A Work Project, presented as part of the requirements for the Award of a Master's degree in (International) Management from the Nova School of Business and Economics.

THE TRANSFORMATIVE IMPACT OF GENERATIVE ARTIFICIAL INTELLIGENCE: A CROSS CASE COMPARISON – ENHANCING ENGAGEMENT

Norell Janan Sanatpour (61522)

Work project carried out under the supervision of:

Professor Marco Berti

Lisbon, December 16th, 2024

Defence: January 24th, 2025

Abstract

This work project investigates the integration of generative AI (GenAI) in organisations, focusing on effective change management (CM), employee engagement, and assessing productivity gains. Through qualitative interviews and a quantitative survey across industries, it analyses challenges and opportunities in GenAI adoption. The study identifies best practices to foster innovation, enhance job satisfaction, and ensure seamless workflow integration. Key findings underscore the importance of tailored approaches, including leadership engagement, clear communication, and continuous training to address GenAI's complexities. By offering actionable insights, the research aims to guide organisations in leveraging GenAI's transformative potential while remaining adaptable to its rapid evolution.

Keywords

Generative AI, AI Integration, Change Management Strategies, Organisational Change, Measuring Productivity Gains, Employee Engagement, Job Satisfaction, Workflow Automation and Argumentation, Measuring Technology Impact, Technological Transformation

This work used infrastructure and resources funded by Fundação para a Ciência e a Tecnologia (UID/ECO/00124/2013, UID/ECO/00124/2019 and Social Sciences DataLab, Project 22209), POR Lisboa (LISBOA-01-0145-FEDER-007722 and Social Sciences DataLab, Project 22209) and POR Norte (Social Sciences DataLab, Project 22209).

Table of Contents

I. List of Abbreviations

AI	Artificial Intelligence
CM	Change Management
ERP	Enterprise Resource System
EV	Electric Vehicle
GenAI	Generative Artificial Intelligence
GPT	General Purpose Technology
IP	Intellectual Property
IT	Information Technology
JCM	Job Characteristics Model
JD-R	Job Demands-Resources
KPI	Key Performance Indicator
LLM	Large Language Models
MNE	Multinational Enterprises
ROI	Return on Investment
SDT	Self-Determination Theory
SME	Small and Medium-Sized Enterprises
TAM	Technology Acceptance Model
TOE	Technology-Organisation-Environment

1 Introduction (Group Part)

Over the past years, artificial intelligence (AI) has rapidly emerged as a transformative and disruptive technology, especially with the introduction of GenAI and tools like OpenAI's ChatGPT and Microsoft's Copilot (Sengar et al. 2024). These innovations appear to be reshaping various industries by potentially increasing efficiency, improving the quality of output and supporting creative problem-solving (Raisch and Fomina 2023). For organisations, GenAI promises unprecedented opportunities to increase productivity, optimise operations and drive growth, which could make it a critical factor in maintaining competitiveness in various sectors in the future (Krakowski, Luger, and Raisch 2022).

Despite the apparent user-friendliness of GenAI tools, successfully integrating them within organisations requires specific CM strategies to maximise their potential and foster employee engagement. Traditional CM models provide foundational guidance as GenAI's unique challenges demand a tailored approach focusing on key aspects such as leadership, communication, and ongoing support (Bellantuono et al. 2021). Yet, integrating GenAI is not a one-time implementation. Instead, it is an evolving process that requires continual adaptation due to GenAI's rapid advancements and emerging capabilities. Additionally, adopting GenAI within a company demands substantial resources, particularly financially, making it crucial to explore approaches for quantifying and qualifying the productivity gains achieved through these investments.

This work project aims to investigate the transformative impact of GenAI in supporting organisational change, enhancing employee engagement, and measuring productivity gains. The investigation began with a comprehensive literature review to provide an overview of the status quo on AI and its usage in various industries. A threefold research structure is adopted to provide recommendations to companies in both manufacturing and non-manufacturing sectors. Thus, this study seeks to answer the following research questions:

1. *What change management strategies are effective for successfully integrating generative AI?*
2. *What is the impact of generative AI on employee engagement and job satisfaction?*
3. *How can the desired productivity gains from the integration of generative AI be assessed?*

A mixed-method approach was employed to address the research questions. First, qualitative interviews were conducted with representatives from manufacturing and non-manufacturing sectors to gain in-depth insights into their experiences with GenAI. These findings were complemented by a quantitative survey targeting participants from the same industries, providing measurable data to corroborate and refine the qualitative results. The data were analysed through a cross-sector comparison to identify shared themes and sector-specific nuances. Finally, this study aims to provide practical insights for organisations across industries by offering strategies for implementing effective CM, improving employee engagement, and establishing frameworks for assessing productivity gains from GenAI integration. By bridging theory and practice, it delivers actionable recommendations to help organisations navigate the complexities of GenAI adoption. Through a critical examination of the challenges and opportunities, the research underscores GenAI's transformative potential while highlighting the importance of strategic planning and continuous adaptation.

2 Literature Review (Group Part)

2.1 Definition and Capabilities of Generative AI

To grasp the progression of AI towards GenAI, it is essential to investigate the various levels and technologies involved, as shown in Figure 1, 'Layers of AI', in the Appendix (McKinsey & Company 2024b). AI is a broad field of research focused on developing machines that can perform tasks typically requiring human intelligence, such as perception, learning, problem-solving, and decision-making (Rai, Constantinides, and Sarker 2019). The emergence of machine learning, which allows computers to identify patterns in vast volumes of data and provide predictions without explicit programming instructions, has been one of the most significant developments in AI. The algorithms process and learn from the data to make decisions and forecasts. Deep learning is an advanced form of machine learning. It uses neural networks that are inspired by the way human neurons work. Deep learning networks go through numerous iterations to recognise increasingly complex features in the data and make sophisticated predictions.

An advanced evolution within deep learning is GenAI, which leverages expansive neural networks known as large language models (LLMs) to generate highly sophisticated outputs. An LLM processes text using the transformer architecture, utilising self-attention mechanisms to capture relationships between words and their contextual meaning. Text is divided into smaller units, called tokens, and during training, the model learns to predict the next token in a sequence by optimising billions of parameters for greater accuracy. The self-attention mechanism assigns varying importance to each word based on its relevance to others, enabling a deeper contextual understanding. After pretraining on extensive datasets, LLMs can be fine-tuned for specific tasks or domains. During inference, the model generates text one token at a time by sampling from probabilities conditioned on prior tokens (Naveed, Haroon, and Mehmood 2023). LLMs empower GenAI to deal with language in complex ways and generate content that is both creative and often ensembles human expression (McKinsey & Company 2024b).

Traditional AI and GenAI differ in their functions and capabilities. Conventional AI uses algorithms to analyse data, recognise patterns and make predictions based on this data. These patterns are used to perform specific tasks, making them the solution of choice for repetitive tasks and numerical processing. In contrast, by drawing on an extensive text database, GenAI can generate its own content in response to prompts, such as images, texts, videos, simulations, audio, and code. This demonstrates a form of creativity and problem-solving adaptability (Bi 2023; Feuerriegel et al. 2024; Höck 2024; McKinsey & Company 2024b). In the corporate context, GenAI tools promise to bring revolutionary opportunities which can be applied to automate or augment tasks and processes (Feuerriegel et al. 2024; Raisch and Krakowski 2021). Hereby, automation implies that a machine takes over a human task, and augmentation means that humans collaborate closely with machines to perform a task (Krakowski, Luger, and Raisch 2023).

GenAI is spreading faster than previous innovative technologies such as the computer or the internet. Its simple and often cost-effective implementation enables the technology to leverage existing digital platforms such as cloud infrastructures. This allows organisations to deploy and scale GenAI applications without significant investments in hardware or infrastructure (Teubner et al. 2023; Sengar et al. 2024). For example, ChatGPT is one of the most used GenAI technologies. It is a public conversational agent from OpenAI based on GPT language modelling technology (Bi 2023; Feuerriegel et al. 2024). ChatGPT can handle a wide range of text-based requests as an intelligent chatbot, from simple questions to complex tasks. ChatGPT is based on principles of Natural Language Processing (NLP), a field of AI that uses algorithms to analyse and interpret human language, such as text and speech (Kaplan and Haenlein 2019).

The tool has sparked significant enthusiasm within the tech community. Released in 2022, ChatGPT-3.5 immediately received global adoption, amassing over 100 million monthly active users within only two and a half months, making it the fastest-growing web technology in history (Hadi, Abdulredha, and Hasan 2023). Its successor, GPT-4, introduces enhanced capabilities, accepting both image and text inputs to produce text-based outputs (Feuerriegel et al. 2024). Furthermore, OpenAI sells ChatGPT Enterprise, offering organisations additional security and privacy features to safeguard sensitive data. Thus, this version is subject to an expensive fee, reflecting its customisation to the specific requirements of companies, including the assurance that no data are used for ChatGPT's further development (OpenAI 2024).

Microsoft developed another popular tool in 2023 called Microsoft 365 Copilot. Microsoft promotes it as the new AI-powered productivity tool integrated into all Microsoft 365 Office programs like Excel, PowerPoint, Outlook and Teams (Microsoft 2023). Unlike ChatGPT, Microsoft 365 Copilot is not publicly accessible without restrictions. Instead, it is specifically tailored for integration within the Microsoft 365 ecosystem, targeting business customers relying on Microsoft's Office suite for daily operations (Microsoft 2024). Copilot's underlying AI is built on an LLM that understands and processes the nuances of human language. Trained on vast amounts of data, this technology provides accurate answers and relevant information. By integrating Microsoft Graph, Copilot can access the user's personal information and provide context-specific answers and suggestions tailored to the specific work situation. Microsoft Graph links data from various Microsoft 365 applications such as emails, calendars, chats, documents and meetings, thus creating a standardised information base. Copilot is embedded directly into Microsoft 365 applications so that it can respond to user requests and adapt the content in real time. It optimises workflows, reduces repetitive tasks and supports both creative and analytical processes by applying the power of GenAI to everyday work processes (Microsoft 2023).

Although GenAI tools are powerful, certain limitations are discussed among researchers and need to be taken into consideration for business-world applications. These include incorrect outputs, bias and fairness, copyright violation, and environmental concerns (Bi 2023). Inaccurate output occurs when GenAI produces incorrect results, often due to the quality of its training data and the effectiveness of the learning process. Limited, outdated, or biased datasets can lead to outcomes that reinforce inaccuracies or irrelevant assumptions. This phenomenon, known as hallucination, arises when results appear correct but lack any factual basis. Managing this limitation is challenging, as the generated responses can seem authentic yet potentially mislead the user (Ji et al. 2023; Feuerriegel et al. 2024). The training data may contain biases perpetuated by GenAI, leading to unfair or stereotypical results. These biases can manifest in sensitive areas such as gender, ethnicity, and socio-political issues. An ethical framework is needed to ensure fairness in model development and mitigate these biases. GenAI can infringe copyrights, especially if it produces results that are very similar to protected works. The unauthorised reproduction or derivation of original content raises significant legal and ethical issues. Finally, large models like GPT-4 require substantial computing resources, resulting in high energy consumption and a considerable carbon footprint, factors that should be carefully considered during GenAI implementation and usage (Bi 2023). Organisations must consider these limitations when implementing GenAI technologies.

The recent McKinsey & Company report, ‘The State of AI in early 2024’, explores the excitement GenAI is generating in organisations. According to their findings, 2023 marked the year the world discovered GenAI, while 2024 is the year organisations truly began using it to derive business value (McKinsey & Company 2024a). This shift reflects an increasing recognition of GenAI’s ability to streamline operations, drive innovation, improve decision-making, and create a competitive advantage across industries.

2.2 Generative AI in Manufacturing versus Non-Manufacturing Industries

GenAI is rapidly transforming both manufacturing and non-manufacturing industries, although the specific applications and challenges vary significantly. Manufacturing industries are those that produce goods through the transformation of raw materials into finished products, typically using machinery, tools, and labour to create tangible items such as automobiles, electronics, and textiles (Cambridge Dictionary 2024a). Conversely, the non-manufacturing industry encompasses sectors that do not produce physical goods but instead provide services or intangible products, including consulting, finance, healthcare, education, and retail (Cambridge Dictionary 2024b). Both sectors leverage this technology to optimise processes, enhance efficiency, and drive innovation, yet each domain's implementation strategies and use cases are distinct. This section provides an overview of how GenAI is applied in manufacturing and non-manufacturing industries, highlighting key similarities and differences in their applications and challenges. A detailed breakdown of these applications can be found in Table 1 ('Applications and Adoption of Generative AI Tools Across Manufacturing and Non-Manufacturing Sectors') in the Appendix.

Manufacturing Industry

GenAI is revolutionising several aspects of the value chain in the manufacturing sector, from product design to supply chain management. This transformation is evident in tools like Autodesk's Fusion 360 platform, which enables engineers to explore a vast design space and optimise product structures for efficiency and functionality (Autodesk 2024). A notable example is Yamaha's development of an electric vehicle (EV) for agricultural use, designed using Autodesk's GenAI tools. By leveraging these capabilities, Yamaha engineers were able to test numerous design configurations, optimising the EV's structure for weight and durability while meeting sustainability goals (Autodesk 2023).

The automotive sector has seen significant advancements due to GenAI. BMW, for example, employs GenAI to refine the design of car components. The BMW iX Flow model demonstrates this application through its use of an e-ink wrap that enables the car to change colour on demand, enhancing personalisation. This generative design process involves machine learning algorithms that iterate through multiple design configurations to identify the most effective solutions based on criteria such as aesthetics, durability, and functionality (Satishkumar and Sivaraja 2024). This example illustrates how GenAI is pushing the boundaries of automotive design, creating highly customised and innovative customer experiences.

In addition to product design, GenAI is enhancing production efficiency and maintenance processes within manufacturing. Siemens, for instance, employs predictive maintenance solutions powered by GenAI to analyse production data, detect bottlenecks, and optimise workflows. By forecasting when machinery requires maintenance, Siemens minimises downtime and maintains a smooth production flow (Siemens 2023).

Non-Manufacturing Industry

While GenAI is transforming manufacturing processes, it also substantially impacts various non-manufacturing industries, including banking, marketing, healthcare, and consulting. In these domains, GenAI applications focus on content creation, customer experience, and process optimisation, offering unique opportunities for innovation.

In marketing, companies increasingly use GenAI to produce high-quality, engaging content. Jasper.ai, for example, combines LLMs with proprietary algorithms to generate tailored marketing copy, social media posts, and blog articles for specific audiences. This enables marketing teams to produce compelling content more efficiently, maximising audience engagement and improving campaign effectiveness (Jasper.ai 2024). GenAI, therefore, offers marketers a tool to rapidly generate creative and personalised content, which would otherwise require extensive time and resources.

The fashion industry also leverages GenAI for customer personalisation (Ooi et al. 2023). Zalando, a major online retailer, utilises GenAI to recommend outfits based on individual customer preferences, such as browsing history, purchase data, and style preferences. By generating tailored outfit suggestions, Zalando enhances the shopping experience, drives sales, and reduces return rates (Zalando 2024). Zalando's AI-powered fashion assistant, launched in 2024, leverages both in-house models and OpenAI's LLM to provide personalised fashion advice to customers across all its markets. This assistant enables customers to navigate Zalando's extensive assortment with intuitive queries and receive informed recommendations based on factors like location, weather, and occasion.

In consulting, firms like McKinsey & Company use GenAI to process large volumes of data and provide insights for strategic decision-making. A 2023 McKinsey & Company report on AI highlights that approximately 35% of consulting firms have adopted AI technologies, marking a substantial increase from 2022, when only 20% reported using AI. This 15-percentage-point rise in adoption highlights the growing importance of AI tools in analysing patterns, predicting trends, and suggesting actionable insights, enabling consultants to offer data-driven recommendations that improve client outcomes and streamline project workflows (McKinsey 2023). Furthermore, AI applications in consulting go beyond simple data analysis; they increasingly support more complex areas such as predictive analytics, customer segmentation, and process automation, helping firms optimise operations and enhance client experiences (McKinsey 2017). By integrating AI into these areas, consultancies can better understand client needs, personalise solutions, and make proactive recommendations that align with emerging market trends.

Comparison of Applications and Challenges

GenAI is transforming manufacturing and non-manufacturing sectors, with application areas being multifaceted and dependent on various factors such as industry-specific requirements and company characteristics. However, it is often deployed in operational tasks, where it either automates routine activities or augments employees by supporting them in more complex processes (Raisch and Krakowski 2021). While GenAI's operational focus is often on automation and augmentation, the applications differ due to varying data types and operational requirements. In manufacturing, GenAI leverages sensor data, production logs, and design models to optimise physical processes, support predictive maintenance and enhance product design efficiency (Doanh et al. 2023). For instance, AI-driven predictive maintenance systems analyse machinery data to minimise downtime, while advanced design tools facilitate rapid prototyping to meet performance and sustainability goals (Autodesk 2024). In non-manufacturing industries, GenAI focuses on customer data, text, and images to drive content creation, personalised marketing, and service automation. Retail and banking sectors, for example, utilise AI to provide tailored product recommendations and improve customer engagement through hyper-personalised experiences (Jasper.ai 2024; Zalando 2024). Additionally, consulting firms harness AI for data analysis and strategic insights, streamlining decision-making and enhancing client outcomes (McKinsey 2023).

Despite these differing focuses—product optimisation in manufacturing and customer engagement in non-manufacturing—both sectors encounter similar challenges. Integrating GenAI with existing systems in manufacturing can be complex, requiring significant infrastructure adjustments to ensure seamless interactions with physical machinery (Vadisetty 2023). Non-manufacturing sectors, particularly those handling sensitive customer data, face stringent data privacy and compliance requirements. Moreover, both sectors need to address employee resistance and skill gaps related to AI technology, necessitating robust data governance and comprehensive training (Ooi et al. 2023). This dual focus on operational efficiency and customer satisfaction highlights how GenAI is tailored to meet each sector's unique demands while presenting common challenges that require careful strategic planning. The following section examines relevant CM theories for integrating GenAI tools into organisational workflows, highlighting strategies to facilitate effective adoption.

