norms.

The first step was data preparation and screening. Before analysis, the dataset was checked to identify missing data, inconsistent responses, and other flaws that may impact statistics. According to Field (2018), data screening is important in quantitative research because it ensures accuracy and validity prior to using inferential techniques. The variables were created by averaging together the items in each cluster (leadership perceptions, perceived change management practices, readiness to change, trust in AI/ML). Making use of composite scores reduce the random measurement error and enhances the stability of assessment without altering the latent variable structure of the data. It also allows for ease in interpretation for subsequent analyses.

The internal consistency of the measurement scales was assessed using reliability analysis. Cronbach's alpha was used as the primary reliability measure to assess the extent to which items in a specific construct measure the same underlying concept. The internal consistency of the composite variable is the most important statistical measure in survey research. It ensures that items of the composite variable accurately reflect theoretical constructs and does not include many unrelated items. According to Tavakol and Dennick (2011), reliability testing adds credibility to quantitative results since it assesses whether the measuring instrument works correctly.

Descriptive statistics were calculated to provide an overview of the responses of participants as well as general trends. An examination of the means and standard deviations for each construct offers a brief summary of how employees perceive leadership, change management, readiness and trust in AI. According to Gravetter and Wallnau (2017), descriptive analysis enables researchers to understand central tendencies as well as variability. At this point, the actual analysis concerned describing the data, not interpreting relation or testing theory assumption.

Pearson correlation analysis was performed to study the relationship between the variables. The relationship of leadership perception, change management practices, readiness for change and trust in AI were measured using correlation coefficients to determine their relationship strength and direction. Pearson correlations are often used in social science research to indicate how variables tend to move together statistically. Based on Schober, Boer and Schwarte (2018), correlation analysis is beneficial for identifying patterns that require testing using inferential statistics. Association is not causation, so they have to be kept separate.

Ultimately, multiple regression analyses were used to measure the proposed relationships of the conceptual framework. Researchers can use regression models to see how independent variables work together to influence a dependent variable while controlling the relationships they have with each other. This research entails the development of two models. The dependent variable in model 1 was trust in AI while leadership perceptions and perceived change management practices were treated as predictors. The second model, similarly, utilizing the identified independent variables, considered the readiness for organizational transformation as the dependent variable. As per Hayes (2018), regression analysis is most appropriate for perception-based research, as its objective is to analyze more complex relationships between the organizational and psychological factors. As pointed out by Kutner et al. (2005), multiple regression analysis enables hypothetical assumptions about the nature of the variables to be tested.

An extensive analytical strategy was ensured through a combination of data screening, reliability testing, descriptive statistics, correlation analysis and regression modelling. With such an approach, findings developed from methodologically sound procedures and concomitantly supported the investigation of employee-coloured dynamics in AI-adjusted organisational change.

3.7 Ethical Considerations

The ethical principles helped with the design and the execution of this procedure of the study. The voluntary participation, informed consent and confidentiality were ethical consideration of the study. The participants in the study were quite clear about the aims of the study and what their participation would involve. Additionally, at any point, they had the option to decline or cease their participation. The adherence to ethical practices for social science research is assured through activities that signpost transparency as well as respect for the individual autonomy of research participants (British Psychological Society, 2018). The research must also be governed by a wider set of ethical frameworks, which reflect on being responsible and ethical, and protecting the participants from harm or coercion (Israel and Hay, 2006). Before answering the questionnaire, the consent statement was presented to the respondents to highlight the use of data and that they could participate in the questionnaire voluntarily.

The General Data Protection Regulation provided guidance on data protection and privacy considerations throughout the project. The questionnaire was designed to collect answers anonymously, therefore avoiding any identification by not collecting any personal information such as names, email IDs and organization names. All the gathered data will be kept in a secure manner and only used for academic research purposes. Ensuring confidentiality is not only a good regulatory compliance but also encourages open feedback especially when they need to assess leadership behaviours or organisational practices. As per Voigt and Von dem Bussche (2017), researchers must limit the data collected to that which is strictly necessary and implement safeguards to ensure that participants' identities are protected during the research process and thereafter.

To mitigate the risk of bias and harm, various safeguards were put in place in addition to legal and procedural safeguards. The questions in the survey were not disturbing to the participants and were related to their work experience. Participants were free to withdraw from the questionnaire at any stage without having to justify. While writing the questionnaire, neutral language was used to mitigate the chances of leading responses or creating pressure to respond in any specific way. This is consistent with ethical integrity and methodological validity. As noted by Orb, Eisenhauer and Wynaden (2001), the ethical research design is a fine balance between the quest for knowledge, as well as the capacity to ensure the participant(s) do not feel discomfort. It means that ethics are imbibed in research, meaning the data was collected with concern and care towards the choice and privacy of the participants.

3.8 Chapter Summary

This chapter outlined and justified the methodology used. The chosen approach to the examination of employee perception regarding leadership, change management, readiness for change and trust in AI was in due accordance with the objective of the study. The association between key constructs was examined using quantitative research strategies through a structured data collection procedure along with stated measurement tools. The emphasis was on the individual and his experience of change as opposed to technological and business measures of change.

In this chapter we provide the FMCG sector's target population, strategy for sampling to access the respondents, and justification of final sample size. Data was collected via online questionnaire from mainly Likert Scale items borrowed from measurement scales. They ensured that constructs used in theory were consistent with the survey design techniques. The series of data preparation steps, reliability test, descriptive statistics, correlation analysis and multiple regression modelling provided a structural framework that served as backbone in examining the relationships amongst leadership, organizational practices, readiness and trust.

The ethical aspects, such as voluntary participation, informed consent, confidentiality, and compliance with data protection standards, were also emphasized. The choices made regarding methodology bolstered the investigation so conducted, on empirical grounds. After discussing the method and analysis in the previous chapter, the next chapter goes to empirical research. Chapter 4 outlines the results of statistical analyses conducted to test how FMCG employees perceive leadership, change management practices, readiness for change, and trust in AI.

CHAPTER 4 – RESULTS AND ANALYSIS

4.1 Introduction

The employee survey results upon which the study is based are presented in an organised manner in this chapter. The objective of this chapter is to systematically discuss and analyse the findings obtained and report the link between the findings and the objectives of the research stated above in the dissertation. Building on the theoretical perspectives laid out in the literature review and the methodological framework elaborated in the previous chapter, this chapter analyzes employee perceptions of leadership behaviour as well as change management and artificial intelligence (AI) practices in select fast-moving consumer goods (FMCG) companies. It aims to shine a light on the human and organisational aspects of AI-driven transformation through the employees' lens.

As outlined in earlier chapters, the main goal of this research is to study how employees experience leadership and change management during the adoption of AI and the influence of these experiences on readiness to change and trust in AI. A quantitative research design was chosen to reach this purpose, which allows for systematic investigation into the relationship between key constructs from the conceptual framework. For conducting the study data were collected by way of a structured questionnaire from the employees of the FMCG organization. Rapid digitalisation and transformations have been taking place in this industry. Due to the quantitative approach, research can go beyond their sample's individual experiences to identify general patterns and trends.

The chapter has been divided into several sections which perform distinct analyses. The first part discusses data preparation and descriptive statistics. It gives sample characteristics, data screening, and descriptive statistics overview. The following section uses appropriate statistics to perform inferential statistical analysis of leadership perception, change management practice, readiness for change and trust in AI. The ensuing results section addresses the most salient findings with regard to the preceding literature and discusses what they could mean for how employees respond to organizational change related to AI. This chapter integrates the findings with the theory presented in Chapter 2 and illustrates the contributions of the findings to the ongoing dialogues on digital leadership, organizational change and the trust to emergent technologies. The chapter will end with a brief overview of findings that will allow the conclusions and implications of the next chapter. Overall, this chapter is the empirical core of the dissertation. It turns the research design into evidence while ensuring a clear distinction between the presentation of results and their theoretical interpretation.