2.3 Change Management Theories

Organisational change refers to the process by which organisations adapt their structures, processes, or strategies to align with shifting internal or external environments to sustain competitive advantages (Pardo del Val and Martínez Fuentes 2003). Organisations face continuous change as unforeseen situations occur rapidly and require fast adaptation (Burnes 2008). Responsible drivers are the shifting lifestyle patterns of new generations, globalisation and technological innovations (Avdeeva et al. 2021). A central challenge in organisational change is resistance, which Lewin describes as a natural reaction to disruption (Dent and Goldberg 1999). Resistance to change among employees can result from uncertainties and a fear of the unknown, e.g. fearing a change in established roles or practices up to losing one's job (Kotter and Schlesinger 2008; Warrick 2023). It arises when employees feel excluded from the decision-making process, lack management trust, or are unprepared to adapt accordingly. Resistance to change is one of the most common reasons why change initiatives fail (Heracleous and Bartunek 2020).

Effective CM is the key element in managing organisational change and ensuring its success (Prasad Agrawal 2024). CM is a leadership competency and describes a structured approach to transition individuals, teams, and organisations from a current state to a desired future state to achieve organisational goals (Hiatt and Creasey 2012; Bellantuono et al. 2021). The foundation of CM is to create acceptance, understanding and readiness for change throughout the organisation (Burnes 2008). However, Hiatt and Creasey emphasise that CM is not simply a mechanism for reducing resistance but needs to align organisational goals with employee readiness. Effective CM strategies need to address both the emotional and psychological factors in change processes, as well as the operational side of change, by educating employees about its relevance and the hard skills required (Bellantuono et al. 2021; Turner Parish, Cadwallader, and Busch 2008).

Historically, the literature presents a variety of theories and strategies for effective CM. However, most approaches converge around three core elements: leadership, communication, and employee inclusion (Bellantuono et al. 2021). These elements are also highlighted as fundamental by Waddell and Sohal, as well as Pacolli, who find that communication, employee inclusion and strong leadership are key elements of successful CM. Leadership is often even referred to as the most critical factor. Leaders create a sense of urgency for change and guide employees through the process (Ba et al. 2024). They must define a clear vision and direction and empower their employees to follow, as well as provide them with the right environment and resources (Waddell and Sohal 1998). However, an essential requirement for this is a strong commitment to change by leadership, which implies that leaders first need to understand the urge for change by themselves to guide employees (Pacolli 2022). Leaders can also establish a task force dedicated to managing the change initiative. According to Ba et al. (2024), this team should consist of people from different functional areas and hierarchical levels with know-how on processes and commitment to change.

Communication is another critical factor in CM. Effective communication from management is clear and consistent to provide clarity and reduce employees' fears (Choi 2021). It can involve discussions, presentations to groups, or reports to help employees understand the urge and potential of a change (Kotter and Schlesinger 2008). In some cases, communication needs to be adjusted according to the stakeholder group (Ba et al. 2024). This becomes even more important with the increasing size and complexity of the organisation. Waddell and Sohal further emphasise the importance of employee inclusion. Involving employees in the learning, planning, and change process can reduce their resistance, as demonstrated by Coch and French (1948). For instance, this can be achieved through means of two-way communication and involvement in decision-making (Firican 2023).

Additionally, technological transformation has introduced new complexities that modern organisations must address (Avdeeva et al. 2021). From the introduction of computers and Enterprise Resource Systems (ERP) to newer digital tools, the operational aspects of CM have gained significant importance in the context of technological transformations (Chhatre and Singh 2024). Abdallah, Shehab, and Al-Ashaab (2021) identify a gap in skills necessary for digital transformation as one of the main challenges for effective CM, especially in manufacturing companies. Equipping employees with the required hard skills thus becomes essential for CM to fully leverage technological changes. Consequently, the literature emphasises how CM can foster a culture of continuous learning and development by offering training opportunities, sharing knowledge, and disseminating best practices (Chhatre and Singh 2024; Turner Parish, Cadwallader, and Busch 2008).

Moreover, establishing feedback channels is critical for identifying resistance and swiftly adapting CM strategies (Ba et al. 2024). Organisations should actively monitor and evaluate CM's progress by collecting employee feedback (Bellantuono et al. 2021). In the context of modern CM, Firican (2023) validates these approaches by comparing digital transformation strategies with Hiatt's ADKAR model, a framework that, despite its historical origins, underscores the significance of individual change. This includes emotional readiness for change and the ability to acquire new skills, as shown in Figure 2, 'ADKAR Model by Jeff Hiatt', in the Appendix (Goyal and Patwardhan 2018). Firican highlights key elements such as leadership support, engaging people managers, building change agent networks, effective communication, training, and reinforcement of change—all of which contribute to improved technological transformation outcomes. These findings align with Bellatuono (2021), who underscores the importance of a participatory approach characterised by strong leadership, clear communication of vision, effective training, and consistent monitoring for successful CM.

The integration of GenAI has further amplified some of the known challenges associated with technological transformations, including the continuous nature of change, its rapid pace, broad scale and scope, as well as emerging ethical concerns in data and intellectual property (IP) protection (Chhatre and Singh 2024; Kewalramani and Neema 2024). Thus, further investigation is needed to determine which strategies are most effective and how their importance may vary across organisations and functional areas in manufacturing and non-manufacturing industries. This exploration will help tailor CM approaches to specific contexts to optimise GenAI integration and its potential impact on diverse organisational settings. In the next chapter, a theoretical foundation for understanding employee engagement and satisfaction will be established, emphasising their critical role in shaping organisational performance, innovation, and long-term employee retention.

2.4 Theoretical Foundations of Employee Engagement, Satisfaction, and the Role of Technological Transformations

Employee engagement and satisfaction are regarded as pivotal to organisational success, influencing motivation, productivity, and retention. Organisational psychology has deeply explored these constructs, offering critical theoretical perspectives that illuminate workplace dynamics. Recent technological innovations, particularly in GenAI, have introduced new challenges and considerations for organisations operating in this space (Kahn 1990; Raisch and Krakowski 2021; Schaufeli et al. 2002).

Employee engagement is frequently described as a deep emotional and intellectual commitment to an organisation. It is typically characterised by three core dimensions: vigour, dedication, and absorption. Vigour refers to high energy levels and mental resilience while working, reflecting an employee's enthusiasm and motivation. Dedication entails a strong sense of involvement, pride, and purpose in one's work, while absorption describes a focused, engrossed approach to tasks where individuals are entirely concentrated and immersed in their roles (Schaufeli et al. 2002). This positive, active work-related state encourages employees to engage fully—physically, cognitively, and emotionally—in their roles, fostering higher levels of performance and job satisfaction (Kahn 1990; Maslach et al. 2001). Employee satisfaction, on the other hand, is defined as a positive emotional response to one's job, influenced by workplace conditions, social relations, autonomy, and perceived status (Maslach et al. 2001). Pioneering studies in job satisfaction, such as Robert Hoppock's seminal work in the 1930s, emphasise its multidimensional nature, encompassing both the intrinsic characteristics of the work itself and interpersonal dynamics within the workplace (Bowling and Cucina 2015).

Several frameworks support the understanding of engagement. A central framework is the Self-Determination Theory (SDT), which outlines three essential needs for sustained motivation: autonomy, competence, and relatedness. Autonomy refers to the ability to self-direct one's actions; competence involves achieving a sense of effectiveness in tasks and relatedness signifies meaningful social interactions. Employees are more engaged, motivated, and fulfilled when these needs are met (Martela and Ryan 2019). SDT is particularly instrumental in workplace contexts, as it highlights the importance of fostering environments that support these psychological needs, which in turn enhances employee engagement and overall organisational effectiveness (Deci, Olafsen, and Ryan 2017).

Another framework, the Job Characteristics Model (JCM), identifies five dimensions of job design—skill variety, task identity, task significance, autonomy, and feedback—that influence intrinsic motivation. For example, roles with higher skill variety and task significance foster engagement by instilling a sense of purpose, while autonomy and feedback enhance competence and control (Hackman and Oldham 1976). SDT and JCM both emphasise how well-structured work environments meet employee needs, driving engagement and satisfaction. The Job Demands-Resources (JD-R) Model offers a complementary perspective, focusing on how job demands (e.g., workload, emotional stress) and job resources (e.g., autonomy, organisational support) interact to shape employee engagement and burnout. The model suggests that when job resources outweigh demands, employees are more likely to experience positive outcomes such as job satisfaction and engagement. Conversely, excessive job demands without sufficient resources can lead to disengagement and burnout (Bakker and Demerouti 2007). The JD-R model is particularly relevant in the context of introducing GenAI to the workforce, where technology can either reduce demands through automation and augmentation or increase them through complexity and training requirements (Scholze and Hecker 2024).

Historical evidence provides valuable context for understanding how technological advances, including GenAI, impact engagement and satisfaction. During the digital transformation of the 1970s and 1980s, the introduction of computers initially caused widespread anxiety among employees, who feared job displacement and skill redundancy. This era illustrated how new technologies can challenge employee engagement, particularly when organisations fail to provide sufficient training and support. Over time, employees became more accustomed to using computers, which improved their integration into daily workflows. These technologies enhanced collaboration between humans and machines by automating repetitive tasks and allowing employees to focus on higher-value work (Brynjolfsson and Hitt 2000).

Similarly, the emergence of the Internet in the 1990s revolutionised connectivity and introduced significant challenges for organisations. As highlighted in a recent study, employees' ability to adapt to technological advancements, such as using the Internet effectively, heavily depends on their self-efficacy. Organisations that provided structured support, training, and resources helped employees overcome initial resistance and anxiety. This approach fostered higher engagement and improved collaboration among team members. Conversely, the absence of such support often resulted in stress and dissatisfaction, underscoring the importance of addressing these transitional challenges to realise the potential benefits of technology (Abun et al. 2022). These historical examples highlight that the impact of technological innovations on engagement and satisfaction is neither uniform nor immediate; rather, it depends on organisational support, training, and the alignment of technology with employee needs. Similarly, the introduction of GenAI presents comparable challenges and opportunities. By automating routine tasks, it has the potential to reduce workload, enhance job satisfaction and align with the JD-R model's emphasis on balancing demands and resources (Scholze and Hecker 2024). At the same time, it creates new challenges, such as the need for employees to acquire advanced digital skills, which may increase job demands if left unaddressed (Raisch and Krakowski 2021). Such dynamics underscore the importance of organisational CM strategies in leveraging GenAI to enhance, rather than diminish, employee engagement and satisfaction (Brynjolfsson and Hitt 2000).

These theoretical insights provide a robust foundation for analysing how GenAI influences employee engagement and satisfaction, which will be further explored in the analysis section. The following section explores the broader implications of technological innovations for organisational productivity measurement.

2.5 Measuring Productivity Gains within Technological Transformation

The measurement of productivity gains through technological innovations has been a central topic in research and practice for decades. This phenomenon is known as the productivity paradox (Solow 1987). Solow (1987) pointed out that the computer age is visible everywhere except in productivity statistics. He also noted that technological advances alone are not enough to realise productivity gains and must be accompanied by structured organisational adjustments (Solow 1987). Brynjolfsson and Hitt (2000) extend this perspective and attribute the paradox to several factors, including lack of diffusion, implementation lags, and the challenge of measuring intangible benefits. While technologies such as computers and the internet led to long-term economic transformations, the short-term benefits were often difficult to recognise. The introduction of computers in the 1970s and 1980s did not immediately lead to the expected productivity gains. It was not until the late 1990s that significant improvements became visible, as time was needed to adapt and utilise the technology effectively (Brynjolfsson and Hitt 2000). Despite substantial investment in information technology (IT), organisations often fail to realise corresponding productivity gains (Brynjolfsson and Hitt 2000). In the past, technological progress was one of the main sources of productivity growth. This has resulted in long-term recognisable effects such as scientific innovation, improved management practices, optimised organisational structures and new products, services and business models (West and Allen 2021). Organisations, therefore, invest in IT with the desire to combat market competition and improve the productivity, quality and profitability of their operations and services (Devaraj and Kohli 2003).

Bresnahan and Trajtenberg (1995) characterised IT not as a conventional capital investment but rather as a General Purpose Technology (GPT). The term is used to describe innovations that are widely adopted across the economy, continuously improving performance and driving innovation in the industries that use them. Historical examples include personal computers or electric motors (West and Allen 2021). Brynjolfsson et al. (2017) argue that GPTs, similar to earlier transformative technologies such as computers or the internet, require ‘complementary innovations’ to realise their full potential. These include organisational adaptations, the creation of new work roles, processes and the training of employees in the effective use of the technology. Otherwise, the benefits will remain limited (Brynjolfsson and Hitt 2000). New technologies such as AI have the potential to bring about far-reaching changes in organisations and work processes. As an example of modern GPT, it promises to increase efficiency through automation, support data-based decision-making processes and promote innovation (Guo et al. 2023). Nevertheless, GPTs present organisations with similar challenges to those observed in earlier phases of technological change, particularly in the context of the productivity paradox (Brynjolfsson et al. 2017). On the one hand, the outputs of GPTs are often difficult to differentiate in the early stages of adoption and offer only limited strategic benefits (Necula et al. 2024). On the other hand, they often realise their full potential in combination with human intelligence by supporting creative and strategic decision-making (Brynjolfsson and McAfee 2014). The right balance between automation and augmentation while implementing is crucial. Raisch and Krakowski (2021) describe this in the context of the ‘automation-augmentation paradox’, where overreliance on automation can weaken human capabilities. Conversely, augmentation through human-machine interactions creates synergistic outcomes. Companies that rely solely on automation run the risk of losing long-term innovation potential. To develop long-term, sustainable competitive advantages, Raisch and Krakowski (2021) advocate for a well-balanced mix of automation and augmentation.

This discrepancy raises fundamental questions about the measurement, acceptance and context-dependent use of new technologies. An essential part of measuring productivity is the distinction between subjective and objective perceptions. Studies show that employees often report being more productive because of technologies such as GPTs, although objective measurements do not always confirm these effects (Necula et al. 2024). Technologies such as GPTs can increase the feeling of productivity by relieving employees of complex tasks and creating creative freedom (Guo et al. 2023). At the same time, traditional metrics such as Return on Investment (ROI) or process cycle times often remain insufficient to capture the qualitative benefits of GPTs, such as decision quality or innovation rate (Brynjolfsson et al. 2017). Traditional productivity metrics often fall short when it comes to new technologies. Guo et al. (2023) suggest developing new approaches that measure qualitative benefits such as creativity, decision quality and the effectiveness of hybrid human-AI interactions.

Similarly, the Technology Acceptance Model (TAM) (Davis 1989) can be used as a theoretical framework for analysing how the acceptance of technology influences its actual use and productivity. According to Venkatesh and Davis (2000), two key factors are crucial: the perceived usefulness of a technology, which convinces employees that it will improve their performance, and the perceived ease of use, which increases willingness to use it. In the context of GPTs, the TAM could help explain the discrepancy between perceived and objective productivity. While employees perceive the technology as useful, its effective use often fails due to a lack of training or organisational barriers. Furthermore, variables like the age and the position of the user should not be ignored when evaluating productivity (Necula et al. 2024).

Moreover, the Technology-Organisation-Environment (TOE) framework can exhaustively explain factors impacting organisations investment and adoption decisions (Wang et al. 2023). The TOE framework initially introduced by Tornatzky, Fleischer, and Chakrabarti (1990) provides a comprehensive basis for analysing the factors that influence the introduction of technological innovations in organisations. The researchers categorise it into three dimensions: The technological context refers to the characteristics of the technology, such as its relative advantage, complexity and compatibility with existing systems, which shape the perception of its usefulness and feasibility. The organisational context includes internal factors such as company size, structure and management support, which are decisive for the willingness to introduce new technologies. Finally, the environmental context considers external influences such as competitive pressures, regulatory requirements and customer expectations that push organisations to adapt to industry trends and customer needs (Tornatzky, Fleischer, and Chakrabarti 1990). The TOE framework emphasises that successful technology adoption requires a close alignment between technological capabilities, organisational readiness and external requirements (Wang et al. 2023).

In summary, the literature highlights the substantial potential of GPTs and similar technologies to drive productivity gains while also acknowledging the constraints posed by the productivity paradox and the inherent difficulties in measuring their effects. Additionally, insights into CM theories and the theoretical underpinnings of employee engagement and satisfaction provide essential context for understanding the organisational and human dimensions of GenAI adoption. Together, these foundations emphasise the importance of establishing robust metrics, strategies, and frameworks to navigate the complexities of GenAI integration. Building on these theoretical insights, this research seeks to address the outlined challenges by systematically investigating the interplay of these factors through a comprehensive methodological approach. The next chapter elaborates on the research design, detailing how the study integrates these perspectives to address the research questions holistically.

3 Research Design and Methodology (Group Part)

3.1 Research Approach

For the present study, a mixed-method research approach was chosen to gain a deeper understanding of the context-specific dynamics around the implementation of GenAI. The approach is based on the findings of Hong et al. (2017) and Östlund et al. (2011), who stress the importance of integrating quantitative and qualitative methods to enhance the understanding of links between theory and empirical evidence and to question existing theoretical assumptions. The qualitative approach in this study involves semi-structured interviews with professionals designed to gather rich, contextual data that serves as a foundation for in-depth analysis (Flick 2011). As part of the quantitative approach, a short online survey provides supporting insights on selected aspects from the qualitative interviews, validating findings and informing meaningful recommendations (Onwuegbuzie and Leech 2005).

3.2 Qualitative Approach

3.2.1 Study Sample

This section outlines the selection criteria for companies and participants, along with an overview of the sample composition, emphasising its alignment with the study's research objectives. Participating companies were chosen based on their active engagement with GenAI technologies, ensuring their relevance to the research focus on AI integration into organisational workflows. Both manufacturing and non-manufacturing companies were included to identify sector-specific differences in GenAI adoption, as outlined in chapter 2.2. These differences are crucial for deriving actionable and nuanced recommendations. Participants for the interviews were identified through the authors' professional networks, peer recommendations, and LinkedIn searches using keywords like 'AI Integration', 'Change Manager', and 'IT Project Lead'. This method ensured the inclusion of experts with direct experience in GenAI adoption and CM. The geographical focus on companies based in or operating within Germany was motivated by Germany's reputation as a hub for advanced manufacturing and its substantial presence in technology-driven industries, making it an ideal setting to explore GenAI adoption (Grashoff, Mayer, and Recker 2024; Hellwig 2024). This approach captures a broader perspective, reflecting practices and strategies across diverse industries and providing insights into AI adoption's unique challenges and opportunities.