4.2 Data Preparation and Descriptive Statistics

4.2.1 Data Screening

A prior examination of dataset was undertaken in order to determine its suitability for quantitative study. This ensured whether the statistical procedures were justifiable. As noted by Hair et al (2019), screening the data is the duty of a researcher that needs to be done to check data for any missing values, inconsistency in responses, other coding errors, etc. A total of 148 valid responses from employees working in the FMCG sector were selected for final study after screening. The sample size is adequate for multivariate analysis, particularly in terms of regression and reliability testing. A sample size of over 100 is sufficient to produce stable and meaningful output (Saunders, Lewis and Thornhill, 2019)

Missing data were first checked before the conclusion of the use's scenario and responses. In general, the collected responses were mostly complete and internally consistent, which indicates that respondents took the questionnaire seriously and the survey design was clear. Data quality was not threatened as missing values were minimal and did not exceed levels. When responses were missing in isolation, listwise exclusion was applied to ensure comparability in analyses. A limited amount of missing data was evident showing respondents rated the measured constructs consistently.

The level of assessment for all perceptual items was determined on a five-point likert-type scale of 1 (strongly disagreed) to 5 (strongly agreed). Many researchers have utilized Likert-type scales in organizational research. This is because they enable the quantification of attitudes, while still allowing the attitude to remain comparable to the others (Bryman, 2016). Aggregated measures on the Likert scale are ordinal in nature but are treated as practically interval level as one may carry out parametric techniques like correlation and regression analysis (Hair et al. 2019). Using a common response format across all constructs reduced measurement error and enhanced structural consistency in the data.

After screening the data, composite variables were created to capture the key theoretical constructs. The variable measuring leadership perception consisted of six items. Perceived change management practices were captured by five of the items. Four measured readiness for organizational change. Another four assessed trust in AI systems. According to Hair et al. (2019), composite scores are commonly used since they enhance the stability of the measurement and minimize the random error that occurs in each item. The data set was considered clean, well coded and reliable to carry out statistical analysis. Consequently, the data set was suitable for additional descriptive and inferential procedures.

4.2.2 Reliability Analysis

After validating the data set materials, the internal consistency reliability of each scale was tested using Cronbach's Alpha test summary. In quantitative research, reliability study is important as it tries to assess whether a number of items consistently measure a concept (Tavakol and Dennick, 2011). The level of reliability indicates that respondents interpreted items in a similar manner, and the constructs can be treated as coherent scales.

The results of the reliability analysis are presented in Table 1.

Table 1: Reliability Analysis of Constructs

Construct	Number of Items	Cronbach's Alpha (α)
Leadership Perceptions	6	0.92
Change Management	5	0.93
Readiness for Change	4	0.91
Trust in AI	4	0.77

As demonstrated above, the internal consistency of all the constructs was acceptable to excellent, indicating the scales reliably measure these constructs' theoretical dimensions. The reliability assessment in quantitative research assesses whether a set of items measures the same construct consistently across respondents (Hair et al., 2019). When a survey instrument has high reliability, it instills confidence that it functioned as planned, and all our later analyses are based on a stable, reliable measurement.

Cronbach's alpha of leadership scale was 0.92 which shows excellent reliability. Thus, it can be concluded that the items vision communication, learning encouragement, and ethical awareness are all seen as reflecting the same idea that is the leadership. Same as above, the perceived change management scale also displayed excellent internal consistency (α = 0.93). Thus, the items measuring the clarity of communication, participation, and training support were well aligned. The respondents seem to take leadership behaviours and organisational change practices as one single experience that they encounter at work.

The readiness for change, which has a useful value of α = 0.91, indicates that the views of employees towards change generally fit together. Efficient measurement in this area is essential particularly since readiness is a key outcome variable in organizational research. The trust in AI construct achieved a Cronbach's alpha of 0.77, which is acceptable in social science studies (Hair et al., 2019). Despite being lower than the other constructs, this value likely indicates that technological trust is a multi-dimensional construct which relies on cognitive assessments of the automated system and beliefs about its fairness and transparency (Glikson and Woolley 2020)

In general, the high reliability coefficients were sufficient to justify the creation of composite variables for perceptions of leadership, change management, readiness and trust in AI. Ensuring internal consistency at this stage improves the integrity of upcoming correlation and regression analysis. In turn, this will reduce the extent that observed patterns reflect measurement error.

4.2.3 Descriptive Statistics

After screening data and testing for reliability, descriptive statistics about the main study variables were computed which gave an overview of respondents' perceptions. Descriptive analysis is one of the initial procedures in quantitative research. It provides a summary of the majority of participants' responses. In addition, it focuses on central tendencies (Field, 2018). According to Table 2, the mean values of the composite variables are presented clearly.

Table 2: Descriptive Statistics of Main Constructs

Variable	Mean (M)
Leadership Perceptions	3.17
Change Management	2.74
Readiness for Change	3.63
Trust in AI	3.25

The descriptive statistics give the first impression of how the employees of the FMCG sector perceive leadership, change management, readiness for change and trust in AI. Employees have a slightly positive view of their leadership behaviours regarding AI (M = 3.17), suggesting their supervisor was a generally supportive and communicative party behind the digital transformation plan. Nonetheless, the score is still close to the neutral midpoint, indicating that there are variations in leadership experiences across organizations and managerial contexts in the sector.

The change management practices perceived by these players received an average rating (M = 2.74) that was the lowest of all the three constructs. The result shows employees were more critical of the organizational efforts relating to communication, participation and training than for leadership behaviours at supervisory level. The outcome does not mean disagreement, but a more cautionary recognition of how an organization applies each transformation powered by AI. It could also suggest the linear, complex, and fast-moving nature of the FMCG sector, making it a little difficult to bring in structured changes.

On contrast, the readiness for organizational change with mean value (M = 3.63) of most respondents signifies that employees were ready for a change. This relatively high level of readiness shows a large degree of flexibility in terms of digital transformation as well as confidence that evolving working methods can easily be adjusted. The moderately positive evaluation of trust in AI (M=3.25) shows the respondents are underestimating the reliability of AI systems while having a balanced view.

All things considered, these results suggest that employees may be more ready to engage with AI than organization change practices fully support. Of utmost importance, at this stage, descriptive statistics only provide an empirical overview, which is no cause and effect. The response distributions were as expected for Likert-scale data, showing no extreme skewness or other anomalies and indicating the dataset's appropriateness for the forthcoming inferential analysis.

4.3 Inferential Statistical Analysis

4.3.1 Correlation Analysis

After presenting the descriptive statistics, a correlation analysis will be conducted to analyze the relationship between the main constructs of the study, leadership perception, perceived change management effectiveness, readiness for organizational change, and trust in AI. Conducting a correlational analysis is usually a relevant first step in quantitative studies. It generally allows researchers to become familiar with what possible associations exist in their data and the strength of such associations. After becoming familiar with the associations established by correlation analysis researchers might engage in more sophisticated inferential techniques such as regression analysis (Field, 2018). The study employed Pearson's correlation coefficient (r) as the variables were treated as approximate interval outcomes from Likert-scale composite scores, something that is often done in organizational studies (Hair et al., 2019).

Table 3 presents the correlation matrix for the main constructs included in the study.

Table 3: Correlation Matrix of Main Constructs

Variable	Leadership	Change Management	Readiness for Change	Trust in AI
Leadership	1.00	—	—	—
Change Management	0.616	1.00	—	—
Readiness for Change	0.301	0.245	1.00	—
Trust in AI	0.495	0.550	0.618	1.00

Note: **p<0.01

All correlations were positive and statistically significant at the 0.01 level, indicating meaningful relationships between the study variables.

The correlation findings demonstrate statistically significant positive interactions among the core constructs. There is a strong association between leadership perceptions and perceived effectiveness of change management practices (r = 0.616), which means that employees who evaluated their supervisors more positively were also more likely to report higher levels of change management effectiveness. This indicates that positive leadership behaviour is closely associated with how employees perceive the organizational change process. While correlation does not imply causation, this relationship can be considered moderately strong according to established guidelines (Cohen, 1988).