The study encompasses eight companies, evenly split between manufacturing and non-manufacturing sectors. Manufacturing companies for this study operate in the automotive, automotive parts supply industry and fashion sectors. The non-manufacturing companies are based in industries such as banking, digital and marketing consultancy, and IT and software services tailored for tax, accounting and legal professionals. A total of 17 interviews were conducted, with the number of participants per company varying based on organisational structure and the availability of relevant stakeholders. This offered a more prosperous, multidimensional perspective on the organisation's AI integration and cross-departmental implications. The interviewees chosen were based on their experience with GenAI and CM, which is why the majority hold a leading position in the company. This sampling approach provided both depth and breadth, allowing for capturing individual employee experiences alongside organisational dynamics.

3.2.2 Interview Design

The interviews conducted for this study followed a semi-structured format, designed to balance flexibility with a clear focus on the research objectives. According to Myers and Newman (2007), these types of interviews are commonly used in qualitative research. This approach allowed participants to provide detailed and nuanced responses while ensuring that key topics aligned with the study's sub-research questions were systematically addressed. The interview comprised 38 open-ended questions divided into sections on the interviewee's background, how GenAI was integrated into workflows, the effect on employee engagement and productivity, CM strategies, and integration into strategy and measurements. By employing open-ended questions, participants were encouraged to share their perspectives freely (Agustianingsih and Mahmudi 2019; Misoch 2019), fostering deeper insights into their experiences with GenAI integration. To avoid priming participants or influencing their answers, the questions were carefully formulated to remain neutral and unbiased, allowing participants to express their authentic views and experiences. In addition, to prevent the findings of this study from becoming one-sided by focusing solely on experts with an affinity for AI, the interview questions were carefully designed to provide a comprehensive and balanced perspective that reflects the organisation as a whole. The detailed design of the interview can be found in Table 2, ‘Interview Questions’, in the Appendix.

3.2.3 Data Collection

All interviews took place virtually using Microsoft Teams, with each session lasting approximately 45 minutes, ensuring accessibility for participants and enabling the inclusion of geographically dispersed organisations and individuals. To ensure high-quality and consistent results, the interview questions were provided to participants in advance via email, giving them sufficient time to prepare. Identical questions were posed to participants from both sectors to enable a clear and systematic comparison. Two of the study’s authors were present during each session: one led the interview, while the other took notes. Participants were also informed that their responses would be kept confidential, their involvement was entirely voluntary, and they could decline to answer any questions or withdraw from the interview at any point. This approach aligns with the best practices outlined by Brinkmann and Kvale (2018), which emphasise fostering openness and candid responses during qualitative interviews. This helps establish transparency and trust, encouraging open and honest discussions.

3.3 Quantitative Approach

3.3.1 Study Sample

The quantitative survey was conducted within the same eight companies as the interviews of the qualitative approach. After the interviews were conducted, interviewees were asked to share the survey within all divisions of the company. Thus, the survey sample comprises employees with different functions and professional experience. This approach aimed to gather additional and broader insights to ensure the interview findings were unbiased and to increase the generalisability of the study's results (Antwi and Hamza 2015).

3.3.2 Survey Design

The survey was designed online via Microsoft Office Forms. As in the interviews, no distinction in design was made between manufacturing and non-manufacturing companies to ensure better comparability. The survey comprises 11 questions and is divided into two sections, with the first focusing on the background of the employee and the second on experiences with GenAI in the day-to-day work. For the second part, questions were designed using a five-point Likert scale ranging from 'significantly less' to 'significantly more' (Tanujaya, Prahmana, and Mumu 2023). In addition, the survey contains several multiple-choice questions with options based on key statements from the interviews and theoretical findings from the literature review. Overall, the survey was designed to be relatively short as it was intended to be a supporting tool for the key findings of the qualitative interviews (Antwi and Hamza 2015). It was, therefore, administered after all the interviews had been completed. The survey can be found in Table 3, 'Survey Questions', in the Appendix.

3.4 Data Analysis

In this report, the qualitative results were analysed using inductive thematic analysis. Thematic analysis is a method of studying qualitative data that involves looking for, analysing, and reporting recurring patterns across multiple data sets (Braun and Clarke 2006). For this study, an inductive approach was used, meaning the themes were derived directly from the data gathered in the interviews to reflect the unique experiences of interviewees. This method is particularly effective because it allows researchers to understand a range of experiences, behaviours, and thoughts by looking for common experiences or shared meanings (Thomas 2006). The method was conducted equally for both manufacturing and non-manufacturing companies. However, the results were captured within a Microsoft Excel workbook and separated into different worksheets to enable a comparison of findings in a later step during the analysis. After the interview process, common themes were identified inductively and gathered in a new Excel sheet with a structured approach that presented the key findings of the analysis. An overview of the identified themes can be found in Table 4, 'Identified Themes from the Interviews', in the Appendix.

The quantitative results of the survey were analysed in Excel. A total of 209 participants completed the survey. This provides a solid and relevant database for the analysis as a sample size of more than 30 participants suggests a normal distribution of the dataset (Krithikadatta 2014). The analysis focused on descriptive statistics to identify trends and patterns in the data, without performing inferential statistical tests. The results were analysed by calculating frequency distributions for the Likert scale and multiple-choice responses to identify trends and patterns. Comparative analyses were conducted to explore differences between manufacturing and non-manufacturing groups.

4 Analysis and Discussion (Individual)

This thesis examines GenAI's transformative potential in reshaping organisational processes, addressing employee engagement, and evaluating productivity gains. Building on the research questions introduced earlier, the study investigates various themes to uncover how GenAI can support organisational transformation, improve workforce dynamics, and enable measurable business outcomes. As the adoption of GenAI tools continues to rise, understanding the opportunities and challenges they present has become increasingly critical for organisations across sectors.

To explore the research question, a mixed-methods approach was employed. Qualitative insights were obtained through interviews, providing rich, context-driven perspectives on how GenAI impacts organisational and employee outcomes. Complementing this, quantitative survey data was used to validate and deepen the findings, creating a robust foundation for a cross-case comparison. This chapter provides a detailed analysis of the results. The findings address how GenAI adoption can be supported through CM, enhance employee engagement and job satisfaction, and measure productivity gains. A particular emphasis is placed on the interplay between employee experiences and organisational transformation. The following sections outline the key findings from this research, focusing on themes derived from interviews and surveys while highlighting sectoral distinctions. By incorporating theoretical foundations and empirical evidence, this chapter contributes to a comprehensive understanding of the transformative potential of GenAI. In chapter 5, practical recommendations for companies will be derived to support the effective integration and utilisation of GenAI.

4.1 Effective Change Management for Generative AI Integration (Krause, S.)

Based on the discussion of key CM strategies and the implications of technological transformation in section 2.3, the following section explores how organisations are managing and perceiving the introduction of GenAI. Specifically, it addresses the research question: *"What change management strategies are effective for successfully integrating generative AI?"* To answer this question, the following analysis will focus on seven themes identified from qualitative and quantitative insights in the manufacturing and non-manufacturing sectors and connect them to the theoretical frameworks discussed in section 2.3. The themes encompass:

1. *Generative AI-Induced Organisational Change*
2. *Resistance to Change*
3. *Change Management Strategies – Communication*
4. *Change Management Strategies – Leadership*
5. *Change Management Strategies – Skill Development through Training*
6. *Change Management Strategies – Continuous Feedback and Monitoring*
7. *Success Factors and Best Practices*

4.1.1 Generative AI-Induced Organisational Change

The introduction of GenAI tools across the interviewed organisations has prompted meaningful organisational changes driven by innovation and competition across manufacturing and non-manufacturing industries. Manufacturing companies focused on integrating tools like ChatGPT and Microsoft Copilot to automate tasks and improve workflows. External competitive pressures often played a key role, with one interviewee stating, "If you're not integrating these tools in the automotive industry, you're already falling behind." Despite this urgency, implementation was methodical and often internally driven. In one manufacturing company, "The introduction was largely employee-driven, with tools being championed by specific teams interested in their application. Leadership provided access but not structured guidance."

Manufacturing companies typically began with small-scale experiments, limiting early use to specific departments to assess value and refine strategies.

Non-manufacturing companies adopted a similarly structured approach, with innovation and competitive positioning as key motivators. One respondent noted, "The main reason is because we like to be at the forefront of innovation." Pilot projects focused on technical readiness and governance, starting small before scaling further. This iterative approach helped identify barriers, align workflows, and minimise disruptions while supporting broader organisational goals.

The findings reveal that adopting GenAI tools drove significant organisational change across manufacturing and non-manufacturing sectors, influenced by external pressures and internal initiatives. Externally, competitive demands and the rising prominence of tools like ChatGPT and Copilot acted as catalysts, which aligns with research by Bi (2023) and Feuerriegel et al. (2024), describing technological adoption as frequently influenced by external trends. However, the findings also highlight a new dimension as, in some cases, the adoption process was internally driven, with employees or specific teams championing the introduction of these tools. This contrasts with traditional assumptions where change is typically proposed by higher levels of management, as also investigated by Waddell and Sohal (1998) and reflects the evolving nature of organisational change in the face of technological transformation, consistent with the findings of Avdeeva et al. (2021). Over time, organisations shifted from experimentation to strategic integration, aligning GenAI adoption with broader goals and processes. These findings resonate with wider trends in CM literature, which increasingly describe technological change as a continuous and evolving process rather than a singular event (Avdeeva et al. 2021; Burnes 2008). The dual nature of reactive and internally driven adoption underscores the importance of adaptability and alignment in navigating ongoing technological transformation, especially with the dynamic nature of GenAI.

4.1.2 Resistance to Change

Resistance to change was observed in both manufacturing and non-manufacturing sectors, manifesting in forms such as scepticism, compliance concerns, and operational challenges. Resistance originated from various parties, including employees, leadership, and workers' councils, but was generally least pronounced among employees. However, section 4.2.3, 'Resistance and Engagement in Generative AI Adoption', will focus more in-depth on employees' resistance and the impact on engagement and satisfaction. In manufacturing companies, employees often displayed excitement and curiosity about the introduction of GenAI tools. Resistance was primarily driven by two factors, which are fear of job replacement and inadequate training on how to maximise the tools' potential, yet also arose due to scepticism. Companies reported that employees had fun and enjoyed testing the capabilities of the tools. However, these tools were frequently underutilised without sufficient training or clear use cases. As one interviewee noted, "People still don't fully understand how to use tools like ChatGPT effectively, leading to hesitancy." Resistance was also present among leadership, often stemming from concerns about the high implementation costs of GenAI tools. This will be examined in more detail in section 4.3.2. Additionally, leadership and workers' councils raised data privacy and compliance issues. In some cases, these concerns delayed the rollout of GenAI tools, as legal frameworks had to be established, communicated and trained to employees before the tools could be formally introduced.

In non-manufacturing companies, resistance appeared in similar forms. While employees were generally enthusiastic about GenAI adoption, frustration replaced initial excitement when proper training was lacking, leading to incorrect usage and suboptimal results. Organisations observed that resistance often evolved into frustration when AI tools failed to meet inflated expectations. Resistance also arose with the introduction of alternative GenAI tools, as employees accustomed to leading tools like ChatGPT were reluctant to adapt to new ones. Legal and data protection concerns were prevalent in both sectors. One interviewee noted apprehension from its workers' council about AI's potential for performance monitoring. As one representative explained, "The idea of meeting transcription being used for evaluations raised significant concerns with our workers' council." However, this resistance diminished once members of the workers' council were included in pilot programmes, where they gained first-hand experience and understanding of the tools' usage.

Overall, resistance factors appeared consistent across both manufacturing and non-manufacturing sectors. These findings resonate with the findings of Kotter & Schlesinger (2008), who highlight the importance of addressing both emotional and practical concerns to facilitate technology acceptance. However, resistance should not only be addressed among employees but should also be closely monitored among all stakeholder groups, such as work councils or senior management, as otherwise, the implementation of GenAI tools may be hindered. Thus, in addition to the findings of Waddell and Sohal (1998), which emphasise the importance of employee involvement, pilot projects should consider including teamwork with members from different stakeholder groups. This underscores the need for a holistic approach to CM, ensuring that all stakeholder groups are actively engaged to support the successful adoption of GenAI tools.

4.1.3 Change Management Strategies – Communication

The adoption of GenAI has introduced significant organisational changes, requiring tailored CM strategies to address resistance and ensure successful implementation. Across the interviewed companies, the role of effective communication emerged as a critical factor. In manufacturing companies, clear, consistent, and inclusive communication was described as essential, particularly for gaining stakeholder buy-in. Interestingly, in some cases, the adoption of GenAI was not initiated by top management but by departments such as IT or individual employees who recognised its potential early on. This underscores the importance of engaging management and decision-makers at an early stage to build awareness of GenAI's potential and secure project sponsorship. Early involvement is crucial for obtaining the necessary resources to purchase tools and develop internal capabilities. Once GenAI tools were adopted, top-down communication became pivotal. This was facilitated through word-of-mouth, newsletters on the intranet, town hall meetings, and training sessions. Key principles included clarity and consistency, particularly given the dynamic nature of GenAI tools, which require regular updates and continuous communication. Companies emphasised the value of personalised and face-to-face communication to better understand employee reactions and manage expectations. Ideally, communication is not a one-way process but rather a feedback loop, enabling employees to voice their concerns and contribute to the adoption process. The importance of feedback, especially regarding enhancing employee engagement and job satisfaction, will be explained later in this analysis.

In non-manufacturing companies, representatives shared similar experiences, highlighting the need to build trust and foster curiosity about GenAI through consistent and transparent communication with all stakeholder groups. In the initial stages, communication from top management was identified as particularly important to encourage widespread adoption among employees. One representative stressed the value of tailored communication, stating, "The biggest risk is not segmenting your audience. If you don't tailor communication to each team, they won't see the value, and that leads to no usage." Effective communication in this sector involved not only providing up-to-date information but also targeting specific groups, including employees from various departments and workers' councils. Personalised and segmented communication ensured that each group understood the value of GenAI in their specific context, thereby fostering engagement and reducing resistance.

The findings reveal that communication strategies in manufacturing and non-manufacturing companies are broadly similar, with differences arising primarily from the complexity of the organisations involved. Across both sectors, clarity and consistency in communication emerged as essential principles, aligning with Choi (2021). Additionally, the importance of tailoring communication strategies to stakeholder groups resonates with the findings of Ba et al. (2024). These insights emphasise that effective communication, tailored to organisational complexity and stakeholder needs, is a cornerstone for successful GenAI adoption.

4.1.4 Change Management Strategies – Leadership

In addition, leadership emerged as a critical driver for successful CM during the adoption of GenAI tools. In manufacturing companies, several interviewees highlighted how senior leaders actively demonstrated their commitment to the change process. One participant noted, “When managers started using the tools in team meetings, it motivated others to do the same.” Leadership played a pivotal role in fostering trust and driving adoption by championing GenAI and addressing employee scepticism. However, the findings also revealed that some leaders needed to be educated about the potential of GenAI before they could take on this promoting role. In certain cases, as stated in section 4.1.1, the initial driver for GenAI adoption came from employees or IT departments, with leadership only stepping in after being convinced of its value. Some companies emphasised that their GenAI implementation was largely employee-driven, with specific teams championing the tools. In these cases, early involvement and targeted pitching to leadership proved crucial. Engaging management early not only secured buy-in but also ensured sponsorship, enabling resources to be allocated effectively—for example, by establishing task forces. These task forces were described as essential for “ensuring the smooth operation of AI tools and addressing any challenges employees face”.

Similar trends were observed in non-manufacturing companies. Leadership promotion and demonstration of GenAI usage were cited as key factors for successful adoption. However, in one case, leadership communication was minimal, and no senior executives demonstrated tool usage, which hindered adoption. One interviewee remarked, “I would have loved to see a sponsor or leader say, ‘This is how I’m using Copilot. Why don’t you give it a try?’ Even a short video would have been impactful.” Instead, most communication in this instance came from the AI initiative team. Nevertheless, the presentation of the initial successes helped to create momentum and ultimately involve the top management level. All interviewed non-manufacturing company representatives agreed that the early involvement of top management simplified the introduction of GenAI tools and fostered employee trust.

The findings show that strong leadership is equally valued in manufacturing and non-manufacturing sectors, with leadership playing a central role in motivating employees, overcoming resistance, and ensuring resources for GenAI adoption. However, both sectors faced challenges in convincing some leaders to take an active role. In practice, leadership was not always the initial driving force; instead, AI-enthusiastic employees often led the charge, convincing leaders of the urgency for change. Prior research by Waddell and Sohal (1998) reflects the importance of strong leadership for successful CM, particularly the role of leaders as role models in defining a guiding vision. While these findings support that perspective, they also highlight that leaders may need to be inspired by employees before fully embracing their role as change champions. This is consistent with Pacolli’s (2022) argument that leaders must first internalise the need for change to lead and inspire their teams. These findings highlight the reciprocal relationship between leaders and employees, emphasising that effective CM often requires mutual inspiration and collaboration to drive GenAI adoption successfully.

4.1.5 Change Management Strategies – Skill Development through Training

Equipping employees with the necessary knowledge and skills to effectively use GenAI tools is a critical aspect of CM. This topic will also be further explored in section 4.2, particularly concerning employee engagement and job satisfaction. Key areas of focus include developing prompting skills and understanding legal limitations regarding data sensitivity. While many employees display intrinsic motivation driven by curiosity and enthusiasm for testing GenAI, maintaining this engagement requires structured training to demonstrate how employees can maximise efficiency gains through the tools. In manufacturing companies, internal knowledge-sharing and informal peer training were identified as particularly effective strategies for fostering engagement and building positive attitudes toward AI tools. Interviewees highlighted the use of diverse training formats to reach as many employees as possible. Peer-to-peer sessions, for instance, are regularly conducted to improve skills with complex tools like Microsoft Copilot. Additionally, monthly workshop series, which evolve alongside the tools, encourage continuous experimentation and learning.

Later stages of implementation often included tailored training sessions specifically designed for team leaders and department heads. This customisation was especially emphasised in manufacturing companies, where diverse departments and functions necessitate targeted training approaches. Interviewees also stressed the importance of showcasing best-practice use cases to inspire employees by demonstrating tangible outcomes achieved through AI tools. For example, showing how individuals in specific roles or projects have utilised AI to drive success has proven effective in highlighting the tools' potential. Live training sessions typically achieve higher participation rates and engagement compared to asynchronous formats such as video tutorials. However, not all manufacturing companies provide regular training. In some cases, optional events such as AI-themed weeks or panel discussions are the primary training methods. Additionally, compliance requirements often mandate that employees complete introductory training videos before gaining access to tools like Copilot, covering topics such as ethical considerations and data responsibility.

Non-manufacturing companies exhibit similar training patterns to address skill gaps. Training on prompt design, tool utilisation, and ethical considerations is often mandatory. One interviewee noted the importance of starting “with clear use cases aligned with business goals and expanding from there”. Investing in employee training and awareness, along with establishing strong data security protocols, is consistently highlighted as essential.

Both manufacturing and non-manufacturing companies demonstrate the critical role of employee training in the successful adoption of GenAI tools. However, training in manufacturing companies appears to be more tailored, likely due to the greater diversity of skills and tasks within these organisations. Survey data demonstrates trends in sectoral approaches to CM, highlighting the importance of tailoring strategies to specific needs. In manufacturing, employees prioritised hands-on training sessions (56%), which aligns with their operational focus and need for visible, immediate results. Non-manufacturing employees, by contrast, emphasised clear instructional guides (36%) that align with their knowledge-driven roles. These findings illustrate that effective CM requires balancing practical and informational resources to address sector-specific priorities during GenAI adoption. This aligns with the findings of Abdallah, Shehab, and Al-Ashaab (2021), who emphasise the importance of targeted training for technology adoption, particularly in manufacturing contexts. Across both sectors, organisations also recognise the importance of fostering a culture of continuous learning and development. Regular workshops, peer-to-peer knowledge exchanges, and sharing best practices are central to maintaining engagement and ensuring employees are equipped with the necessary skills. These findings align with the work of Chhatre and Singh (2024) and Turner Parish, Cadwallader, and Busch (2008), who emphasise the relevance of sustained learning environments in CM. Ultimately, equipping employees with the necessary hard skills not only enhances their ability to use GenAI tools effectively but also leverages their intrinsic motivation to explore and experiment, while simultaneously reducing resistance to organisational change.

4.1.6 Change Management Strategies – Continuous Feedback and Monitoring

Furthermore, continuous feedback and monitoring during the adaption and use of GenAI tools are central aspects of CM. In manufacturing companies, e-mail channels and monthly questionnaires were established where users could share their feedback or issues with GenAI tools at any time. Additionally, user interviews were conducted which helped understand potential resistances and issues but also reinforced the importance of personal communication. This enabled immediate understanding of problems and faster improvement of the tools and user experience. Besides, "feedback loops [are] critical for refining use cases" and gaining insights into how employees use the tools. Analysing feedback is key to decreasing resistance and increasing employee satisfaction, which is why feedback will be further analysed in section 4.2. To gather as much feedback as possible, one company has set up a thumbs-up function where users can rate in real time the benefits they have gained from using the tool. In addition to feedback, monitoring GenAI usage is described as critical. Manufacturing companies anonymously track the usage of the tools, e.g., how many prompts are being entered and whether the result is copied, to gain an even better understanding of the user and tool improvement potentials. The topic of value creation assessment and establishing key performance indicators (KPI) will be further investigated in section 4.3.

For non-manufacturing companies, similar patterns in the collection of feedback can be identified. Like in manufacturing companies, feedback shall be given in real-time, regularly, and ideally personally to quickly identify resistance and other issues. Companies make use of surveys and also collect feedback through face-to-face communication in workshops. Besides, team leads with an overview of day-to-day work in their specific department collect feedback from employees. This way, employees are also involved in further development and improvement of the tools. The findings resonate with the study of Ba et al. (2024) and Bellantuono et al. (2021), who point out that establishing feedback channels is critical for identifying resistance and swiftly adapting CM strategies. For GenAI adoption, feedback channels need to be efficient due to the fast-evolving nature of the tool. These insights underline the importance of efficient and accessible feedback mechanisms to address resistance and adapt strategies in the dynamic context of GenAI adoption.

4.1.7 Success Factors and Best Practices

Building on strategies for communication, leadership, training, and feedback, additional best practices were identified across the investigated companies to support the successful adoption of GenAI tools. In manufacturing companies, interviewees emphasised the importance of employee-driven innovation and voluntary participation in pilot projects. Employees selected for these pilots were chosen based on their interest and willingness to dedicate time to experimenting with the tools. This approach fostered intrinsic motivation and created a foundation for sharing best practices. A flexible implementation timeline was also highlighted as critical, with companies avoiding excessive pressure on employees and allowing them to adapt to the tools at their own pace. To ensure consistency, change champions and task forces were established to guide the implementation process. These individuals acted as advocates for the tools, sharing use cases and best practices across teams. Some companies found establishing a dedicated GenAI team early in the process beneficial. This approach ensured the necessary focus on implementation, as regular employees often lacked the time to manage the change effectively. Clear guidelines were also deemed essential for providing structure to the adoption process, particularly in ensuring employees understood how to integrate GenAI into their workflows and comply with legal requirements.

While most companies relied on flexible, informal approaches to CM—often focusing on training, communication, and task forces—one interviewee reported leveraging the ADKAR model as part of their structured CM strategy. This model, which the company had used successfully in the past, was adapted iteratively for GenAI adoption to account for the rapidly evolving nature of the tool. The focus was primarily on building awareness and creating desire through regular updates and education. The company highlighted the need to repeat elements of the model, such as awareness and desire, for each iteration of GenAI-related updates. For example, major feature releases, which occurred every few weeks, required ongoing communication to ensure employees remained engaged and informed.

In non-manufacturing companies, similar practices were observed. One organisation, for example, implemented a three-pillar approach focussing on training and education, communication, and multipliers or first movers, which refers to Pilot users and early adopters who were empowered to support and mentor their peers, helping to scale adoption across teams. This multiplier concept proved to be highly effective in engaging employees and driving wider tool adoption. A representative from one company emphasised the importance of starting small, stating: “Just do it. Start small, get a pilot team, and then decide if it works. But you need to start somewhere.” This iterative approach ensured that adoption efforts were both manageable and scalable, allowing organisations to adjust strategies based on pilot results before implementing large-scale changes.

The findings show that best practices for GenAI adoption in both manufacturing and non-manufacturing companies share key principles: voluntary participation, employee-driven innovation, and structured support through change champions and pilot projects. Flexibility, clear guidelines, and regular communication for reinforcement were consistently identified as crucial factors for building trust and engagement. While many companies did not formally apply CM frameworks, their approaches align with the principles of the ADKAR model by Hiatt, emphasising awareness, reinforcement, and employee inclusion at every stage of the process. However, the rapid evolution of GenAI necessitates more frequent adjustments to traditional change models. These iterative approaches enable companies to stay agile, ensuring both employees and organisations can keep pace with the transformative potential of GenAI.

These findings emphasise the importance of adaptability and iterative approaches in GenAI adoption, ensuring that organisations remain agile and employees continuously engage in the transformation process.

4.2 Impact of Generative AI Integration on Employee Engagement and Satisfaction (Sanatpour, N.)

Building on the theoretical foundations of engagement and satisfaction discussed in section 2.4, this section examines how GenAI influences these frameworks and impacts organisational and employee dynamics. The analysis draws on qualitative insights from interviews and quantitative survey data to explore how GenAI impacts employee attitudes, behaviours, and workplace experiences. Specifically, it addresses the research question*: "What is the impact of generative AI on employee engagement and job satisfaction?"* This section examines five critical themes, offering a comparative analysis between manufacturing and non-manufacturing organisations:

1. *Adoption of Generative AI*
2. *Efficiency, Creativity, and Employee Satisfaction*
3. *Resistance and Engagement in Generative AI Adoption*
4. *Feedback and Employee Engagement*
5. *AI's Role in Talent Retention and Development*

By exploring sector-specific practices and challenges, the findings provide actionable insights for organisations seeking to integrate GenAI into their operations effectively.

4.2.1 Adoption of Generative AI

The first theme explores the adoption of GenAI tools, examining how organisations integrate these technologies into their workflows, with a focus on initial employee reactions and changes in engagement. Interview insights reveal that in non-manufacturing sectors, the adoption process demonstrated varied responses based on employee familiarity with AI applications. While some employees embraced the technology enthusiastically, others expressed uncertainty due to a lack of understanding about what GenAI entails and how it operates. This disparity often translated into differing skill levels when using prompts effectively. To address these challenges, organisations implemented structured workshops, practical demonstrations, and communication campaigns to showcase the tangible benefits of GenAI. Tools such as ChatGPT were especially lauded for enhancing productivity in creative and administrative tasks. One respondent reported a "60% increase in productivity" within their team, attributing this to the automation of mundane, time-intensive activities such as transcription and document drafting. Employees who actively engaged with the tools often reported a higher sense of motivation and job satisfaction, as GenAI allowed them to focus on more strategic and value-added tasks.

As discussed in section 4.1.2, 'Resistance to Change,' the adoption of GenAI in manufacturing sectors revealed a complex interplay of enthusiasm, initial scepticism, and eventual integration. These tools were primarily deployed for technical applications, such as predictive maintenance, quality control, and optimising production workflows. Employees widely acknowledged the potential of GenAI to automate repetitive tasks, enhance efficiency, and minimise production downtime. One respondent illustrated this impact: "Predictive maintenance applications enabled our team to pre-emptively address equipment failures, saving time and resources." However, the initial reactions varied significantly among employees. While some were immediately open and proactive in embracing the technology, others expressed hesitation due to concerns about job security and data privacy. Scepticism was particularly evident among employees unfamiliar with GenAI's capabilities or its underlying mechanics.

Survey data further highlighted this challenge, with 34% of manufacturing employees identifying a lack of training or knowledge on using GenAI as a key barrier to adoption. In one case, an employee shared how they were initially unsure of the technology's benefits but grew more comfortable after their manager actively encouraged its use through demonstrations and training sessions. Such interventions played a critical role in overcoming resistance and fostering a culture of acceptance. Tailored CM strategies proved instrumental in shifting attitudes. Workshops, real-world demonstrations, and consistent managerial advocacy helped employees recognise GenAI as a tool to complement their skills rather than replace them. For instance, employees who initially struggled with creating effective prompts for AI tools benefited from structured training that simplified the process, boosting their confidence and engagement. Over time, these efforts led to a marked increase in the tools' adoption and integration into daily workflows.

Survey data underscores the broad adoption patterns of GenAI tools across industries, revealing that 61% of employees use such tools daily, with ChatGPT being the most commonly employed (71%), followed by Copilot (23%). This consistent usage highlights how GenAI has become embedded in employees' workflows. Moreover, the data demonstrates a high level of engagement among employees, with no respondents reporting that they had 'never used' GenAI tools at work. These findings reflect the widespread enthusiasm for the technology when integrated effectively into daily processes.

Insights from the JD-R model (Bakker and Demerouti 2007) help contextualise these findings. The model highlights how the introduction of tools like GenAI can reduce job demands by automating repetitive tasks, thereby enabling employees to focus on more meaningful work. At the same time, the model underscores the importance of providing adequate resources, such as training and managerial support, to mitigate the challenges of learning new systems. In manufacturing, for example, managers tailored adoption strategies, including role-specific training sessions and real-world demonstrations, to help employees view GenAI as a resource that complements their skills rather than a threat to their job security. Patil, Rane, and Rane (2024b) further argue that GenAI tools streamline decision-making processes and foster adaptability, enhancing employees' capacity for creative problem-solving. This adaptability promotes what the authors describe as functional resilience, enabling employees to respond effectively to dynamic work environments. Martínez-Sánchez et al. (2009) emphasise that organisational support amplifies these benefits by aligning technological adoption with broader organisational goals, ensuring employees feel equipped and motivated to leverage AI tools effectively.

However, challenges remain. Concerns about AI's limitations—such as "hallucinations" or inaccuracies in outputs—highlight the need for measures that enhance transparency and trust in the tools. Interview insights indicate that IT teams play a pivotal role in adapting AI systems to address these issues, ensuring employees understand the technology's capabilities and limitations. This ongoing dialogue fosters a culture of critical engagement with GenAI, empowering employees to leverage its benefits while recognising its constraints.

4.2.2 Efficiency, Creativity, and Employee Satisfaction

This theme explores how GenAI enhances productivity, creativity, and its potential influence on job satisfaction across sectors. In non-manufacturing organisations, GenAI-driven tools have significantly reduced time spent on repetitive tasks, particularly in administrative and knowledge-based workflows. For instance, "Meeting minute creation, previously a labour-intensive process requiring one to two weeks, is now completed within a single day using tools like Otter.ai and ChatGPT." Similarly, Copilot has optimised routine activities such as generating emails, summarising text, and debugging code, improving workflow efficiency. Survey data corroborates this, with 82% of non-manufacturing employees and 76% of manufacturing employees reporting time savings on repetitive tasks due to GenAI tools. Respondents in non-manufacturing sectors emphasised that these tools enable employees to focus on higher-value tasks, such as strategic planning, creative problem-solving, and client engagement. As one participant noted, “By automating repetitive tasks, we’ve achieved a significant time reduction in daily workflows, freeing up capacity for innovation.” This resonates with survey findings, where 75% of non-manufacturing employees highlighted how GenAI helps generate creative ideas, compared to 62% in manufacturing, suggesting a more prominent role for GenAI in fostering creativity in non-manufacturing contexts.

This aligns with the broader use of GenAI for strategic and conceptual tasks in these environments, particularly in enabling brainstorming sessions and exploring innovative solutions. For example, one respondent in non-manufacturing stated, “GenAI is a great partner for creativity, amplifying human ideas rather than replacing them.” Tools such as ChatGPT were frequently employed to generate alternative perspectives, allowing employees to refine and develop innovative approaches. However, as Eapen et al. (2023) highlight, the true potential of GenAI lies not in replacing human ingenuity but in augmenting it by fostering divergent thinking and challenging expertise biases. This collaborative process enhances creativity by encouraging employees to consider unconventional solutions and refine them collaboratively with AI tools, promoting more profound innovation. At the same time, this augmentation is most effective when employees actively engage their critical thinking skills rather than relying solely on the AI’s outputs. One interviewee observed that creativity emerges when employees use AI to explore new perspectives or refine their own ideas rather than expecting the technology to generate complete solutions autonomously.

Moreover, Raisch and Krakowski’s (2021) exploration of the automation–augmentation paradox highlights the importance of understanding AI applications as complementary rather than opposing forces. While automation can streamline repetitive tasks and free up resources, augmentation leverages human intuition and creativity to maximise the value derived from AI tools. This relationship highlights the necessity of striking a balance between automation and augmentation to fully harness AI's creative potential while avoiding the pitfalls of over-reliance on either approach.

In manufacturing organisations, GenAI adoption focuses on both operational efficiency and administrative support, with applications ranging from streamlining production processes to simplifying routine tasks. For example, one respondent described how Copilot supported their team in debugging software and generating actionable recommendations, improving workflow accuracy. Survey findings underscore this operational emphasis, with 78% of manufacturing employees identifying GenAI as helpful in providing actionable insights or recommendations, slightly higher than 69% in non-manufacturing. Additionally, 59% of manufacturing employees highlighted how GenAI increases overall productivity in their daily tasks, compared to 56% in non-manufacturing. Despite this operational focus, GenAI still positively impacts engagement, with 59.4% of manufacturing employees reporting improved engagement and motivation due to GenAI compared to 46.3% in non-manufacturing.

The observed productivity gains align with the JD-R model (Bakker and Demerouti 2007), which posits that automating resource-intensive tasks reduces job demands, enhancing engagement and satisfaction. By decreasing the manual and cognitive burden of repetitive tasks, GenAI enables employees to redirect their focus toward more rewarding and meaningful work. These findings also echo Brynjolfsson and Hitt's (2000) research, which demonstrates that digital tools enhance employees' capacity to engage in higher-value activities, and Martínez-Sánchez et al.'s (2009) study, which emphasises the importance of organisational support in aligning technological adoption with broader organisational goals. However, sectoral differences in task design influence engagement and job satisfaction outcomes. Non-manufacturing organisations leverage GenAI to introduce task variety and allocate resources strategically, aligning with broader employee aspirations for creativity and innovation. The survey data further supports this distinction: while 47% of manufacturing employees reported improvements in work quality, only 40% of non-manufacturing highlighted similar gains, reflecting the operational focus of manufacturing, where quality improvements are derived more from efficiency than intrinsic motivation.

To fully harness GenAI's potential, organisations must ensure that productivity gains contribute to sustained employee engagement and satisfaction. Non-manufacturing firms should continue leveraging GenAI for creativity and innovation, reinforcing its role as a tool that enhances strategic and meaningful work. Manufacturing organisations can focus on demonstrating GenAI's broader potential beyond operational tasks, fostering a more profound sense of empowerment and innovation within their workforce.

4.2.3 Resistance and Engagement in Generative AI Adoption

The adoption of GenAI tools has the potential to impact employee engagement and job satisfaction, with the degree of influence depending on how effectively organisations manage resistance to these technologies. While section 4.1.2 'Resistance to Change' explores the broader organisational resistances in GenAI integration, this section focuses on their impact on employees' psychological engagement and satisfaction.