A similar moderate relationship was observed between trust in AI and perceived change management effectiveness (r = 0.550). The findings suggest that employees are more likely to express confidence in AI systems when effective communication, participation opportunities, and adequate training support are present. In addition, readiness for change showed the strongest association with trust in AI (r = 0.618), indicating that employees who feel psychologically prepared for AI-driven transformation also tend to exhibit higher levels of trust in AI systems. Taken together, these results point to a consistent pattern of co-occurring positive perceptions across the examined constructs.

All correlation coefficients were positive, suggesting that these constructs do not represent opposing dimensions of employee experience, but rather complementary aspects of how employees perceive AI-driven change. Furthermore, all correlation values were below commonly accepted thresholds for multicollinearity (Hair et al., 2019), supporting their inclusion in subsequent regression analyses. It is important to note that correlation analysis identifies associations rather than causal relationships. Therefore, the purpose of this analysis is to establish empirical links among leadership, change management, readiness, and trust in AI, which provide the foundation for the inferential analyses that follow.

4.3.2 Regression Analysis

To further investigate the relationships found in correlation analysis and to identify whether leadership perceptions and perceived change management practices generate any predictive implications, multiple regression analysis was conducted. Due to its immense usefulness in determining how much our independent variable is able to explain variation in a dependent variable while controlling for other predictors, regression analysis is one of the most used activities in organizational research (Hair et al., 2019). The present study aimed to develop two regression models to analyze the explanatory power of perceptions of leadership and change management on two outcome variables that relate to AI. In Model 1, trust in AI was the dependent variable; while, in Model 2, readiness for organizational change was the dependent variable.

The first regression model sought to examine whether employees' perceptions of leadership and perceived change management practices significantly predicted trust in AI systems and was constructed for this purpose. The independent variables were leadership perceptions and perceived effectiveness of change management, while trust in AI was the dependent variable. The regression analysis was noted in Table 4.

Table 4: Regression Model 1 – Predicting Trust in AI

Predictor	B	Std. Error	t	p
Constant	1.917	0.168	11.43	.000
Leadership	0.179	0.061	2.93	.004
Change Management	0.279	0.060	4.62	.000

Model statistics: R^2 = **0.342**, $F(2,145) = 37.61$, $p < .001$

The model was statistically significant and explained about 34.2% of the variance in AI trust. As per the standard benchmarks in social science research, this is a considerable amount of explanatory power (Hair et al., 2019). Trust in AI is positively influenced by both leadership perceptions and perceived change management practices in a significant way. Higher assessments of leadership behaviours corresponded with a greater degree of trust in AI ($B = 0.179$, $p = .004$). Moreover, perceived change management exhibited an even stronger predictive capacity, as reflected by ($B = 0.279$, $p < .001$).

As a result of their findings, the employees that had better communication, support, and participation during an organizational change also reported better trust in AI. Notably, the standardized regression outcomes indicate a stronger influence of change management practices on trust in AI compared to leadership perceptions alone. According to the Durbin–Watson statistic (1.93), there were no significant problems with autocorrelation. And the residual diagnostics indicated satisfactory assumptions of the model.

In a second regression model, readiness for AI-driven organizational change was regressed on leadership and perceived change management practices. The dependent variable in the research was readiness for change while leadership and change management were the predictors. Table 5 presents the results of the study.

Table 5: Regression Model 2 – Predicting Readiness for Change

Predictor	B	Std. Error	t	p
Constant	2.736	0.238	11.48	.000

Predictor	B	Std. Error	t	p
Leadership	0.209	0.087	2.41	.017
Change Management	0.082	0.086	0.96	.339

Model statistics: R^2 = **0.096**, F(2,145) = 7.70, p < .001

The model was statistically significant overall, although it explained a smaller proportion of variance than Model 1 and hence only 9.6 % variance in readiness for change. The findings indicated that leadership perceptions were a positive significant predictor of readiness (B = 0.209, p = .017). This suggests that those who feel encouraged to speak up by their leadership will feel ready to embrace AI-related change. Conversely, when we included leadership, the perceived change management practices were not a significant predictor of readiness (p = .339).

Perceptions of leadership may influence employees' psychological readiness for change in a more direct way than the change management practices which may impact readiness in more indirect way. The observed value of the Durbin-Watson statistic (2.13) suggests there are no violations of independence of the residuals and no serious violations of normality.

To summarize, the results shed light on the influence of leadership and organizational change processes on employee attitudes towards AI and other such responses. Model 1 showed that leadership and change management are significant predictors for trust in AI. Additionally, the organizational context is found to be significant for technology acceptance. On the contrary, Leadership perceived readiness to change is found to be a better predictor of change management practices.

The study progresses from mere association to showing the contribution of the individual predictive variable by using regression analysis. The analysis of a variety of relationships will be performed using regression modelling and not just those that are a result of variance shared only (Field, 2018). Consequently, the results further substantiate that the measures employed in this study, while being empirically divergent, are nevertheless interrelated, as indicated by the significance of the regression coefficients alongside moderate R^2 values.

As a whole, the regression results strengthen the empirical foundation of this study as they show that leadership perceptions and perceived change management practices are statistically predictive of key employee outcomes in relation to AI adoption rather than merely associated with them. The findings lay strong groundwork for the interpretative discussion to follow, which examines the results in the light of the theoretical framework developed earlier in the dissertation.

4.4 Discussion of Key Findings

4.4.1 Overview of Empirical Patterns in Employee Perceptions

According to the results of this study, employees have a particular perception about leadership, change management, readiness to change, and trust in AI within the FMCG sector. On the whole, employees appear to be relatively open to AI. In other words, there is a measurable psychological readiness for change. Employees may not be resistant to AI-generated change; rather they may already perceive the increased presence of digital technology within organizational practices. Raisch and Krakowski (2021) have studied and indicated that when the adoption of technologies happens not just through technical execution but also how legacy shaped sense-making of employees and their usage towards new systems, it leads to a successful technology change.

Meanwhile, leadership behaviours were assessed more positively than practices associated with the broader change management of organisations. The employees seemed to distinguish between their managers and the company's approach to the change brought about by AI. This implies that the local-level leadership interactions may seen as being readily responsive and supportive compared to the (formal) organizational processes that may be seen as slower to act or less apparent. As we have learned, a leader can be instrumental in keeping things on an even keel during times of uncertainty when other means of transformation may not work.

How organizations work together with their AI systems has a big impact on how they get trusted. According to the findings of the report, artificial intelligence in the workplace enjoyed quite a bit of employee confidence. This reinforces the assertion that utilizing AI should be interpreted as a socio-technical process (Raisch and Krakowski, 2021).

Employees view AI with more than just a technical eye. Their evaluation of AI systems is also influenced by organizational practices, leadership behaviour and their experiences as agents of change. The change from descriptive results to interpretative perspectives from employment may be an important entry point to an understanding of the grounded reality of AI-driven transformation.

4.4.2 Explaining the Gap Between Readiness and Change Management Perceptions

One of the notable findings of this study was the relatively high readiness of employees for change compared to a less favourable assessment of change management. The divergence in belief is that an employee believes that they can adapt to an Artificial Intelligence driven transformation, whereas there are inefficient/not supportive corporate structure or processes. This means that psychological readiness does not necessarily mean that employees believe that their organizations are completely ready to handle technical change.

Research on organizational change emphasizes that readiness for change is primarily a psychological state based on beliefs about capability, necessity and personal impact (Rafferty, Jimmieson and Armenakis, 2013). Exposure to digital tools, informal learning, or society's better knowledge of AI can prepare employees, whether or not the organization is involved. The findings of this research indicate that individual attitudes towards AI may change faster than the change system of the organization. In industries like FMCG where speed and tech innovations have become the norm, employees at firms might see ‘digital transformation’ as already a given for workplace operations.

Nonetheless, the less favourable evaluation of change management practices raises important questions about the preparedness of the organization. Organizations might be more focused on how to utilize technology instead of an organized proper change process. The implementation of AI usually starts as a strategic or operational initiative focused on efficiency; thus communication, participation or training frameworks that help employees at transition are given less importance. According to Raisch and Krakowski (2021), there is a discrepancy in the modern literature of digital transformations that says that many organizations adopt a technology-centric approach that simplistically views humans.

Consequently, they may feel they are ready to adapt but wonder whether organizational change strategies are sufficient to be able to help them.

The difference between readiness and change management also reflects AI-driven transformation's ever-emerging quality. Unlike traditional change actions that are usually relatively clear in their beginning and end, the adoption of AI occurs through updates, experimentation and iteration. With changes happening on a regular basis, even in the absence of any structural change programme, employees may develop adaptive mindsets. While one view of this adaptability is positive, another discussion of it indicates concern with organizational rather than employee resilience and the lack of institutional support. From a critical point of view, this begs the question whether organizations check to see if they are making the employee responsible for adapting to the technology or the organizational learning.

Furthermore, the difference in perception of readiness and change management indicates the need to understand the individual and organization level of change. Employees view readiness as a personal quality, based on their skills and openness. Change management refers to what organisations do in practice, like clarity of communication, or training availability. The employee may be confident about their own ability to adapt to the new environment but may not feel confident about the organization's strategy when these two dimensions are misaligned. This finding contributes to ongoing discussions about employee-centered digital transformation, suggesting that readiness should not merely be interpreted as a sign of the success of the organization; it can also equally be achieved by employees to adapt to changing technologies.

All in all, the gap between readiness and perceived change management effectiveness evidences an interpretation of AI adoption in the FMCG sector. Staff members produce the willingness and ability to engage with technological change, but organizational processes may not fully match this. Considering this insight, it requires looking at the implementation of AI not just from a technological perspective but also from the perspective of the employee's attitude towards organizational change practices.

4.4.3 Trust in AI as an Outcome of Perceived Change Management

The results of this study illustrate the relationship between perceived change management practices and trust in artificial intelligence (AI) among employees. Although accuracy, transparency, or other technical performance objectives are typically stated, these findings indicate that trust is more than a technical evaluation; it is also an organisationally embedded evaluation. According to employees, the most important for interpretation of AI is in a context in which AI is deployed, such as the communication approach, training opportunities, fairness of organizational decision and more. As noted by Raisch and Krakowski (2021), this argument supports the assertion that an AI being adopted on the work process must be seen as a socio-technical phenomenon rather than just a tech breakthrough.

It is convincingly clear that the way change is managed impacts trust. Consequently, people may become more confident about AI systems due to the facilitated upcoming changes. When change initiatives are participative, transparent and supportive, employees often see AI as a means of improving their work. They don't like being controlled or under supervision. As a result of inconsistent change management practices, employees may not accept that the application of AI technology will yield stronger outcomes even though it might. The paper identifies a gap in research and knowledge regarding human reliance on AI collaboration. The influence of organizational theory on AI is important to develop a more sophisticated understanding of how institutional theory can impact human reliance on AI collaboration.

Indeed, these finding challenges the literature on AI, which often puts a lot of weight on design, without thinking about whether the dynamics of the organization matter differently. Trust is considered a function of explainability or reliability of the system in many studies. They implicitly assume more acceptability of technology. Nevertheless, the current findings indicate that organizations do manage the change process itself and do mediate employee trust Even well-designed AI systems run into trouble when employees see implementation as complicated, rushed, and not aligned with their needs. This observation indicates the gap that motivates a techno-centric explanation that overlooks the human-managerial problem of AI.

There has been an idea that trust is mediated by organizations. This reflects the wider developments in digital transformation research. AI systems adapt the workflow, decision rights and professions. Consequently, they are socially integrated within processes playing out in society. Through their implementation of AI tools, firms do not merely provide employees with a means of execution. They also signal their values. Trust emerges from relationships formed between leadership, technology and change management practice within an organization. This research study demonstrates evidence of a relationship between trust in AI and perceptions of change management effectiveness. Thus, these findings contribute to the existing literature that underlines the significance of organizational and technological perspectives in studying AI adoption (Raisch and Krakowski, 2021).

To foster trust in AI, organizations should increase overall communications, participation and trainings in tandem with tech features, the results reported. Trust will not be generated through technical mechanisms but through organizational practices that consistently signal fairness, competence, and transparency. Glikson and Woolley (2020) support this view asserting that dependence on artificial intelligence is socially constructed. Empirical evidence shows that change management processes underpin the construction of trust in organizations.

4.4.4 The Role of Leadership in AI-Driven FMCG Contexts

The regression analysis found that leadership perception was a significant predictor of employees' readiness to change. In addition, when implementing change management practices, they had a less direct impact on trust in the AI model. The trend points towards how leadership in AI-led transformation is significant in Fast-Moving Consumer Goods sector. The behavior of leaders appears to shape employees' perceptions and emotional reactions to technology, though the bond of trust in AI in general appears stronger than that of any one organization process.

Leaders in organizations such as those in the FMCG industry operate with severe operational pressure like tight production schedules, fierce competition and continuous digitalization. Leadership comprehension must change based on the context of AI. Leaders do not only act as strategists. They also act as implementers, making strategies happen. The authority is interpretive, and this is consistent with research demonstrating that leadership affects how employees come to understand change. That is, leaders influence how employees construct their ideas of uncertainty and priorities (Rafferty, Jimmieson and Armenakis, 2013). In this way, leadership assists with encouraging the adoption of A.I. as an opportunity for learning and growth rather than as a risk to jobs.

Nonetheless, the lower-than-expected direct association between leadership and trust in AI indicates that leadership may not be adequate for the establishment of technological trust. Employees may differentiate between trusting their line managers and trusting the artificial intelligence systems established by the organization. When change is accompanied by supportive leadership, it leads to openness to change. However, in the case of trust in AI, it seems that this is more dependent on structural conditions rather than supportive leadership.This difference indicates that while leaders have a role in the process of digital transformation, they are not the sole drivers of a technology's acceptance.

This interpretation is supported by the FMCG context. Leaders in industries that have a lot of output and intensive use are likely to chase efficiency and delivery first and are thus only able to spare very limited time and discussion of technical change. Thus, employees may judge AI systems on the organizational practices they can see, rather than the rhetoric of management. It indicates that contemporary and future leaders, whose archetype will be based more on sensemaking than on inspiring with a vision and wisdom, are likely to emerge. To inspire greater adoption of AI by others, leaders must do more than state a strategic direction. They will assist employees to cope with uncertainty, understand the impact of technology and discover ways to incorporate into their work.

A critical examination of the findings reveals that the identified problems cannot be resolved by leadership alone. It is not enough to state the need for leadership in improving readiness and reducing resistance. Powerful change management frameworks are needed to convert aspirations into institutional backing. According to the results of the study leadership is more than just an isolated contributor to trust in new technologies. As such, leadership bridges the organizational strategy-employee perception connection.

4.4.5 Integrative Interpretation of Findings

Overall, the results of the current investigation indicate that leadership perceptions, perceived effectiveness of change management, employee readiness, and trust in AI are interconnected. The constructs do not appear to work like separate variables but rather as an interconnected system reflecting the socio-technical nature of the AI-driven transformation. Leadership behaviours significantly linked to employees' readiness for change which indicates that the leaders also influence psychological readiness and openness to technology. Meanwhile, trust in AI was found to be largely influenced by perceived change management practices. In this regard, employees' evaluation of the technology is influenced by the organization's processes.

It shows that employees are likely more adaptable than the systems that uplift them. Data shows that citizens are largely ready for digital transformation while their change management perceptions indicate organisations may not be able to keep up with the human side of AI in the process. Digital transformation is more human than a technological process as the gap indicates (Raisch and Krakowski, 2021). Workers do not only respond to technological features that appear on the job. They interpret AI through organizational narratives and leadership practices as well as through social interactions.

The study also revealed that trust in AI was moreover technological in nature yet organizational in nature which needs to be perfected. In spite of the significance of the performance of a system, it seems that trust tends to emerge through social mechanisms such as the quality of communication, perception of fairness, and the credibility of leadership. This explanation is in-line with research indicating trust in AI is formed from contextual and relational factors; and not the technical characteristics (Glikson and Woolley, 2020). The study demonstrates that the combination of human lens and technology lens is necessary for AI adoptions. It notes that leaders' behaviours and management of change together influence readiness and trust.