The integration of GenAI tools in manufacturing organisations revealed initial scepticism, particularly around job security in automation-prone roles. As highlighted earlier in section 4.1.2, these concerns were gradually addressed through tailored communication and training strategies. This included department-specific workshops and targeted sessions on use cases like predictive maintenance. However, these initial programmes often emphasised technical applications, limiting broader engagement with GenAI's strategic potential. As Abun et al. (2022) suggest, technological self-efficacy is a key predictor of job satisfaction and adaptability to new systems. Developing these competencies could be pivotal in enabling broader acceptance and application of GenAI tools. In both sectors, tailored training emerged as a critical strategy for building employee trust and confidence. Non-manufacturing organisations leveraged structured CM strategies, including targeted workshops on prompt engineering, gamified learning sessions, and department-specific demonstrations. Leadership advocacy also played a role in building trust, with one respondent noting, “Seeing senior managers actively use these tools made the whole team feel confident about their relevance and impact.”

In manufacturing, fears of job displacement remained a significant barrier to full-scale adoption. One manufacturing manager stated, “There’s always this lingering question of whether the AI is here to help or to replace us.” This highlights the importance of transparent communication that frames GenAI as a complementary tool, alleviating anxieties by demonstrating how it enhances rather than replaces human roles. Legal uncertainties around data privacy and intellectual property further hindered adoption efforts across departments, though they were more pronounced in manufacturing. Resistance in non-manufacturing appeared lower, as employees were generally more open to experimenting with GenAI tools. Nonetheless, unclear communication about long-term benefits occasionally dampened enthusiasm. These insights highlight the importance of tailored CM strategies in addressing resistance and maintaining engagement. Drawing on SDT, addressing employees’ psychological needs for competence, autonomy, and relatedness during transitions can mitigate resistance and foster engagement. This was evident in organisations that encouraged hands-on experimentation with GenAI tools, allowing employees to experience their benefits directly. Similarly, from the JD-R model perspective, insufficient managerial support and unclear communication can increase job demands, leading to disengagement. In manufacturing, where job security concerns are more pronounced, transparent communication about how GenAI will complement existing roles is critical.

Survey data reveals that tailored approaches to CM play a critical role in enhancing employee engagement and satisfaction during GenAI adoption. Employees' prioritisation of hands-on sessions (56% in manufacturing) and clear instructional guides (36% in non-manufacturing) highlights their need for practical support that builds competence and confidence in using new tools. In manufacturing, employees' preference for hands-on training reflects their desire for visible operational benefits, fostering a sense of competence and alignment with their roles. Meanwhile, non-manufacturing employees' emphasis on clear instructions underscores their preference for structure and clarity, enabling them to engage more effectively with GenAI in knowledge-based tasks. These tailored approaches meet employees' psychological needs, increasing their trust and satisfaction with GenAI tools.

These findings underscore the importance of tailored approaches to CM, reflecting sector-specific differences in how practical and informational resources are valued during GenAI adoption. Effective CM not only facilitates adoption but also supports employees' psychological engagement and satisfaction, ensuring these remain central to technological innovation.

4.2.4 Feedback and Employee Engagement

While 'Change Management Strategies – Continuous Feedback and Monitoring' in section 4.1.6 broadly outlines the organisational frameworks for tracking feedback during GenAI adoption, this section emphasises the influence of feedback on employee engagement and satisfaction. Drawing from interview insights, feedback mechanisms in manufacturing industries are often limited to periodic surveys or ad hoc email exchanges. For example, one respondent noted the existence of a monthly feedback questionnaire and user interviews but acknowledged that formal, continuous feedback loops remain underdeveloped. While these tools provide valuable insights, employees in manufacturing frequently expressed a need for more comprehensive mechanisms that actively address concerns about job security and tool functionality. Satisfaction ratings with the GenAI tools used within the organisation ranged from 7/10 to 8/10, with several participants highlighting the need for improved tools and structured support.

In contrast, non-manufacturing organisations demonstrated more diverse approaches to gathering feedback, including structured surveys, employee satisfaction tracking, and usage-based data collection. As one respondent noted, "Usage analytics were leveraged to optimise tool deployment and license allocation, indirectly reflecting employee engagement with GenAI tools." Despite these efforts, some respondents reported challenges in maintaining regular feedback processes in high-paced environments, with satisfaction levels generally ranging from 6/10 to 8/10. Survey insights highlight additional context: 23% of respondents indicated that peer support or mentoring would help them better use GenAI tools. This underscores the potential of informal feedback loops, where employees exchange experiences and collaboratively address challenges related to GenAI. Such peer-driven systems complement formal mechanisms, fostering a culture of mutual learning and engagement while addressing employees' psychological needs for competence and relatedness.

Building on these insights, SDT highlights the critical role of feedback in addressing employees' needs for autonomy, competence, and relatedness. Feedback mechanisms, particularly those embedded in peer mentoring or collaborative environments, empower employees to take ownership of their interactions with GenAI tools. This sense of agency not only mitigates resistance but also fosters sustained engagement. Recent research by Patil, Deshmukh, and Mehta (2024a) extends this perspective by demonstrating that while feedback on AI use improves employee engagement, AI itself can enhance feedback processes. For instance, AI tools can enable personalised and adaptive communication, creating a feedback loop that aligns organisational goals with user needs. In workplace contexts, this dual dynamic positions GenAI as both a subject and an enabler of feedback, amplifying employee satisfaction by tailoring responses to individual experiences and challenges. Moreover, the JD-R model suggests that structured feedback reduces job demands by clarifying uncertainties and aligning tasks with employee capacities. In non-manufacturing contexts, where feedback mechanisms are more advanced, the application of these models appears to contribute to higher levels of perceived satisfaction and engagement compared to manufacturing, where feedback systems remain more fragmented.

In summary, both interview insights and survey data highlight the importance of feedback in fostering employee engagement during GenAI adoption. While formal feedback loops are less common in manufacturing, informal mechanisms like peer mentoring could enhance collaboration and continuous improvement, positioning GenAI as a tool for both operational efficiency and employee engagement.

4.2.5 AI's Role in Talent Retention and Development

The final theme in this section examines GenAI's impact on talent retention and development. Sector-specific dynamics highlight contrasting perceptions of GenAI's potential to drive workforce engagement, professional growth, and job satisfaction. Interview findings reveal that in non-manufacturing industries, employees frequently describe GenAI as a career enabler, offering opportunities for skill enhancement and a focus on strategic, high-value tasks. As one respondent said, "Working with AI gives me a sense of being at the forefront of my industry." This optimism was often linked to structured training programmes and clear messaging about how GenAI supports, rather than replaces, human capabilities. By contrast, employees in manufacturing expressed more profound apprehensions, with many viewing GenAI as a driver of automation and potential job displacement. A participant noted, "AI feels like a tool designed to phase out workers rather than support us." This reflects widespread concerns about workforce reduction and the limited focus on broader professional development.

Survey findings provide additional context to these interview insights. Concerns about GenAI replacing current tasks were cited by 13% of manufacturing employees, compared to just 5% in non-manufacturing, underscoring the heightened anxiety in manufacturing about GenAI's role in workforce automation. These findings highlight the importance of effective training and support to address such fears, helping employees view GenAI as an enabler of skill enhancement and career development rather than a threat to job security.

Research highlights the potential of GenAI to serve as a competitive advantage when strategically implemented. Cui, van Esch, and Phelan (2024) argue that organisations leveraging GenAI not just for automation but to enhance workflows and foster creativity are better positioned to attract and retain top talent. By aligning GenAI with employee-centric goals—such as automating repetitive tasks to enable strategic focus—organisations can create a work environment that promotes innovation and engagement. This is particularly critical in competitive markets, where demonstrating the value of employee contributions and fostering adaptability strengthens both satisfaction and retention. Applying these insights to GenAI adoption and involving employees in the planning and deployment of AI systems can enhance their perception of GenAI as a tool for empowerment and career growth rather than a threat.

In summary, theme 5 highlights the contextual nature of GenAI's impact on talent retention and development. While non-manufacturing sectors leverage GenAI to enhance satisfaction and foster innovation, manufacturing organisations must address specific fears about automation and expand training programmes to focus on long-term skill development. By aligning GenAI integration with employee aspirations and engaging them in its deployment, organisations can maximise both operational efficiency and workforce engagement.

The analysis across these themes underscores the critical role of sector-specific strategies in aligning GenAI adoption with workforce engagement and satisfaction. By addressing challenges and leveraging GenAI as a competitive differentiator, organisations can build resilience and foster employee commitment. The following section, 4.3, explores how the desired productivity gains through the integration of GenAI can be effectively evaluated.

4.3 Assessing Productivity Gains through the Integration of Generative AI (Scheiding, F.)

The assessment of productivity gains is another key aspect when analysing the transformative potential of GenAI. This section aims to address the research question: "*How can the desired productivity gains from the integration of generative AI be assessed?*" The analysis and discussion will focus on six identified themes, drawing on insights from both the manufacturing and non-manufacturing sectors and connecting them to the theoretical frameworks discussed in section 2.5. The themes concern:

1. *Strategic Alignment with Organisational Goals*
2. *Cost-Benefit Analysis for Generative AI Integration*
3. *Measuring Productivity Gains*
4. *Productivity Gains Dependence on the Application*
5. *Perceived versus Actual Productivity Gains*
6. *Balancing Quantitative versus Qualitative Gains*

By interpreting the findings from the interviews and survey data, the following analysis explores how organisations across the sectors are navigating these themes to assess and maximise the potential productivity gains of GenAI adoption. Sectoral differences not only characterise the adoption of GenAI but also determine the methods used to measure its impact. Understanding the challenges and opportunities is a fundamental step in developing practical recommendations for effective integration and long-term success.

4.3.1 Strategic Alignment with Organisational Goals

GenAI plays a pivotal role in aligning organisational strategies with evolving market demands, supporting both short-term objectives and long-term competitiveness. In manufacturing, GenAI drives operational efficiency, accelerates product development, and enhances supply chain optimisation. One participant from the manufactoring sector noted "GenAI aligns with our 'speed to business value' strategy pillar." Similarly, in non-manufacturing sector, GenAI fosters innovation and customer-centricity by enabling tailored service delivery and more efficient decision-making processes. As a respondent from this sector remarked "It supports our vision of combining technology and innovation to drive market leadership."

Beyond supporting existing goals, GenAI enables strategic reinvention. Several organisations have redefined their priorities to leverage GenAI's transformative potential, integrating it into core operations and services. However, such shifts require robust CM strategies, as highlighted in section 4.1 'Effective Change Management for Generative AI Integration', to ensure workforce adaptation and seamless integration. For example, pilot programmes and iterative rollouts help organisations test and refine GenAI applications before scaling, mitigating resistance and fostering trust. The TOE framework underscores the influence of external factors, such as customer expectations and competitive dynamics, in shaping adoption strategies (Tornatzky, Fleischer, and Chakrabarti 1990). Survey data and interviews indicate that manufacturing firms often align GenAI with efficiency-driven goals, while non-manufacturing organisations prioritise innovation and customer-focused applications. Organisational readiness also plays a critical role, as sufficient managerial support and structural preparedness significantly influence the speed and effectiveness of adoption.

Industries with advanced digital infrastructures are better positioned to extract value from GenAI. As Xie and Yan (2024) highlight, the benefits of AI adoption depend on industry-specific conditions, such as technological readiness and innovation ecosystems. Similarly, Khanna and Sharma (2024) note that network spillover effects amplify the benefits of AI adoption in sectors with robust digital infrastructures, reinforcing the interconnected nature of strategic alignment. Participants from both sectors noted that while GenAI tools hold significant potential, successful implementation requires phased integration and alignment with organisational culture. For instance, pilot programmes in manufacturing emphasise operational compatibility, while non-manufacturing sectors focus on enhancing creative processes and customer engagement.

By aligning GenAI adoption with strategic goals, organisations can ensure measurable outcomes, such as enhanced innovation, operational excellence, and market adaptability. This alignment positions GenAI as both a driver of productivity gains and a catalyst for long-term transformation.

4.3.2 Cost-Benefit Analysis for Generative AI Integration

Another recurring theme from the interviews is the need to balance significant financial investments in GenAI with measurable productivity outcomes. Across both sectors, a cautious investment approach was evident, with companies prioritising thorough application testing before committing to significant expenditures. However, some differences and shared challenges emerged across the sectors.

In the manufacturing sector, strict compliance requirements concerning data protection and security have a considerable impact on investment decisions. The utilisation of isolated systems, such as ChatGPT Enterprise, to fulfil these requirements has been identified by interviewees as a factor contributing to increased costs. The integration of chatbots with company-specific data often necessitates extensive customisation and development efforts, thereby increasing overall investment costs. Companies in this sector tend to conduct extensive pilot tests within selected user groups before committing to large-scale investments. The emphasis is on identifying measurable productivity gains before justifying these expenses. As one participant stated, “The high costs for licenses are not yet justified by the current productivity gains.”

Furthermore, a gap between GenAI’s expectations and its actual performance was noted. While the potential of AI tools is widely acknowledged, the lack of consistent productivity outcomes has led to frustration among the management: “AI tools are promising, but their high cost sometimes leaves me questioning the overall value.” Similarly, the non-manufacturing sector prioritises extensive evaluation and pilot phases. One example involved a task force conducting a detailed review of implementation challenges, including costs and data security concerns, before rolling out tools like ChatGPT. As one participant shared, “Licenses are expensive, so we are working to justify ROI through productivity measurement.” This shows the importance of implementing productivity measures. Despite these differences, both sectors share common challenges, such as the delayed realisation of productivity gains and the need for upfront investments in infrastructure and workforce training. Both also acknowledge that such investments are necessary to successfully adopt GenAI. The cautious, methodical approach observed across the industries highlights a shared understanding that the successful integration of GenAI depends on aligning costs with measurable outcomes, mitigating resistance, and ensuring compliance with security standards.

These observations reflect the IT Productivity Paradox, described by Brynjolfsson (1993), where high upfront costs and slow organisational adjustments delay the transformative potential of new technologies. Similar to the early adoption of computers, GenAI demands significant investments in licensing, integration efforts, training, and further organisational change (Saam 2024; Brynjolfsson and Hitt 2000). Furthermore, Necula et al. (2024) and Guo et al. (2024)

identify negative short-term impacts on financial metrics, such as return on assets (ROA), during early adoption phases due to mismatched costs and benefits. However, Brynjolfsson, Rock and Syverson (2017) argue that these investments are justifiable when aligned with long-term organisational strategies, which ensure sustained returns over time. This underscores the importance of leadership to recognise and evaluate intangible factors, such as complementary organisational assets and process adjustments, which Brynjolfsson and Hitt (2000) highlight as essential. They stress that a comprehensive assessment of the impact of technology must account for these intangible costs and benefits in order to uncover its true potential (Brynjolfsson and Hitt 2000). This finding underscores the need for phased investment strategies that align with both financial constraints and broader organisational goals.

The cost-benefit analysis theme reveals the financial and organisational trade-offs companies make to realise productivity gains. Understanding these trade-offs allows organisations to balance immediate investments with long-term returns, which is crucial for effectively assessing the economic feasibility of GenAI adoption.

4.3.3 Measurement of Productivity Gains

The absence of standardised KPIs to measure GenAI's productivity impact poses a significant challenge across both sectors. Organisations rely heavily on experimental approaches, such as tracking feature utilisation or ad hoc feedback, but these methods remain inconsistent and lack scalability. A manufacturing interviewee remarked, "Measurement frameworks are still under development, so many AI-automated or augmented processes remain assessed on an individual level." In this sector, experimental approaches, such as monitoring prompt usage and specific feature adoption, are used to assess value creation and quantify GenAI's impact. For instance, one participant explained, "If certain functions, such as the 'copy button,' are used, we assume that added value has been generated." However, these methods remain inconsistent and lack standardisation across various applications. In the non-manufacturing sector, the challenge lies in employee perceptions of measurement systems. While companies reported visible productivity and communication improvements, some employees expressed concern that these systems might be misinterpreted as control mechanisms, which could impact motivation negatively. A participant noted, “We want an efficiency measurement system, but there’s a risk it might turn into a monitoring mechanism that discourages employees.”

Both sectors face additional challenges due to the young state of GenAI tools in their organisations. Interviewees highlighted that the tools are too new to allow comprehensive assessments of their efficiency and benefits. As one participant shared, “It’s too early to assess overall productivity because some departments are only experimenting with AI tools for their workflows.” Despite these limitations, initial steps are being taken. In manufacturing, companies are experimenting with product-oriented KPIs and real-time tracking of feature utilisation, such as the thumbs-up button, to assess GenAI’s impact. In non-manufacturing, organisations emphasise designing measurement frameworks that align with workforce acceptance. Feedback, gathered through mechanisms like surveys or user ratings, serves as a key data source for iteratively refining these frameworks. However, these methods remain inconsistent and lack standardisation, highlighting the need for more robust systems.

These findings align with critiques in the literature, such as those by Brynjolfsson, Rock, and Syverson (2017), who argue that traditional metrics often fail to capture intangible benefits like stress reduction and creative enhancements. Organisations should adopt hybrid frameworks that combine quantitative indicators, such as task completion rates, with qualitative insights, such as employee feedback on work satisfaction and innovation outcomes (Chatterjee et al. 2021; Mogaji et al. 2024). Necula et al. (2024) further highlight the limitations of current measurement frameworks, calling for innovative methodologies that encompass both quantitative and qualitative aspects. Similarly, Raisch and Krakowski (2021) advocate for augmentation-focused strategies, integrating human and AI capabilities to track synergies, such as enhanced decision-making and problem-solving. These perspectives underscore the need for tailored, hybrid measurement systems that align with organisational objectives while addressing employee concerns. Furthermore, the TAM framework suggests that perceived usefulness and ease of use significantly influence technology adoption and its productivity outcomes (Davis 1989). This highlights the importance of designing measurement systems that are not only accurate but also perceived as fair and non-intrusive, particularly in non-manufacturing roles where employee trust is critical.

In summary, the theme provides a methodological foundation for assessing productivity gains. The lack of standardised KPIs highlights the challenges of quantifying GenAI's impact while emerging frameworks and experimental approaches offer pathways to developing robust, context-specific metrics that capture both quantitative and qualitative outcomes.