The overall discussion suggests that successful transformation aided by AI depends on the harmony of leadership behaviour, organisational change practices and employee perceptions. Leaders influence how people interpret changes. The procedures for managing change turn strategic intention into organizational experiences that create trust. In simple terms, the results endorse the larger argument of this paper regarding the adoption of AI is a social and managerial process embedded in an organization. This will lead to Theoretical Integration in the next section of the paper.

4.5 Integration with Theoretical Framework

The purpose of this section is to connect the findings to the theoretical frame developed in Chapter 2. The findings will show how the findings contribute to the academic debate on leadership, change, and AI. The present work does not claim to present new data; rather, the aim is to conceptualise the data and relate the observed patterns to a broader interpretive framework regarding employee-centred digital transformation and trust in socio-technical systems. These ideas show how this research can contribute to employee-centered models and also refine existing models through a dual trust perspective, specifically, trust in leadership and trust in AI.

Literature reviews primarily enhance our understanding of AI adoption as a social process governed by human interpretation and organizational arrangements, not a technological problem. The conclusion is supported by the evidence. The relationship between perceptions of leaders, perceptions of handling changes, readiness for changes, and trust in AI show that employees assess new technology with respect to their organization. It aligns with the notion of AI as a socio-technical system which was investigated by Raisch and Krakowski (2021) along with the interaction between technology and organizations. The study established a relationship between perceived change management and acceptance of artificial intelligence to determine trust in artificial intelligence.

It also adds to literature that proposes employee-oriented initiatives for digital transformation. Employees are willing to accept technology quickly once they realize the ramifications of the usage. In the neighbouring spectrum, perceptions of employees are significant forces shaping readiness and trust. This validates the viewpoint that digital transformation is an ongoing phenomenon in which organizations use their communications, leadership and support structures. Moreover, the findings offer support for the dual trust model, which differentiates trust in leadership and trust in AI. According to previous research conducted by Glikson and Woolley (2020), a stronger positive correlation was identified between the element of leadership and the variable of readiness. Furthermore, a similar correlation was observed between the element of organizational change practices and the variable of trust.

To illustrate the matching of observed relationships and theoretical constructs, Table 6 presents a summary of the matching relationships.

Table 6: Integration of Empirical Findings with Theoretical Framework

Theoretical Construct	**Empirical Observation**	**Theoretical Interpretation**
Leadership Behaviours	Strong relationship with readiness	Leadership shapes employee sensemaking and psychological preparedness (Rafferty et al., 2013)
Change Management Practices	Strong relationship with trust in AI	Trust emerges through organizational context and social cues (Glikson and Woolley, 2020)
Employee Perceptions	Central role across all constructs	Supports employee-centered digital transformation (Raisch and Krakowski, 2021)
Trust in AI vs Trust in Leadership	Distinct but interrelated outcomes	Evidence for a dual trust framework

Table 6 incorporation shows how the empirical results support important theoretical assumptions made in the earlier parts of a dissertation. Mainly, the route from leadership to readiness and change management to trust follows the sequential logic of the conceptual framework in Chapter 2. Furthermore, leadership behaviours shape the way employees understand the meaning and necessity of AI adoption, which aids a readiness for change. It is important to note that mechanisms of organizational change provide structural conditions through which employees build trust in the AI-system. The evidence shows that leadership and change management are working side by side rather than acting as independent forces.

The research findings show that people deal with technology but in doing so neglect human experience when theorizing risk. Most AI literature assumes algorithmic improvements will increase employee acceptance. The trust issue regarding artificial intelligence is more associated with organizational practices rather than the technical specifications. This support calls for more comprehensive frameworks that integrate leadership, change management, and employee perceptions into models of AI adoption (Raisch and Krakowski, 2021) and challenges techno-centric narratives that bracket social dynamics.

The above results also refine existing theories of leadership discussed in Chapter 2. Transformational leadership as well as authentic leadership emphasize vision, ethics, and transparency; and the findings partially support these expectations by linking perceived leadership to readiness for change. However, the fact that leadership has a more indirect relationship with trust in AI may suggest that leadership acts indirectly to shape the experience of change processes, rather than directly generating trust in the technology. It reveals how important it is to look at the structure of the organization as well as the individual behaviour.

The integration of the results with the theory strengthens the argument that AI adoption is human-centred and deeply situated. The effect of leadership on readiness, change management on trust, and the distinction between trust in leadership and trust in AI can create a dual trust frame. The dual trust frame can illustrate the complexity of employee experience in an AI-driven transformation.

4.6 Summary of Findings

This chapter enumerated the research findings, which investigated the perception of the employees in the FMCG sector regarding leadership, change management practices, readiness to change and trust in AI. The study covered everything from data preparation to descriptive statistics to inferential testing and interpretive discussion. Overall, the study gives us a coherent picture of employee experiences during AI-led transformation. These findings make an important contribution to the literature on organizational change process and leadership behaviour.

Testing for reliability showed that the measurement scales were reliable (consistent). Each construct attained a high level of internal consistency, indicating that all survey questions measure well. Due to the robustness of the aforementioned methods, we became more confident in the correlation and regression tests that followed as well as the constructs in the study. An analysis of the descriptive statistics showed that employees appear to have a positive attitude regarding AI adoption. The employees also feel relatively ready to adapt to technological change and out of the three components, readiness was rated highest. Simultaneously, lower grades were assigned to perceived change management practices, indicating that survey respondents were more critical of organizational communication, participation, and training. The disconnect that exists between individual readiness and organizational processes is a key realization; employees may actually be more adaptable than the processes designed to help them.

These correlations were further distinguished through inferential analyses. The readiness for change was strongly associated with the perceptions of leadership, while the perceived practices of change management were closely associated with trust in AI systems. When combined, the findings indicate that AI is adopted on the basis of human and organizational factors rather than technological features. The present results provide an empirical basis for conclusions and implications drawn in Chapter 5.

CHAPTER 5 - CONCLUSIONS, IMPLICATIONS, LIMITATIONS AND FUTURE RESEARCH

5.1 Introduction

This chapter ends this dissertation by synthesizing the findings. Furthermore, this chapter discusses how these findings matter for leadership, change management, and the adoption of Artificial Intelligence (AI). The research investigates the perception of leadership behaviours and practices of organizational change with regard to the implementation of AI and the readiness and trust generated by employees in AI. A study of the literature focused on the employees of the Fast-Moving Consumer Goods (FMCG) sector that is fast-changing operationally as well as becoming more digitalized.

This chapter, however, moves away from empirical analysis toward interpretation and reflection. The conclusion begins with the basic results and the major trend that we find from the results. The implications of the study on a theory level, particularly on employee-centred digital transformation, leadership, and trust in technology, will then be discussed. The study makes available practical implications for leaders and organizations as they navigate AI-enabled changes.

In addition, it notes the methodological and contextual limitations that affect the interpretation and generalisability of findings. Ultimately, recommendations for future research are put forth indicating directions for future knowledge expansion on leadership and change management in AI settings. In sum, this chapter bridges the gap between evidence and conclusion in the present study and discusses its contribution to both theory and practice.

5.2 Key Conclusions

The results of this study yield several important conclusions regarding the human and organizational aspect of AI-adoption in the FMCG segment. Results suggest that leadership behaviour, perceived change management practices and employee perceptions interact with each other to determine readiness for change and trust in AI rather than just figures. Combining these insights help organizations and human-centered processes to understand better about AI adoption.

The first outcome that emerged was employee readiness. It has been revealed that resistance to the transformation of jobs as a consequence of AI by employees is not a major barrier to digital transformation. According to the research, the employees appear already willing to work with AI as they are getting accustomed to digital tools. One implication is that organizations may need a structural organization to help their employees. Even when people are open to change, organisational practices governing technology's communication, involvement and training may turn out not to be very significant. This indicates that the bigger challenge may be aligning organizational processes to willingness rather than overcoming resistance.

Furthermore, perceived change management practices strongly predicted trust in AI in the second place. More than particular features of technology, how change is achieved and communicated development of trust explains more of our case studies. As a social construction, trust is shaped by the context in which the organisations are embedded. The implementation of AI systems in businesses is acknowledged to influence communication processes. This enhancement enhances how employees and the organization interact with employees.

The leaders' various types of behaviors were important to implement the changes. Within organizations, leadership has had an impact on their employees' interpretation ofthe transformation caused by technology. It provided clear information which gave assurance and knowledge. Yet, beyond the important functions of leadership, designs and processes also drove trust in AI applications. The results show that AI adoption should be viewed as primarily human phenomenon embedded in our intra-organizational relations rather than just technology.

5.3 Implications of the Study

5.3.1 Theoretical Implications

This study's findings contribute to ongoing academic debates on Artificial Intelligence (AI) adoption with a reminder to take employee-centred perspectives seriously to understand digital transformation. Most literature focused on technology, strategic-fit, or system performance as the most important predictor of successful AI. The thesis presents strong evidence suggesting that employees' perceptions are the main driver for adopting and using AI. The employees' experiences with leadership behaviours and organisation change processes were strongly associated with their readiness for change and trust in AI. By focusing on digital transformation, it is needed to focus not only on talent but also on technology and transformation. According to Raisch and Krakowski 2021, there is mutual dependence of technology and humans, and this perspective is in line with the socio-technical view. This empirical study shows that employee perceptions shape readiness and trust, thus contributing to theoretical debates which conceptualise or theorise employees as active agents and not passive recipients of technological change.

An additional significant consequence for theory refers to the establishment of a two-pronged trust framework that incorporates a trust in leadership and a trust in AI. Past research has often seen trust as a unidimensional concept. The authors' analysis shows that employees use different, but related, lenses to assess both leadership and technology systems. Change, a significant part of the organisation's aforementioned change management plan and activities by the leadership in question and their perceptions vis-a-vis the AI-based change has more influence. Future research should reconceptualise trust as a multi-dimensional construct that operates at an interpersonal as well as technological level. According to the results, an alternate conceptualisation of AI-driven transformation from a dual trust perspective that considers organisations as their relationship and evaluation technology is presented here. The findings of the study do not suggest that leadership creates trust in technology. The results indicate a mediation role of organisational processes which extends existing theories of trust to the digital domain.

Another consequence concerns the applicability of the traditional change management theory to AI implementation. The development of classical change models has basically occurred in discontinuous and time-bound niches. On the contrary, the empirical study conducted as part of this paper demonstrates a setting where change appears to be continuous and iterative in nature, whilst employees demonstrate a relatively high readiness despite change management practices being assessed more critically. The pattern suggests that traditional models may need adjustments when it comes to AI tools as the technological upgrades and changing workflows continue to transform apart from one-point changeover. As a result, they help inform theoretical debate by drawing attention to the limitation of linear change and making good a case for dynamic employee-centred change. The results also challenge techno-centric views believing technology is the only driver for the organization. The organizations affirm that future models need to account for leadership, employee perceptions, and the organizational context instead.

5.3.2 Practical Implications

The findings of this study offer many practical implications for leaders and organizations hoping to use AI in more complex operational environments such as FMCG beyond theoretical contributions. A significant implication is that leadership creates a context for readiness. The findings suggest that the conduct of leaders significantly shapes the interpretations and reactions of employees in a period of technological change. In order for AI efforts to succeed, leaders need to show clarity in communication regarding targets, benefits and drawbacks. It would be more effective for leaders to address the ethical angle of new technology and how it works to alleviate employees' fears regarding fairness, autonomy and job loss rather than creating an agency within AI. Generating a feeling of psychological safety is essential. It is when employees feel safe to not knowing and asking questions that they seek to engage with new technology.

Findings indicate that formal structured change management practices at the organization level assist in building trust in AI. It seemed that the trust was not placed in the capabilities of the AI systems themselves but rather on the experiences through the application process. Providing training to employees will help them understand artificial intelligence and its utility in the processes and execution methods of the organization. Employee participation methods can enhance employee engagement. Channels for feedback, collaborative workshops, and similar initiatives can allow staff to influence how AI tools are used in practice. When AI's decision-making is transparent, consumers will be less apprehensive about using AI-enabled products, and able to trust them. These suggestions stem from a significant observation, which shows that an organization builds trust in Artificial Intelligence through its processes, not its functions.

In light of the highly competitive and swift nature of FMCG, it makes a very relevant context for the use of these. The imposition of all these pressures on manufacturing companies and the permanent demand for new product cycles and innovations presupposes a commonplace use of technology. Leaders must recognize the demands for efficiency while providing employees with lasting support in changing times. Therefore, adaptive leadership is required under such conditions.

Instead of acknowledging AI as a technology initiative, FMCG firms should consider AI implementation as an operational strategy. It should not be confined to a technological solution. Since AI applications have always required human skills. This involves substantial teamwork, training and communication. When organizations promote leadership behaviours aligned with structured change management processes, this can help build readiness and trust.

Overall, the practical implications of this research state that investing in technology is not sufficient to successfully adopt AI. Leaders must promote sensemaking and psychological readiness. The organization must facilitate, reassure and be transparent at all times. Organizations need to take a long view when implementing AI and not just consider it as a technical upgrade. It should ideally be seen as an organizational change rather than just a change for the time being. This research offers managerial recommendations to organizations to keep engaging with the employees in course of their journey towards AI transformational change through meaningful use of AI and trust.

5.4 Research Limitations and Delimitations

Although the study provides valuable insight into leaders, change and the adoption of artificial intelligence (AI), there are limitations to take into consideration. Understanding these limitations may not take away from the contribution of the research; it can help clarify the coverage of the results.

From a methodological point of view, the study employed a cross-section design, collecting data at one point in time. This method allows for identification of meaningful relations between leadership perceptions, change management practices, change readiness and trust in AI but does not permit causal conclusions. As a result, findings show correlation and not causation. Besides the data were gathered from perception based on a questionnaire which was self-reported. In organizational research, perceptual measures are frequently employed; however, there is a risk of subjective interpretation from the participants, resulting in common method bias.

Another limitation pertains to the sample used, as the study particularly looked at employees of Fast-Moving Consumer Goods (FMCG). The empirical examination is concentrated on one organization within one particular industry. It is possible that how leadership and adoption of AI is perceived and discussed is influenced by national cultures and institutions. Measurement choices are also interpreted by the study as not examining actual measuring performance of technology but rather perception.

Several delimitations were intentionally established that included the employee-centered perspective and the perception of AI adoption, not technical implementation. As a whole, these limitations close the study but open the floor for future research through longitudinal designs, cross-sector comparisons and more integrated approaches to AI-driven organizational change.

5.5 Recommendations for Future Research

Taking into consideration the current research findings and limitations, future research could investigate other styles of leadership in change management. Future studies may also check if the employee perception affects the organization's employee AI usage. To start with, researchers can use longitudinal research designs to study how readiness for change, trust in AI and perceptions of leadership change by experiment. The technological updates and adaptation of organisations in this AI-driven transformation are constantly taking place. Using longitudinal-based approaches enables examination of whether employees' attitudes stabilize or even change over time with more AI use experience. This solution is also applicable to cross-section data constraints.

Comparative analysis between sectors could make the result more generalizable. Despite the focus of this research on the FMCG sector, possible future studies can focus on the banking, healthcare, or manufacturing sector. Different regulatory systems and technological expectations exist among these sectors. The relationships among leadership, change management, readiness and trust can much perhaps be contextual or industry specific, if such comparisons are made.

One additional possible approach is mixed-methods research designs that combine quantitative surveys with qualitative methods, in this case interviews or focus groups. Qualitative data can improve knowledge of how staff interprets adoption of AI, makes sense of leaders' behaviours and experience change in day-to-day working. Future studies could explore the extent to which leadership styles that emphasize transparency and fairness in the workplace shape employees' perceptions of the AI being used and the technical development of trustworthy AI. Future studies should investigate both the technical and human perspectives of organisations' changing practices and processes through AI.