4.3.4 Productivity Gains Dependence on the Application

GenAI's productivity gains depend heavily on its application to specific use cases. The most notable efficiencies arise in repetitive, low-cognitive tasks, such as creating meeting minutes or translations. This automation allows employees to allocate more time to creative and strategic tasks. Though, the impact on these higher-level functions remains limited. For instance, one manufacturing company uses an AI tool based on ChatGPT, customised with company-specific data, performs best with tasks such as workshop preparation, analyses, and basic calculations. However, as one participant observed, "Efficiency varies; tools like that work well for repetitive tasks, but we don't see comparable gains in higher-level processes." Non-manufacturing interviewees similarly highlighted GenAI's impact on tasks such as content creation and data analysis, noting significant streamlining in these processes. Nevertheless, the most pronounced productivity gains still appear in repetitive tasks, such as automating routine administrative or data-handling activities. While respondents acknowledged improvements in personal productivity, particularly in automating repetitive tasks, the benefits in creative or analytical tasks remain largely at the individual level rather than translating into systemic organisational gains. One participant summarised this limitation, stating, “The biggest productivity gains come from individual use, not yet from processes.” This underscores the current focus on individual task efficiency in both repetitive and creative contexts, with broader organisational impact yet to be fully realised. Despite these reported benefits, the dependence on clear and relevant use cases and established best practices plays a decisive role in the acceptance and effective utilisation of GenAI.

The observations align with the TAM and TOE framework’s broader theoretical insights. The TAM framework highlights the importance of perceived ease of use and usefulness in determining the adoption of GenAI tools, especially for repetitive and structured tasks, as seen in manufacturing contexts (Mogaji et al. 2024). However, it also underscores that the lack of well-documented use cases and systemic workflows can hinder broader organisational adoption. Similarly, the TOE framework offers a complementary perspective, emphasising the role of organisational readiness and external factors, such as industry-specific innovation ecosystems, in shaping the effective utilisation of GenAI technologies (Chatterjee et al. 2021). These frameworks collectively suggest that while individual-level productivity gains are achievable, realising organisation-wide benefits requires strategic alignment, leadership support, and tailored integration approaches. The survey findings reinforce this need, as 73% of manufacturing and 63% of non-manufacturing respondents identified the absence of structured use cases as a significant barrier to adoption, further highlighting the critical role of organisational and environmental readiness in achieving sustained productivity gains. Developing comprehensive case studies and best practices could address this barrier, as suggested by Chatterjee et al. (2021), who argue that clearly defined applications enhance user acceptance and organisational readiness.

Overall, GenAI's dependence on specific use cases highlights the contextual nature of productivity gains. By identifying tasks where GenAI excels, such as automating repetitive processes and augmenting creative and strategic processes, organisations can assess and optimise its impact in a way that aligns with their unique operational needs.

4.3.5 Perceived versus Actual Productivity Gains

The discrepancy between perceived and actual productivity gains emerged as a significant theme across both sectors. Employees frequently reported that GenAI saves time on repetitive tasks, but these efficiency gains are often offset by the need to review outputs for errors (e.g., hallucinations) and refine prompts. A non-manufacturing interviewee noted, "AI saves time on repetitive tasks, but reviewing outputs or handling hallucinations can take longer than expected." This sentiment was supported in the survey data, where 42% of manufacturing respondents and 59% of non-manufacturing respondents identified 'errors or inaccuracies in AI-generated outputs' as a challenge when using GenAI. This suggests that both sectors face this challenge. However, non-manufacturing roles, which often require high-quality outputs for creative or advisory tasks, may face even more significant challenges in addressing inaccuracies. Despite these challenges, many employees expressed a perception of improved productivity. For example, 88% of respondents in the manufacturing sector view GenAI as beneficial for productivity, yet the majority reported being 'slightly more productive' rather than 'significantly more productive'. Similarly, in non-manufacturing, 85% of respondents felt more productive. Although a higher proportion reported 'no noticeable impact' compared to manufacturing.

These findings indicate that while GenAI offers incremental benefits, it has not yet delivered transformative productivity improvements across organisations. The improper use of GenAI tools and the lack of employee trust in AI outputs further exacerbate these challenges. A manufacturing interviewee observed, "Overestimating AI capabilities leads to inefficiencies, especially when the tools are applied in ways they weren't designed for." Similarly, in non-manufacturing, an interviewee noted, "If employees don't critically evaluate the results, they risk wasting time on corrections." These inefficiencies come from tool limitations and insufficient training, which prevents employees from fully utilising GenAI's capabilities. A notable observation is the expressed need for 'hands-on training sessions', highlighted by 56% of respondents in the manufacturing sector and 33% in the non-manufacturing sector. This disparity suggests that manufacturing employees may encounter more challenges in effectively utilising GenAI tools. Insufficient training could exacerbate the gap between the perceived benefits of GenAI—such as time savings—and the actual productivity gains realised, as employees may struggle to fully leverage the tools without adequate guidance.

The TAM framework provides valuable insights into how perceived usefulness influences employees' initial impressions of productivity gains, even when these perceptions fail to align with measurable outcomes (Chatterjee et al. 2021). As highlighted by Necula et al. (2024), generational differences further complicate this dynamic, with younger employees often demonstrating greater adaptability and proficiency in leveraging GenAI tools compared to their older colleagues. Addressing these generational gaps through tailored training programs can help bridge the divide between perception and reality, aligning subjective impressions with actual performance improvements. However, Mogaji et al. (2024) underscore the lack of systematic frameworks to validate whether perceived improvements are supported by tangible productivity outcomes. This issue is particularly pronounced in non-manufacturing roles, where trust in AI outputs is crucial, and errors or inaccuracies can directly hinder productivity. Integrating qualitative observations, such as employee satisfaction and creativity, into standard productivity metrics is critical for a holistic assessment of GenAI's impact (Mogaji et al. 2024). By adopting these approaches, companies can better evaluate the alignment of subjective perceptions with measurable outcomes, creating a more inclusive and effective framework for GenAI adoption.

This theme bridges the gap between subjective perceptions and measurable outcomes, offering organisations critical insights into how GenAI adoption can be tailored to user needs and expectations. By understanding how employees perceive GenAI's impact versus its actual contributions to productivity, organisations can develop strategies to enhance trust, improve utilisation, and optimise long-term outcomes.

4.3.6 Balancing Quantitative versus Qualitative Gains

In the manufacturing sector, GenAI's impact is primarily observed through quantitative benefits, such as time savings on routine tasks. One interviewee commented, "It helps reduce stress by automating tedious tasks, but we don't track these softer impacts formally." This automation allows employees to shift their focus to other responsibilities, reducing their workload and increasing operational efficiency. While time savings are measurable, qualitative effects—such as stress reduction and enhanced creativity—often go unmeasured, representing a missed opportunity to fully capture GenAI's benefits. The non-manufacturing sector, however, places greater emphasis on the qualitative gains associated with GenAI adoption. Interviewees highlighted that the technology significantly reduces work stress and fosters creativity among employees. One respondent noted: "While we don't track qualitative improvements, employees report feeling less overwhelmed and more creative." Survey findings show that respondents across both sectors recognise GenAI's contribution to fostering creative ideas, 75% in non-manufacturing and 62% in manufacturing.

Although these benefits are challenging to quantify using traditional metrics, employees consistently recognise their value. This illustrates that both sectors frequently fail to assess the qualitative benefits. While traditional metrics, such as time savings and output volume, effectively measure quantitative impacts, they fail to account for intangible outcomes like creativity, improved job satisfaction or enhanced team collaboration. One participant summarised this gap: “While time savings are measurable, the creative boost that AI provides in brainstorming is just as valuable.” This gap in measurement aligns with findings in the literature, emphasising the need for frameworks that integrate both quantitative and qualitative metrics.

Brynjolfsson, Rock, and Syverson (2017) emphasise that traditional productivity metrics often overlook the qualitative and transformative aspects of emerging technologies like GenAI. These limitations are especially evident in early adoption phases, where intangible benefits, such as reduced stress and enhanced creativity, are not immediately visible in KPIs. Similarly, Chatterjee et al. (2021) argue that integrating user-centred metrics grounded in the TAM can better reflect employees’ perceptions of qualitative workflow improvements. Further, McKinsey & Company (2024) report that while many organisations acknowledge the potential of GenAI to drive value, only a few have adopted advanced metrics to capture both quantitative and qualitative gains. Top-performing organisations, as noted by Bain & Company (2024), adopt hybrid models to integrate financial KPIs with indicators of engagement and innovation. This balanced approach ensures that qualitative gains, such as enhanced creativity and stress reduction, are recognised as critical drivers of organisational success. This balanced approach aligns with Mogaji et al. (2024), who advocate for combining quantitative data, such as task completion times, with qualitative insights, including employee feedback on stress reduction and collaborative problem-solving. In both manufacturing and non-manufacturing industries, the survey findings highlight the predominance of quantitative benefits, with 79% of respondents valuing time savings and 57% recognising productivity gains. However, qualitative improvements, such as reduced stress and creative support, are equally acknowledged but remain underutilised. This underscores the need for organisations to develop comprehensive measurement systems that integrate both quantitative and qualitative metrics. The dual approach will help to capture the transformative potential of GenAI fully. This theme explores the dual nature of productivity gains, providing a comprehensive framework for assessing both measurable outcomes, like time savings, and intangible benefits, such as creativity and stress reduction.

Overall, the analysis of the five themes underscores the necessity of adopting a holistic approach to assessing productivity gains from GenAI. This requires balancing both quantitative and qualitative aspects of its utilisation. Key factors, including specific use cases, robust productivity measurement frameworks, the alignment of perceived and actual impacts, and thorough cost-benefit analyses, emerge as critical considerations. The findings highlight the importance of tailoring measurement frameworks to sector-specific needs and organisational contexts, ensuring that GenAI's integration is both strategically aligned and operationally effective.

Building on the analysis and discussion of the central themes for the topics—CM strategies, employee engagement, and the assessment of productivity gains—this study underscores GenAI's transformative potential in organisations. Simultaneously, the findings highlight the intricate challenges associated with CM theories, employee satisfaction, and the evaluation of productivity gains. Chapter 5 builds upon these insights to propose practical recommendations. These recommendations address the identified challenges, offering actionable strategies to leverage GenAI opportunities while addressing complexities fully.

5 Practical Recommendations for Companies (Individual)

Following the analysis and discussion of the key themes identified in this study, it becomes evident that the rapid pace of GenAI development and the widespread excitement about its capabilities create a pressing imperative for organisations to move from consideration to action. As highlighted by interviewees in both manufacturing and non-manufacturing sectors, the crucial step is to simply "start somewhere". Waiting for perfect conditions can lead to lost opportunities and diminished competitiveness. Instead, businesses should view GenAI as a strategic enabler, an invitation to invest, reassess existing business models, and develop the organisational agility needed to thrive amid constant technological and market evolution. Although the recommendations presented here draw on sector-specific insights, the underlying principles are broadly transferable, offering a valuable reference point for companies across various industries.

5.1 Change Management as a Foundation for Integration (Krause, S.)

Introducing GenAI into organisational processes requires more than technical adjustments; it demands a cultural shift supported by strong CM. The findings underline the importance of managing expectations, fostering stakeholder inclusion, tailoring communication and training, and maintaining flexibility to adapt to ongoing developments. Effective CM is not just about mitigating resistance but managing expectations. The investigated companies showed that, while GenAI initially sparks excitement, unmet expectations from immature technology or unclear use cases might cause frustration. Transparent communication about capabilities, limitations, and the iterative nature of adoption ensures realistic perceptions and sustained engagement. Creating awareness about the iterative nature of adoption further supports alignment between expectations and outcomes. Stakeholder inclusion emerges as a key factor, involving not only employees but also leadership, workers' councils, and IT teams early in the process. Proactively addressing compliance, privacy, and practical concerns reduced resistance and increased organisational readiness. Tailored communication and training strategies foster competence and confidence. Personalised messaging clarifies the value of GenAI tools for specific roles, while hands-on training—such as peer mentoring and collaborative workshops—enables experimentation and skill-building. Sharing best practices and showcasing real-world use cases further motivated adoption. Leadership has a critical role in demonstrating visible support and championing the tools. Early involvement of leaders ensures alignment with organisational goals and secures resources, while their active engagement inspires employees to embrace the change. In some analysed cases, employees drove initial adoption, motivating leadership to take on a more supportive role. Continuous feedback mechanisms support dynamic CM by enabling organisations to adapt strategies in real time. Surveys, workshops, and anonymous reporting systems allow rapid identification of challenges while monitoring usage patterns refined workflows and user experiences. This iterative approach helps maintain momentum and strengthens trust. Flexibility in CM strategies ensures success amidst the fast-evolving nature of GenAI tools. Phased implementations, beginning with pilot projects, allow organisations to test and refine their approaches before scaling adoption. This gradual rollout can minimise disruption while aligning adoption with broader goals.

5.2 Enhancing Employee Engagement and Satisfaction (Sanatpour, N.)

The thoughtful implementation of GenAI can significantly enhance employee engagement and satisfaction, provided organisations adopt strategies that align technology deployment with employee needs and expectations. Insights from the interviews reveal several actionable recommendations to achieve this alignment. Organisations should involve employees early in the GenAI implementation process, particularly through pilot projects that allow hands-on experience with the tools. This approach not only builds confidence but also generates valuable feedback for refining tool functionality. One interviewee noted that employees were particularly enthusiastic when they saw their suggestions directly impact tool performance, reinforcing a sense of ownership and engagement.

Clear, role-specific training is also essential to demonstrate how GenAI can enhance employees' daily workflows. These sessions should focus on tangible benefits, such as automating repetitive tasks or simplifying complex processes, and be supported by accessible resources like on-demand tutorials or peer mentoring systems. Additionally, appointing AI advocates or change champions provides employees with approachable sources of guidance, ensuring they feel empowered rather than overwhelmed by the technology. Beyond this, organisations can further enhance engagement by creating a personalised experience with GenAI tools. For instance, some employees reported a sense of excitement and connection when companies developed in-house chatbots with unique names and branding that reflected the organisation's culture. Such personalisation makes tools feel more approachable and aligned with company values, reinforcing employee buy-in.

While the strategic shift observed in one organisation was not explicitly identified as a theme in the inductive analysis, it emerged as a significant insight during the interview review process. The adoption of GenAI tools, in this case, not only optimised workflows but also drove a reorientation of the company's overall strategy, reflecting the transformative potential of these technologies. This underscores the strong connection between employee engagement and strategic alignment, as employees demonstrated higher levels of enthusiasm and motivation when actively involved in discussions about the broader strategic implications of GenAI adoption. By positioning employees as key contributors to the company's evolving strategy, organisations can foster a deeper sense of ownership and engagement. Recommendations include integrating GenAI into broader organisational strategy sessions and ensuring that employees are informed about and participate in shaping these shifts.

Supporting employees in unlearning outdated processes is another critical aspect of successful GenAI implementation. Structured workshops can guide employees through the transition, helping them let go of workflows that no longer add value. Transforming these workshops into engaging, event-like experiences or incorporating playful elements, such as gamified challenges or rewards, can further stimulate interest and active participation. Celebrating successes—whether through individual recognition or team-wide achievements—reinforces the positive impact of GenAI on both operational outcomes and employee satisfaction. Transparent and continuous communication about GenAI's capabilities, limitations, and compliance with ethical standards is equally vital. This is particularly relevant in manufacturing sectors, where data security and job displacement concerns are more prominent. Regular updates, Q&A sessions, and channels for anonymous feedback ensure that employees feel heard and supported throughout the implementation journey.

5.3 Measuring and Maximising Productivity Gains (Scheiding, F.)

For a proper evaluation of GenAI's impact, organisations must take a holistic approach to productivity measurement. While quantitative metrics like time savings and efficiency improvements provide clear evidence of GenAI's benefits, qualitative factors such as reduced stress, improved decision-making, and enhanced creativity are equally important. Together, these measures offer a balanced view of how GenAI contributes to organisational performance. Careful planning is required to identify where GenAI can deliver the most significant value. As interviewees highlighted, the need to define clear use cases and goals at the outset, ensuring alignment between technological capabilities and organisational needs. High-impact use cases, such as automating routine administrative tasks or streamlining production processes, should be prioritised. Pilot projects allow organisations to test these applications in a controlled environment and refine their approach before scaling. Moreover, while some initiatives, such as personalising GenAI tools, may involve higher initial investments, the potential benefits—

such as improved adoption rates and stronger alignment with organisational culture—highlight the need for comprehensive cost-benefit analyses. Clearly documented best practices and case studies can further enhance the effectiveness of pilot programmes, addressing challenges related to employee trust and adoption.

Long-term tracking is crucial to bridge the gap between initial perceptions and actual productivity gains, ensuring delayed benefits such as enhanced collaboration and creativity are fully realised. Many of the benefits of GenAI—such as increased creativity or enhanced collaboration—become more apparent over time as employees grow accustomed to the tools. Regularly revisiting metrics ensures that organisations capture these delayed benefits and can adapt their strategies to maximise long-term returns. For example, organisations should establish hybrid measurement frameworks that combine quantitative indicators, such as task completion times, with qualitative metrics, such as employee feedback on stress reduction, creative engagement, or perceived value from personalised tools. Initiatives like in-house branded chatbots can deliver intangible benefits, such as reinforcing cultural alignment and trust, which should be systematically evaluated to justify their higher implementation costs. This dual approach aligns with findings from both the survey data and the literature, which underscore the importance of capturing intangible benefits. The successful measurement of productivity gains relies not only on robust frameworks but also on a foundation of effective CM and deep employee engagement. Technological advancements must be accompanied by cultural readiness to ensure their full potential is realised.

Transparent communication about the opportunities and limitations of GenAI fosters employee trust and engagement while supporting honest feedback. This is critical for understanding qualitative benefits, such as creativity and collaboration. In sectors with strict compliance requirements, prioritising data security and privacy—through measures like deploying isolated systems such as ChatGPT Enterprise—ensures regulatory compliance while enabling efficiency gains. Customised solutions, though costlier, further align with organisational needs by addressing privacy concerns and enhancing user adoption. These practices provide a foundation for quantifying productivity gains and refining strategies to maximise GenAI's long-term value.