References

Armenakis, A.A., Harris, S.G. and Mossholder, K.W. (1993) 'Creating readiness for organizational change', *Human Relations*, 46(6), pp. 681–703.

Avolio, B.J. and Gardner, W.L. (2005) 'Authentic leadership development: Getting to the root of positive forms of leadership', *The Leadership Quarterly*, 16(3), pp. 315–338.

Bass, B.M. (1985) *Leadership and Performance Beyond Expectations*. New York: Free Press.

Bharadwaj, A., El Sawy, O.A., Pavlou, P.A. and Venkatraman, N. (2013) 'Digital business strategy: Toward a next generation of insights', *MIS Quarterly*, 37(2), pp. 471–482.

Boateng, G.O., Neilands, T.B., Frongillo, E.A., Melgar-Quiñonez, H.R. and Young, S.L. (2018) 'Best practices for developing and validating scales for health, social, and behavioral research: A primer', *Frontiers in Public Health*, 6, pp. 1–18.

Bornstein, M.H., Jager, J. and Putnick, D.L. (2013) 'Sampling in developmental science: Situations, shortcomings, solutions, and standards', *Developmental Review*, 33(4), pp. 357–370.

British Psychological Society (2018) *Code of Ethics and Conduct*. Leicester: BPS.

Brynjolfsson, E. and McAfee, A. (2014) *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. New York: W.W. Norton & Company.

Coch, L. and French, J.R.P. (1948) 'Overcoming resistance to change', *Human Relations*, 1(4), pp. 512–532.

Cohen, J. (1992) 'A power primer', *Psychological Bulletin*, 112(1), pp. 155–159.

DeVellis, R.F. (2017) *Scale Development: Theory and Applications*. 4th edn. Thousand Oaks, CA: Sage.

Dietvorst, B.J., Simmons, J.P. and Massey, C. (2015) 'Algorithm aversion: People erroneously avoid algorithms after seeing them err', *Journal of Experimental Psychology: General*, 144(1), pp. 114–126.

Dillman, D.A., Smyth, J.D. and Christian, L.M. (2014) *Internet, Phone, Mail, and Mixed-Mode Surveys: The Tailored Design Method*. 4th edn. Hoboken, NJ: Wiley.

Dwivedi, Y.K., Hughes, D.L., Ismagilova, E., et al. (2021) 'Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy', *International Journal of Information Management*, 57, 101994.

Etikan, I., Musa, S.A. and Alkassim, R.S. (2016) 'Comparison of convenience sampling and purposive sampling', *American Journal of Theoretical and Applied Statistics*, 5(1), pp. 1–4.

Faraj, S., Pachidi, S. and Sayegh, K. (2018) 'Working and organizing in the age of the learning algorithm', *Information and Organization*, 28(1), pp. 62–70.

Field, A. (2018) *Discovering Statistics Using IBM SPSS Statistics*. 5th edn. London: Sage.

Floridi, L., Cowls, J., Beltrametti, M., et al. (2018) 'AI4People—An ethical framework for a good AI society', *Minds and Machines*, 28(4), pp. 689–707.

Frazier, M.L., Fainshmidt, S., Klinger, R.L., Pezeshkan, A. and Vracheva, V. (2017) 'Psychological safety: A meta-analytic review and extension', *Personnel Psychology*, 70(1), pp. 113–165.

Glikson, E. and Woolley, A.W. (2020) 'Human trust in artificial intelligence: Review of empirical research', *Academy of Management Annals*, 14(2), pp. 627–660.

Gravetter, F.J. and Wallnau, L.B. (2017) *Statistics for the Behavioral Sciences*. 10th edn. Boston: Cengage.

Günther, W.A., Mehrizi, M.H.R., Huysman, M. and Feldberg, F. (2017) 'Debating big data: A literature review on realizing value from big data', *Business Research*, 10(1), pp. 191–209.

Hayes, A.F. (2018) *Introduction to Mediation, Moderation, and Conditional Process Analysis*. 2nd edn. New York: Guilford Press.

Hiatt, J. (2006) *ADKAR: A Model for Change in Business, Government, and Our Community*. Loveland, CO: Prosci.

Hinkin, T.R. (1998) ‘A brief tutorial on the development of measures for use in survey questionnaires’, *Organizational Research Methods*, 1(1), pp. 104–121.

Hoff, K.A. and Bashir, M. (2015) ‘Trust in automation: Integrating empirical evidence on factors that influence trust’, *Human Factors*, 57(3), pp. 407–434.

Holt, D.T., Armenakis, A.A., Feild, H.S. and Harris, S.G. (2007) ‘Readiness for organizational change: The systematic development of a scale’, *The Journal of Applied Behavioral Science*, 43(2), pp. 232–255.

Israel, M. and Hay, I. (2006) *Research Ethics for Social Scientists*. London: Sage.

Jarrahi, M.H. (2018) ‘Artificial intelligence and the future of work: Human–AI symbiosis in organizational decision making’, *Business Horizons*, 61(4), pp. 577–586.

Jobin, A., Ienca, M. and Vayena, E. (2019) ‘The global landscape of AI ethics guidelines’, *Nature Machine Intelligence*, 1(9), pp. 389–399.

Jöhnk, J., Weißert, M. and Wyrtki, K. (2021) ‘Ready or not, AI comes—An interview study of organizational AI readiness factors’, *Business & Information Systems Engineering*, 63(1), pp. 5–20.

Joshi, A., Kale, S., Chandel, S. and Pal, D.K. (2015) ‘Likert scale: Explored and explained’, *British Journal of Applied Science & Technology*, 7(4), pp. 396–403.

Kane, G.C., Palmer, D., Phillips, A.N., Kiron, D. and Buckley, N. (2015) ‘Strategy, not technology, drives digital transformation’, *MIT Sloan Management Review*, 14, pp. 1–25.

Kellogg, K.C., Valentine, M.A. and Christin, A. (2020) ‘Algorithms at work: The new contested terrain of control’, *Academy of Management Annals*, 14(1), pp. 366–410.

Kotter, J.P. (1996) *Leading Change*. Boston, MA: Harvard Business School Press.

Kotter, J.P. and Schlesinger, L.A. (1979) ‘Choosing strategies for change’, *Harvard Business Review*, 57(2), pp. 106–114.

Kutner, M.H., Nachtsheim, C.J., Neter, J. and Li, W. (2005) *Applied Linear Statistical Models*. 5th edn. New York: McGraw-Hill.

Lee, J.D. and See, K.A. (2004) ‘Trust in automation: Designing for appropriate reliance’, *Human Factors*, 46(1), pp. 50–80.

Lewin, K. (1947) ‘Frontiers in group dynamics’, *Human Relations*, 1(1), pp. 5–41.

Lines, R. (2004) ‘Influence of participation in strategic change’, *Journal of Change Management*, 4(3), pp. 193–215.

Logg, J.M., Minson, J.A. and Moore, D.A. (2019) ‘Algorithm appreciation: People prefer algorithmic to human judgment’, *Organizational Behavior and Human Decision Processes*, 151, pp. 90–103.

Mayer, R.C., Davis, J.H. and Schoorman, F.D. (1995) ‘An integrative model of organizational trust’, *Academy of Management Review*, 20(3), pp. 709–734.

McCarthy, P., Sammon, D. and Alhassan, I. (2022) ‘Digital transformation leadership characteristics: A literature analysis’, *Journal of Decision Systems*, 32(1), pp. 79–109.

Meijerink, J., Boons, M., Keegan, A. and Marler, J. (2021) ‘Algorithmic human resource management’, *The International Journal of Human Resource Management*, 32(12), pp. 2545–2562.

Müller, S. D., Konzag, H., Nielsen, J. A., & Sandholt, H. B. (2024). Digital transformation leadership competencies: A contingency approach. *International Journal of Information Management*, *75*, pp.102734.

Nambisan, S., Lyytinen, K., Majchrzak, A. and Song, M. (2017) ‘Digital innovation management: Reinventing innovation management research in a digital world’, *MIS Quarterly*, 41(1), pp. 223–238.

Orb, A., Eisenhauer, L. and Wynaden, D. (2001) ‘Ethics in qualitative research’, *Journal of Nursing Scholarship*, 33(1), pp. 93–96.

Oreg, S. and Berson, Y. (2011) ‘Leadership and employees’ reactions to change’, *Personnel Psychology*, 64(3), pp. 627–659.

Oreg, S., Vakola, M. and Armenakis, A. (2011) ‘Change recipients’ reactions to organizational change’, *The Journal of Applied Behavioral Science*, 47(4), pp. 461–524.

Rafferty, A.E. and Griffin, M.A. (2004) ‘Dimensions of transformational leadership: Conceptual and empirical extensions’, *The Leadership Quarterly*, 15(3), pp. 329–354.

Rafferty, A.E., Jimmieson, N.L. and Armenakis, A.A. (2013) ‘Change readiness: A multilevel review’, *Journal of Management*, 39(1), pp. 110–135.

Rai, A. (2020) ‘Explainable AI: From black box to glass box’, *Journal of the Academy of Marketing Science*, 48(1), pp. 137–141.

Raisch, S. and Krakowski, S. (2021) ‘Artificial intelligence and management: The automation–augmentation paradox’, *Academy of Management Review*, 46(1), pp. 192–210.

Schober, P., Boer, C. and Schwarte, L.A. (2018) ‘Correlation coefficients: Appropriate use and interpretation’, *Anesthesia & Analgesia*, 126(5), pp. 1763–1768.

Shin, D. (2021) ‘The effects of explainability and causability on trust in AI’, *International Journal of Human–Computer Studies*, 146, 102551.

Shrestha, Y.R., Ben-Menahem, S.M. and von Krogh, G. (2019) ‘Organizational decision-making structures in the age of artificial intelligence’, *California Management Review*, 61(4), pp. 66–83.

Tabachnick, B.G. and Fidell, L.S. (2019) *Using Multivariate Statistics*. 7th edn. Boston: Pearson.

Tarafdar, M., Cooper, C.L. and Stich, J.F. (2019) ‘The technostress trifecta – techno eustress, techno distress and design’, *Information Systems Journal*, 29(1), pp. 6–42.

Tavakol, M. and Dennick, R. (2011) ‘Making sense of Cronbach’s alpha’, *International Journal of Medical Education*, 2, pp. 53–55.

Teece, D.J. (2018) ‘Business models and dynamic capabilities’, *Long Range Planning*, 51(1), pp. 40–49.

Vakola, M. (2014) ‘What’s in there for me? Individual readiness to change and the perceived impact of organizational change’, *Leadership & Organization Development Journal*, 35(3), pp. 195–209.

Verhoef, P.C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J.Q., Fabian, N. and Haenlein, M. (2021) 'Digital transformation: A multidisciplinary reflection and research agenda', *Journal of Business Research*, 122, pp. 889–901.

Vial, G. (2019) 'Understanding digital transformation', *The Journal of Strategic Information Systems*, 28(2), pp. 118–144.

Voigt, P. and Von dem Bussche, A. (2017) *The EU General Data Protection Regulation (GDPR): A Practical Guide*. Cham: Springer.

Warner, K.S.R. and Wäger, M. (2019) 'Building dynamic capabilities for digital transformation', *Long Range Planning*, 52(3), pp. 326–349.

Weber, E. and Krehl, E. (2022) 'The digital transformation leadership framework: Conceptualization and evidence from field studies', *Journal of Leadership Studies*, 16(1), pp. 6–22.

Weber, E., Krehl, E. H., & Büttgen, M. (2022). The digital transformation leadership framework: Conceptual and empirical insights into leadership roles in technology-driven business environments. *Journal of Leadership Studies*, *16*(1), pp.6-22.

Westerman, G., Bonnet, D. and McAfee, A. (2014) *Leading Digital: Turning Technology into Business Transformation*. Boston, MA: Harvard Business Review Press.

Wright, K.B. (2005) 'Researching internet-based populations: Advantages and disadvantages of online survey research', *Journal of Computer-Mediated Communication*, 10(3), article JCMC1034.

Appendix I – The questionnaire

Questionnaire: Leadership, Change Management and AI

This questionnaire is conducted as part of a postgraduate dissertation within the Master of Business Administration (MBA) programme of the Hellenic Open University (HOU). The purpose of this research is to investigate employees' perceptions of digital transformational leadership, change management practices, and the adoption of Artificial Intelligence (AI) in organizations operating within the Fast-Moving Consumer Goods (FMCG) sector. The study seeks to understand how AI-driven organizational change is experienced by employees and how leadership and change management practices influence employee readiness for change and trust in AI systems.

Participation in this study is entirely voluntary. The questionnaire is expected to take approximately **5–7 minutes** to complete. All responses are collected anonymously, and no personal identifiable information will be requested. Participants may discontinue their participation at any stage without providing a reason and without any negative consequences.

The data collected will be used solely for academic purposes and will be analyzed in aggregated form as part of the dissertation requirements. This research fully complies with the General Data Protection Regulation (GDPR), ensuring confidentiality, secure data handling, and the protection of participants' rights.

By proceeding with the questionnaire, you confirm that you have read and understood the above information and that you provide your informed consent to participate in this research.

Section A: Demographic Information

1. **Gender**

- ☐ Male
- ☐ Female
- ☐ Prefer not to say

2. **Age group**

- ☐ 18–29
- ☐ 30–39
- ☐ 40–49
- ☐ 50–59
- ☐ 60+

3. **Years of work experience**

- ☐ Less than 2 years
- ☐ 2–5 years
- ☐ 6–10 years
- ☐ More than 10 years

4. **Current organizational role**

- ☐ Non-managerial employee
- ☐ First-line supervisor
- ☐ Middle management
- ☐ Senior management

5. **Level of exposure to AI systems in your work**

- ☐ None
- ☐ Low
- ☐ Moderate
- ☐ High

Section B: Digital Transfomrtional Leadership Perceptions (Likert Style/ 1- Strongly Disagree…5- Strongly Agree)

6. My immediate supervisor communicates a clear vision regarding the use of AI in our organization.
7. My supervisor encourages employees to learn and develop new skills related to digital technologies.
8. My supervisor is open and transparent when discussing the impact of AI on employees' roles.
9. My supervisor considers ethical implications when introducing AI-related changes.
10. I trust my supervisor to act in the best interests of employees during AI-driven change.
11. My supervisor encourages employees to express concerns or questions about AI implementation.

Section C: Perceived Change Management (Likert Style/ 1- Strongly Disagree…5- Strongly Agree)

12. Changes related to AI have been clearly communicated to employees.
13. Employees are given opportunities to participate in decisions related to AI implementation.
14. Adequate support is provided to help employees adapt to AI-related changes.
15. Training has been provided to help employees use AI systems effectively.
16. Overall, AI-related change in my organization is well managed.

Section D: Readiness for Change (Likert Style/ 1- Strongly Disagree…5- Strongly Agree)

17. I feel prepared to adapt to changes in my work caused by AI.
18. I believe I have the skills required to work effectively with AI systems.
19. I am willing to adjust my work practices to accommodate AI-driven changes.
20. I feel confident in my ability to cope with ongoing digital transformation.

Section E: Trust in AI (Likert Style/ 1- Strongly Disagree…5- Strongly Agree)

21. I trust AI systems used in my organization to perform their tasks reliably.

22. I understand how AI systems influence decisions related to my work.

23. I feel comfortable relying on AI systems in my daily tasks.

24. I believe that AI systems in my organization are used fairly and responsibly.

Author's Statement:

I hereby declare that, in accordance with article 8 of Law 1599/1986 and article 2.4.6 par. 3 of Law 1256/1982, this dissertation is solely a product of personal work and does not infringe any intellectual property rights of third parties and is not the product of a partial or total plagiarism, and the sources used are strictly limited to the bibliographic references.