The recommendations presented here, derived from the analysis and interview insights, form a cohesive blueprint for GenAI integration. While rooted in specific industry contexts, the core principles—robust CM, deep employee engagement, and balanced productivity assessment—can be applied across various organisational settings. By addressing uncertainties, fears, and ethical considerations head-on, companies can strengthen their foundation for long-term adaptability and competitiveness. As this chapter concludes, it provides a foundation for the subsequent sections on conclusions and limitations. These final chapters will reflect on the broader implications of this research, acknowledging its boundaries and exploring opportunities for further study. By acting now and taking a deliberate, inclusive approach, organisations can position themselves not only to benefit from GenAI today but to adapt and thrive in an increasingly technology-driven future.

6 Conclusion (Group Part)

6.1 Summary of the Key Aspects

This work project aimed to investigate the transformative impact of GenAI in supporting organisational change, enhancing employee engagement, and measuring productivity gains in both manufacturing and non-manufacturing sectors. The findings highlight GenAI's potential to drive significant improvements in operational efficiency, foster innovation, and enhance employee satisfaction when implemented strategically. However, the research also identified critical challenges organisations must address to fully harness its benefits.

Effective CM emerges as a cornerstone for successful GenAI integration. Across sectors, managing awareness and expectations, leadership advocacy, clear communication and tailored training are consistently identified as key factors for overcoming resistance and fostering employee engagement. Both sectors value customised messaging, with manufacturing favouring hands-on training and structured communication and non-manufacturing emphasising collaboration. The iterative nature of GenAI adoption reveals the necessity for flexible approaches, where ongoing updates and feedback loops are integrated into the change process. The findings align with existing CM theories, such as ADKAR, while emphasising the need for faster adaptation cycles due to the rapid evolution of GenAI technologies.

Employee engagement and satisfaction remain central themes in this research, with GenAI offering significant opportunities to reduce repetitive tasks and enhance meaningful work. While employees generally show enthusiasm for GenAI tools, the study reveals that inadequate training and unclear use cases often hinder effective adoption. The findings demonstrate that fostering a culture of continuous learning and involving employees in pilot projects can mitigate resistance and build trust. Moreover, organisations that position GenAI as a tool for augmentation rather than replacement report higher levels of employee acceptance and satisfaction. This highlights the importance of addressing emotional and practical concerns to ensure a smooth transition.

The study also explored the assessment of productivity gains from GenAI, revealing both quantitative and qualitative impacts. While time savings and task automation are commonly reported, qualitative benefits, such as reduced stress and increased creativity, remain underutilised in assessment frameworks. The findings call for a hybrid approach to measuring productivity, combining traditional metrics with insights into employee well-being and collaboration. Organisations in both sectors express challenges in aligning perceived productivity gains with actual outcomes, underscoring the need for robust evaluation frameworks that address this gap. Additionally, the research highlights the dependency of GenAI's success on specific use cases, reinforcing the importance of strategic alignment and tailored applications.

Key success factors and best practices are identified throughout the study, including the establishment of change champions, voluntary participation in pilot projects, and the development of clear guidelines. Both sectors recognise the value of iterative adoption strategies, where small-scale implementations are tested and refined before broader rollouts. These approaches not only enhance organisational agility but also ensure that GenAI tools are integrated in a way that aligns with broader business objectives. By addressing these aspects, the study provides insights into the three research questions: effective change management strategies (RQ1), the impact of GenAI on employee engagement and satisfaction and how organisations can enhance these outcomes (RQ2), and the importance of defining measurable goals and tracking outcomes to assess productivity gains (RQ3). Despite these promising findings, the study acknowledges significant challenges, such as legal and compliance concerns, resistance among leadership and workers' councils, and the high costs associated with

GenAI adoption. Addressing these barriers requires a comprehensive approach that includes transparent communication, strong leadership, and investments in employee training and infrastructure.

In conclusion, the integration of GenAI offers organisations transformative opportunities but requires deliberate planning and execution to overcome associated complexities. By prioritising CM, fostering employee engagement, and adopting balanced productivity assessment frameworks, organisations can position themselves to maximise the benefits of GenAI while navigating its challenges. This research provides actionable insights and recommendations to guide organisations in leveraging GenAI's potential effectively, laying a foundation for sustainable growth and innovation in an increasingly AI-driven landscape.

6.2 Limitations of the Study

Despite the comprehensive analysis and integration of both qualitative and quantitative data, this study has several limitations that should be acknowledged to provide a balanced perspective on its findings. These limitations pertain to the scope, methodology, contextual factors, and evolving nature of GenAI technologies.

Scope of the Study

The study focused exclusively on the integration and impact of GenAI on employee engagement, satisfaction, and the assessment and realisation of productivity gains. The focus was structured around three key dimensions: the effectiveness of CM strategies during GenAI adoption, the impact of GenAI on employee engagement and job satisfaction, and how productivity gains from GenAI can be measured. While this allowed for in-depth exploration of these themes, it excluded the analysis of other AI tools and their potential influence on similar organisational outcomes. This narrow lens may have limited a more holistic understanding of AI's broader implications. Furthermore, sustainability considerations were not addressed, even though they are increasingly relevant in evaluating technological adoption. Lastly, while the study centred on GenAI's unique capabilities, it did not investigate how complementary AI tools might interact with GenAI to shape organisational and employee outcomes.

Methodological Constraints

The research employed a mixed-methods approach, combining qualitative interviews with quantitative surveys, providing a robust analysis foundation. However, certain methodological constraints should be noted. The relatively small survey sample was a practical limitation due to the emerging nature of GenAI adoption, which restricted the availability of diverse case studies at this stage. As GenAI adoption continues to grow and policies mature, future studies could expand the sample size to include a broader range of companies and industries for greater reliability. Additionally, the survey focused on comparing manufacturing and non-manufacturing sectors, leaving correlations between variables such as professional roles or years of experience unexplored. While this was beyond the study's scope, such analyses could provide valuable insights into additional factors influencing employee engagement or perceptions of GenAI.

While interviews included diverse roles, IT professionals were more heavily represented due to their pivotal role in implementing GenAI systems and providing technical insights. Although this emphasis offered a critical understanding of GenAI's operational challenges, it may have underrepresented perspectives from employees in non-technical roles or those with less direct engagement with GenAI. Additionally, the study was geographically focused on German organisations, excluding international comparisons. This limits the findings' applicability to regions such as North America or Asia, where regulatory frameworks, adoption rates, and cultural attitudes towards GenAI differ significantly.

Contextual Factors

The contextual focus of this research further constrained its applicability to broader organisational contexts. The study compared manufacturing and non-manufacturing sectors but did not comprehensively explore specific sub-sectors within these categories. Moreover, it did not examine how differences in roles and hierarchical levels within organisations shape the adoption and outcomes of GenAI. For example, while leadership roles might focus on leveraging AI for strategic gains, lower-level roles might encounter challenges in integrating AI into routine workflows. Similarly, generational differences in digital literacy and openness to AI tools were not considered. Younger employees, often more familiar with digital environments, may find it easier to adapt to AI, whereas older employees might require more extensive training and support. These factors could create dynamics that influence both individual and organisational outcomes, suggesting the need for a more nuanced understanding of these variations in future research. As a result, findings may be less applicable to industries with unique operational or cultural characteristics.

Furthermore, the study did not differentiate between small and medium-sized enterprises (SMEs) and multinational enterprises (MNEs). Variations in resources, organisational readiness, and adoption rates between smaller and larger companies were therefore not captured. Another limitation arises from the emphasis on organisations within Germany, which are subject to strict data privacy regulations. These regulations often require higher investments and longer adoption timelines compared to countries with less restrictive environments. Consequently, findings may not translate directly to organisations operating under different regulatory frameworks.

Analytical Limitations

The study predominantly captured short-term outcomes, such as initial reactions to GenAI, without examining longer-term impacts on workforce structure, innovation, or employee well-being. These aspects often require extended observation as organisations adapt to the technology. Additionally, the rapid evolution of GenAI capabilities means the findings could quickly become outdated, particularly as new tools, applications, and best practices emerge. Ethical considerations, particularly related to algorithmic fairness, bias, and transparency, play a crucial role in shaping employee trust and the broader acceptance of GenAI. These issues are critical in shaping trust and broader acceptance of GenAI but were outside the study's scope.

6.3 Future Research Opportunities

Despite these limitations, the study provides significant insights into the integration of GenAI, offering a strong foundation for further exploration in both research and practice. Expanding the geographical scope to include international comparisons could provide valuable insights into how regional and cultural factors influence the adoption and outcomes of GenAI. Similarly, examining organisations of varying sizes could shed light on the unique challenges and opportunities faced by SMEs versus MNEs. Future studies should also explore the long-term impacts of GenAI, particularly its influence on workforce dynamics, employee adaptability, and organisational and financial performance. Investigating ethical implications, such as algorithmic fairness and data governance, could further enrich the understanding of GenAI's role in creating equitable and inclusive workplaces. Lastly, integrating complementary AI tools into the analysis could provide a more comprehensive perspective on how organisations can maximise the value of AI-driven transformation. By addressing these limitations, future research can refine strategies for implementing GenAI across industries, fostering not only operational efficiency but also ethical accountability and long-term workforce adaptability.

7 References

Abdallah, Yasser Omar, Essam Shehab, and Ahmed Al-Ashaab. 2021. "Digital Transformation Challenges in the Manufacturing Industry." In Advances in Manufacturing Technology XXXIV, 9–14. IOS Press. https://doi.org/10.3233/ATDE210004.

Abun, D., J. P. G. Javier, J. I. B. Gamponia, T. Magallanes, and F. P. Julian. 2022. "The Effect of Employees' Computer and Internet Self-Efficacy on Job Satisfaction." International Journal of Research in Business and Social Science, 11(3): 130–140. https://doi.org/10.20525/ijrbs.v11i3.1727.

Agustianingsih, R., and A. Mahmudi. 2019. "How to Design Open-Ended Questions? : Literature Review." Journal of Physics: Conference Series 1320 (1): 012003. https://doi.org/10.1088/1742-6596/1320/1/012003.

AI Expert Network. 2023. Case Study: How Nike is Leveraging AI Across its Operations. Accessed December 5, 2024. https://aiexpert.network/case-study-how-nike-is-leveraging-ai-across-its-operations/.

Al Naqbi, Humaid, Zied Bahroun, and Vian Ahmed. 2024. "Enhancing Work Productivity through Generative Artificial Intelligence: A Comprehensive Literature Review." Sustainability 16(3): 1166. https://doi.org/10.3390/su16031166.

Antwi, Stephen Kwadwo, and Kasim Hamza. 2015. "Qualitative and Quantitative Research Paradigms in Business Research: A Philosophical Reflection." European Journal of Business and Management, 7(3): 217–225. https://www.iiste.org/Journals/index.php/EJBM/article/view/19543

Autodesk. 2024. "Autodesk Fusion 360: Basics of Manufacturing Fundamentals." Accessed November 1, 2024. https://www.autodesk.com/products/fusion-360/blog/autodesk-fusion-360-basics-manufacturing-fundamentals.

Autodesk. 2023. "Yamaha Motor Company Uses Generative Design to Develop a New Electric Vehicle for Challenging Terrain." Accessed December 1, 2024. https://www.autodesk.com/design-make/articles/yamaha-ev.

Avdeeva, Irina, Lyudmila Kulakova, Vasiliy Krestov, Rashid Mugutdinov, and Kaisar Alpysbayev. 2021. "Change Management Strategy in the Framework of Digital Transformation of Economic System Business Models." In 3rd International Scientific Conference on Innovations in Digital Economy, 293–300. Saint - Petersburg Russian Federation: ACM. https://doi.org/10.1145/3527049.3527121.

Ba, Zedong David Herbert, Qian Wang, Chen Chen, Ziwen Liu, Luke Lu Chang Peh, and Robert Lee Kong Tiong. 2024. "Change Management of Organizational Digital Transformation: A Proposed Roadmap for Building Information Modelling-Enabled

Facilities Management.” Buildings 14 (1): 27. https://doi.org/10.3390/buildings14010027.

Bain & Company. 2024. Technology Report 2024: Technology Meets the Moment as AI Delivers Results. Bain & Company. Accessed December 5, 2024. https://www.bain.com/insights/topics/technology-report/.

Bakker, A. B., and E. Demerouti. 2007. “The Job Demands-Resources Model: State of the Art.” Journal of Managerial Psychology, 22(3): 309–328. https://doi.org/10.1108/02683940710733115.

Bellantuono, Nicola, Angela Nuzzi, Pierpaolo Pontrandolfo, and Barbara Scozzi. 2021. “Digital Transformation Models for the I4.0 Transition: Lessons from the Change Management Literature.” Sustainability 13 (23): 12941. https://doi.org/10.3390/su132312941.

Bi, Y. 2023. “Analysis of the Application of Generative AI in Business Management.” Asia-Pacific Economic Review6(1): 36–49. https://doi.org/10.56028/aemr.6.1.36.2023.

BMW. 2024. “AI Design and Digital Art.” Accessed December 5, 2024. https://www.bmw.com/en/design/ai-design-and-digital-art.html.

BMW Group. 2022. “BMW iX Flow with E Ink: A New Way to Experience Exterior Colour.” Accessed December 5, 2024. https://www.bmwgroup.com/en/news/general/2022/ixflow.html.

Bowling, Nathan A., and Jeffrey M. Cucina. 2015. “Robert Hoppock: Early Job Satisfaction and Vocational Guidance Pioneer.” The Industrial-Organizational Psychologist, 53(2): 109–113. https://web.p.ebscohost.com/ehost/detail/detail?vid=0&sid=26265315-3bfd-4b5b-a31f-944af0ec69be%40redis&bdata=JkF1dGhUeXBlPXNzbyZzaXRlPWVob3N0LWxpdmUmc2NvcGU9c2l0ZQ%3d%3d#AN=110232273&db=a9h.

Braun, Virginia, and Victoria Clarke. 2006. “Using Thematic Analysis in Psychology.” Qualitative Research in Psychology 3 (2): 77–101. https://doi.org/10.1191/1478088706qp063oa.

Bresnahan, Timothy F., and Manuel Trajtenberg. 1995. “General Purpose Technologies: Engines of Growth?” Journal of Econometrics 65(1): 83–108. https://doi.org/10.1016/0304-4076(94)01598-T.

Brinkmann, Svend, and Steinar Kvale. 2018. Doing Interviews. London: SAGE Publications. https://doi.org/10.4135/9781529716665.

Brynjolfsson, Erik, and Andrew McAfee. 2014. The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. New York: W.W. Norton.

Bryniolfsson, Erik, and Lorin M. Hitt. 1996. "Paradox Lost? Firm-Level Evidence on the Returns to Information Systems Spending." Management Science 42(4): 541–58. https://doi.org/10.1287/mnsc.42.4.541.

Brynjolfsson, Erik, and Lorin M. Hitt. 2000. "Beyond Computation: Information Technology, Organizational Transformation and Business Performance." Journal of Economic Perspectives, 14(4): 23–48. http://dx.doi.org/10.1257/jep.14.4.23.

Brynjolfsson, Erik, Daniel Rock, and Chad Syverson. 2017. "Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics." NBER Working Paper Series, No. 24001. https://doi.org/10.3386/w24001.

Brynjolfsson, Erik, Daniel Rock, and Chad Syverson. 2021. "The Productivity J-Curve: How Intangibles Complement General Purpose Technologies." American Economic Journal: Macroeconomics 13(1): 333–72. https://doi.org/10.1257/mac.20180386.

Brynjolfsson, Erik. 1993. "The Productivity Paradox of Information Technology: Review and Assessment." Communications of the ACM 36(12): 66–77. https://doi.org/10.1145/163298.163309.

Burnes, Bernard. 2008. Approaches to Change Management. In Managing Change: A Strategic Approach to Organisational Dynamics, 4th ed., 259–86. Harlow: Prentice Hall.

Cambridge Dictionary. 2024a. "Manufacturing Industry." Cambridge Dictionary. Accessed November 6, 2024. https://dictionary.cambridge.org/dictionary/english/manufacturing-industry.

Cambridge Dictionary. 2024b. "Non-Manufacturing." Cambridge Dictionary. Accessed November 6, 2024. https://dictionary.cambridge.org/dictionary/english/non-manufacturing.

Chatterjee, Sheshadri, Nripendra P. Rana, Yogesh K. Dwivedi, and Abdullah M. Baabdullah. 2021. "Understanding AI Adoption in Manufacturing and Production Firms Using an Integrated TAM-TOE Model." Technological Forecasting and Social Change 170: 120880. https://doi.org/10.1016/j.techfore.2021.120880.

Chhatre, Rohan, and Seema Singh. 2024. "AI And Organizational Change: Dynamics And Management Strategies." https://doi.org/10.13140/RG.2.2.16082.98246.

Choi, Youngkeun. 2021. "A Study of Employee Acceptance of Artificial Intelligence Technology." European Journal of Management and Business Economics 30 (3): 318–30. https://doi.org/10.1108/EJMBE-06-2020-0158.

CNBC. 2024. “How Amazon is using generative AI to drive more same-day deliveries.” Accessed December 5, 2024. https://www.cnbc.com/2024/09/17/how-amazon-is-using-generative-ai-to-drive-more-same-day-deliveries.html.

Coch, Lester, and John R. P. French. 1948. “Overcoming Resistance to Change.” Human Relations 1 (4): 512–32. https://doi.org/10.1177/001872674800100408.

Davis, Fred D. 1989. “Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology.” MIS Quarterly 13(3): 319–40. https://doi.org/10.2307/249008.

Deci, Edward L., Anja H. Olafsen, and Richard M. Ryan. 2017. “Self-Determination Theory in Work Organizations: The State of a Science.” Annual Review of Organizational Psychology and Organizational Behavior, 4: 19–43. https://doi.org/10.1146/annurev-orgpsych-032516-113108.

Dent, Eric, and Susan Goldberg. 1999. “Challenging ‘Resistance to Change.’” The Journal of Applied Behavioral Science 35 (March):25–41. https://doi.org/10.1177/0021886399351003.

Devaraj, Sarv, and Rajiv Kohli. 2003. “Performance Implications of Information Technology: A Process-Oriented Perspective.” Management Science 49(1): 19–36. https://doi.org/10.1287/mnsc.49.1.19.12780.

Doanh, D. C., Z. Dufek, J. Edjys, R. Ginevičius, P. Korzynski, G. Mazurek, J. Paliszkiewicz, K. Wach, and E. Ziemba. 2023. “Generative AI in the Manufacturing Process: Theoretical Considerations.” Engineering Management in Production and Services, 15(4): 76–89. https://doi.org/10.2478/emj-2023-0029.

Eapen, Tojin T., Daniel J. Finkenstadt, Josh Folk, and Lokesh Venkataswamy. 2023. “How Generative AI Can Augment Human Creativity.” Harvard Business Review, 101(4): 56–64. https://hbr.org/2023/07/how-generative-ai-can-augment-human-creativity.

Feuerriegel, Stefan, Timo Heinz, David Joseph, Ralf Peters, and Stefan Seiler. 2024. “Generative AI in Business and Society: Challenges and Opportunities.” SSRN Working Paper. https://doi.org/10.2139/ssrn.4443189.

Firican, Diana Andreea. 2023. “Change Management in the Context of Digital Transformation: A Comparison Between a Theoretical Model and Successful Approaches in Organizations.” In New Trends in Sustainable Business and Consumption, 472–79. Editura ASE. https://doi.org/10.24818/BASIQ/2023/09/056.

Flick, Uwe. 2011. Triangulation: Eine Einführung. 3. Aufl. Erscheinungsort nicht ermittelbar: VS Verlag für Sozialwissenschaften (GWV).

GE Vernova. 2024. Equipment Downtime Predictive Analytics. Accessed December 5, 2024. https://www.gevernova.com/software/products/asset-performance-management/equipment-downtime-predictive-analytics.

Goyal, Charu, and Manoj Patwardhan. 2018. “Role of Change Management Using ADKAR Model: A Study of the Gender Perspective in a Leading Bank Organisation of India.” International Journal of Human Resources Development and Management 18: 297. https://doi.org/10.1504/IJHRDM.2018.093442.

Grashoff, Imke, Thomas Mayer, and Jan Recker. 2024. “Challenges, Success Factors, and Potential Benefits of GenAI Development: Insights from an Ongoing Case Study at a German Automotive Manufacturer.” ICIS 2024 Proceedings, December 15. https://aisel.aisnet.org/icis2024/aiinbus/aiinbus/20.

Guo, Xiaojie, Mengmeng Li, Yanlin Wang, and Abbas Mardani. 2023. “Does Digital Transformation Improve the Firm’s Performance? From the Perspective of Digitalization Paradox and Managerial Myopia.” Journal of Business Research 163: 113868. https://doi.org/10.1016/j.jbusres.2023.113868.

Hackman, J. R., and G. R. Oldham. 1976. “Motivation Through the Design of Work: Test of a Theory.” Organizational Behavior and Human Performance, 16(2): 250–279.

Hadi, Musadaq A., Mohammed Najm Abdulredha, and E. Hasan. 2023. “Introduction to ChatGPT: A New Revolution of Artificial Intelligence with Machine Learning Algorithms and Cybersecurity.” Science Archives 4 (4): 276–285. https://doi.org/10.47587/SA.2023.4406.

Hellwig, Vanessa. 2024. “Tech Hubs within Cities—Determinants and Dynamics.” The Annals of Regional Science 73 (4): 1885–1916. https://doi.org/10.1007/s00168-024-01299-6.

Heracleous, Loizos, and Jean Bartunek. 2020. “Organization Change Failure, Deep Structures and Temporality: Appreciating Wonderland.” SSRN Scholarly Paper. Rochester, NY. https://doi.org/10.2139/ssrn.3602800.

Hiatt, Jeffrey M., and Timothy J. Creasey. 2012. Change Management: The People Side of Change. Prosci Learning Center Publications.

Höck, Martin. 2024. “How Do German Companies Use Generative Artificial Intelligence (AI)?” KPMG Germany. https://kpmg.com/de/en/home/insights/2024/10/how-are-german-companies-using-generative-ai.html.

Hong, Quan Nha, Pierre Pluye, Mathieu Bujold, and Maggy Wassef. 2017. “Convergent and Sequential Synthesis Designs: Implications for Conducting and Reporting Systematic Reviews of Qualitative and Quantitative Evidence.” Systematic Reviews 6 (1): 61. https://doi.org/10.1186/s13643-017-0454-2.

Jasper.ai. 2024. “Elevate All Marketing and All Marketers with the Power of AI.” Accessed November 4, 2024. https://www.jasper.ai/company.

Ji, Ziwei, Nayeon Lee, Xinjiang Lu, Hsiu-Yuan Liang, Zhuohan Li, Yonatan Belinkov, and Percy Liang. 2023. “Survey of Hallucination in Natural Language Generation.” Transactions of the Association for Computational Linguistics 11: 709–26. https://doi.org/10.1162/tacl_a_00559.

Johns Hopkins University. 2022. “Artificial Intelligence Detects Sepsis Early, Saving Lives.” Accessed December 5, 2024. https://hub.jhu.edu/2022/07/21/artificial-intelligence-sepsis-detection/.

Kahn, W. A. 1990. “Psychological Conditions of Personal Engagement and Disengagement at Work.” Academy of Management Journal, 33(4): 692–724. https://doi.org/10.5465/256287.

Kaplan, Andreas, and Michael Haenlein. 2019. “Siri, Siri, in My Hand: Who’s the Fairest in the Land? On the Interpretations, Illustrations, and Implications of Artificial Intelligence.” Business Horizons 62(1): 15–25. https://doi.org/10.1016/j.bushor.2018.08.004.

Kewalramani, Chhaya, and Shantanu Neema. 2024. “Generative AI In Change Management: A New Framework For Organizational Transformation.” INTERNATIONAL JOURNAL OF RESEARCH AND ANALYTICAL REVIEWS 11 (April):838–42. https://ijrar.org/papers/IJRAR24B1389.pdf

Khanna, Rajeev, and Chandan Sharma. 2024. “Beyond Information Technology and Productivity Paradox: Analysing the Channels of Impact at the Firm-Level.” Technological Forecasting and Social Change 203: 123369. https://doi.org/10.1016/j.techfore.2024.123369.

Kotter, John, and Leonard Schlesinger. 2008. “Choosing Strategies for Change.” Harvard Business Review 57 (July):106–14. https://doi.org/10.1007/978-1-349-20317-8_21.

Krakowski, Sebastian, Julia Luger, and Sebastian Raisch. 2022. “Artificial Intelligence and the Changing Sources of Competitive Advantage.” Strategic Management Journal 44 (6): 1425–52. https://doi.org/10.1002/smj.3387.

Krithikadatta, Jogikalmat. 2014. “Normal Distribution.” Journal of Conservative Dentistry and Endodontics 17, no. 1: 96. https://doi.org/10.4103/0972-0707.124171.

Martela, Frank, and Richard M. Ryan. 2019. “Distinguishing Between Basic Psychological Needs and Basic Wellness Enhancers: The Case of Beneficence as a Candidate Psychological Need.” Journal of Happiness Studies, 20: 1281–1302. https://doi.org/10.1007/s11031-019-09800-x.

Martínez-Sánchez, Aurora, María J. Vela-Jiménez, Manuel Pérez-Pérez, and Pilar De-Luis-Carnicer. 2009. "Inter-Organizational Cooperation and Environmental Change: Moderating Effects Between Flexibility and Innovation Performance." British Journal of Management, 20(4): 537–561. https://doi.org/10.1111/j.1467-8551.2008.00605.x.

Maslach, Christina, Wilmar B. Schaufeli, and Michael P. Leiter. 2001. "Job Burnout." Annual Review of Psychology, 52(1): 397–422. https://www.researchgate.net/publication/211390827.

Mayo Clinic. 2024. "Transforming Healthcare and Research with AI-Driven Tools." Accessed December 5, 2024. https://www.mayoclinic.org/medical-professionals/ophthalmology/news/transforming-healthcare-and-research-with-ai-driven-tools/mac-20572024/.

McKinsey & Company. 2017. Artificial Intelligence: The Next Digital Frontier? McKinsey Global Institute. Accessed November 5, 2024. https://www.mckinsey.com/de/~/media/mckinsey/industries/advanced%20electronics/our%20insights/how%20artificial%20intelligence%20can%20deliver%20real%20value%20to%20companies/mgi-artificial-intelligence-discussion-paper.pdf.

McKinsey & Company. 2023. The State of AI in 2023: Generative AI's Breakout Year. Accessed November 4, 2024. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2023-generative-ais-breakout-year.

McKinsey & Company. 2024a. The State of AI in Early 2024: Gen AI Adoption Spikes and Starts to Generate Value. McKinsey & Company. Available at: https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai#/auth-download/%2F~%2Fmedia%2Fmckinsey%2Fbusiness%20functions%2Fquantumblack%2Four%20insights%2Fthe%20state%20of%20ai%2F2024%2Fthe-state-of-ai-in-early-2024-final.pdf%3FshouldIndex%3Dfalse.

McKinsey & Company. 2024b. What Is AI (Artificial Intelligence)? McKinsey Explainers. Accessed November 4, 2024. https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-ai.

Microsoft. 2023. "Introducing Microsoft 365 Copilot: Your Copilot for Work." Microsoft Blogs. March 16, 2023. https://blogs.microsoft.com/blog/2023/03/16/introducing-microsoft-365-copilot-your-copilot-for-work/.

Microsoft. 2024. "Microsoft 365 Copilot." Microsoft Official Site. Accessed November 12, 2024. https://www.microsoft.com/en-us/microsoft-365/copilot.

Misoch, Sabina. 2019. Qualitative Interviews. Walter de Gruyter GmbH & Co KG. https://doi.org/10.1515/9783110545982.

Mogaji, Emmanuel, Giampaolo Viglia, Pallavi Srivastava, und Yogesh K. Dwivedi. 2024. "Is It the End of the Technology Acceptance Model in the Era of Generative Artificial Intelligence?" International Journal of Contemporary Hospitality Management, 36(10): 3324–3339. https://doi.org/10.1108/IJCHM-08-2023-1271.

Myers, Michael, and Michael Newman. 2007. "The Qualitative Interview in IS Research: Examining the Craft." Information and Organization 17 (December 31): 2–26. https://doi.org/10.1016/j.infoandorg.2006.11.001.

Naveed, Humza, Muhammad Haroon, und Khalid Mehmood. 2023. "A Comprehensive Overview of Large Language Models." arXiv preprint arXiv:2307.06435. https://arxiv.org/abs/2307.06435.

Necula, Ioana, and Sebastian Raisch. 2024. "Artificial Intelligence and the Changing Nature of Work." Academy of Management Journal 67(2): 335–53. https://doi.org/10.5465/amj.2023.0024.

Nielsen, J. 2023. "AI Improves Employee Productivity by 66%." Nielsen Norman Group. Accessed September 10, 2024. https://www.nngroup.com/articles/ai-tools-productivity-gains/.

Onwuegbuzie, Anthony J., and Nancy L. Leech. 2005. "On Becoming a Pragmatic Researcher: The Importance of Combining Quantitative and Qualitative Research Methodologies." International Journal of Social Research Methodology: Theory & Practice 8 (5): 375–87. https://doi.org/10.1080/13645570500402447.

OpenAI. 2024. "ChatGPT Enterprise." OpenAI. Available at: https://openai.com/chatgpt/enterprise/. (accessed November 30, 2024).

Ooi, Keng-Boon, et al. 2023. "The Potential of Generative Artificial Intelligence Across Disciplines: Perspectives and Future Directions." Journal of Computer Information Systems. https://doi.org/10.1080/08874417.2023.2261010.

Östlund, Ulrika, Lisa Kidd, Yvonne Wengström, and Neneh Rowa-Dewar. 2011. "Combining Qualitative and Quantitative Research within Mixed Method Research Designs: A Methodological Review." International Journal of Nursing Studies 48 (3): 369–83. https://doi.org/10.1016/j.ijnurstu.2010.10.005.

Pacolli, Melinda. 2022. "Importance of Change Management in Digital Transformation Sustainability." IFAC-PapersOnLine, 21st IFAC Conference on Technology, Culture and International Stability TECIS 2022, 55 (39): 276–80. https://doi.org/10.1016/j.ifacol.2022.12.034.

Pardo del Val, Manuela, and Clara Martínez Fuentes. 2003. "Resistance to Change: A Literature Review and Empirical Study." Management Decision 41 (2): 148–55. https://doi.org/10.1108/00251740310457597.

Patil, A., S. Deshmukh, and R. Mehta. 2024a. “The Future of Customer Loyalty: How ChatGPT and Generative Artificial Intelligence Are Transforming Customer Engagement, Personalization, and Satisfaction.” In Advances in AI-Driven Organizational Practices, edited by S. Gupta and N. Sharma, 82–97. Mumbai: Deep Science Research Publishing. Accessed December 9, 2024. https://doi.org/10.70593/978-81-981367-8-7_2.

Patil, Deepak, Nidhi L. Rane, and Jyoti Rane. 2024b. “Enhancing Resilience in Various Business Sectors with ChatGPT and Generative Artificial Intelligence.” In The Future Impact of ChatGPT on Several Business Sectors, 146–200. Mumbai: Deep Science Publishing. https://doi.org/10.70593/978-81-981367-8-7_4.

Pfizer. 2024. “Pfizer Is Using AI to Discover Breakthrough Medicines.” Accessed December 5, 2024. https://insights.pfizer.com/pfizer-is-using-ai-to-discover-breakthrough-medicines/.

Plathottam, Siby Jose, Arin Rzonca, Rishi Lakhnori, and Chukwunwike O. Iloeje. 2023. “A Review of Artificial Intelligence Applications in Manufacturing Operations.” Journal of Advanced Manufacturing and Processing, 5(3): e10159. https://doi.org/10.1002/amp2.10159.

Prasad Agrawal, Kalyan. 2024. “Towards Adoption of Generative AI in Organizational Settings.” Journal of Computer Information Systems 64 (5): 636–51. https://doi.org/10.1080/08874417.2023.2240744.

Rai, Arun, Panos Constantinides, and Saonee Sarker. 2019. “Next-Generation Digital Platforms: Toward Human-AI Hybrids.” MIS Quarterly 43(1): iii–ix. https://www.researchgate.net/publication/330909988_Next-Generation_Digital_Platforms_Toward_Human-AI_Hybrids.

Raisch, S., & Fomina, K. (2023). Combining human and artificial intelligence: Hybrid problem-solving in organizations. Academy of Management Review, online first https://doi.org/10.5465/amr.2021.0421.

Raisch, Sebastian, and Sebastian Krakowski. 2021. “Artificial Intelligence and Management: The Automation–Augmentation Paradox.” Academy of Management Review 46(1): 192–210. https://doi.org/10.5465/amr.2018.0072.

Saam, Marianne. 2024. “The Impact of Artificial Intelligence on Productivity and Employment – How Can We Assess It and What Can We Observe?” Intereconomics 59(1): 22–27. https://doi.org/10.2478/ie-2024-0006.

Satishkumar, D., and M. Sivaraja. 2024. Using Real-Time Data and AI for Thrust Manufacturing. Hershey, PA: IGI Global.

Schaufeli, Wilmar B., Marisa Salanova, Vicente Gonzalez-Roma, and Arnold B. Bakker. 2002. “The Measurement of Engagement and Burnout: A Two Sample Confirmatory Factor Analytic Approach” Journal of Happiness Studies, 3(1): 71–92. http://dx.doi.org/10.1023/A:1015630930326.

Scholze, Alexander, and Achim Hecker. 2024. “The Job Demands-Resources Model as a Theoretical Lens for the Bright and Dark Side of Digitisation.” Computers in Human Behavior, 155: 108177. https://doi.org/10.1016/j.chb.2024.108177.

Sengar, Ram, et al. 2024. “Generative Artificial Intelligence: A Systematic Review and Applications.” Multimedia Tools and Applications 83(4): 1–27. https://doi.org/10.1007/s11042-024-20016-1.

Siemens. 2023. Generative Artificial Intelligence Takes Siemens’ Predictive Maintenance Solution to the Next Level. Accessed November 7, 2024. https://press.siemens.com/global/en/pressrelease/generative-artificial-intelligence-takes-siemens-predictive-maintenance-solution-next.

Solow, Robert M. 1987. “We’d Better Watch Out.” The American Economic Review 77(2): 251–53. https://www.jstor.org/stable/1805487.

Tanujaya, Benidiktus, Rully Prahmana, and Jeinne Mumu. “Likert Scale in Social Sciences Research: Problems and Difficulties.” FWU Journal of Social Sciences 16 (January 24, 2023): 89–101. https://www.researchgate.net/publication/366425620_Likert_Scale_in_Social_Sciences_Research_Problems_and_Difficulties.

Teubner, Alexander, et al. 2023. “Zwischen Forschung und Praxis: Fähigkeiten und Limitationen generativer KI.” HMD Praxis der Wirtschaftsinformatik 60: 1–15. https://doi.org/10.1365/s40702-024-01050-x.

Thomas, David R. 2006. “A General Inductive Approach for Analyzing Qualitative Evaluation Data.” American Journal of Evaluation 27 (2): 237–46. https://doi.org/10.1177/1098214005283748.

Tornatzky, Louis G., Mitchell Fleischer, and Alok K. Chakrabarti. 1990. The Processes of Technological Innovation. Issues in Organization and Management Series. Lexington, MA: Lexington Books.

Toyota. 2023. Toyota and Generative AI: It’s Here, and This Is How We’re Using It. Accessed December 5, 2024. https://pressroom.toyota.com/toyota-and-generative-ai-its-here-and-this-is-how-were-using-it/.

Turner Parish, Janet, Susan Cadwallader, and Paul Busch. 2008. “Want to, Need to, Ought to: Employee Commitment to Organizational Change.” Journal of Organizational Change Management 21 (1): 32–52. https://doi.org/10.1108/09534810810847020.

Vadisetty, R. 2023. “AI and Privacy Concerns in Data Security.” Corrosion Management, 33(1): 65. Accessed November 7, 2024. https://www.researchgate.net/publication/383693183_AI_and_Privacy_Concerns_in_Data_Security.

Venkatesh, Viswanath, and Fred D. Davis. 2000. “A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies.” Management Science 46(2): 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926.

Waddell, Dianne, and Amrik S. Sohal. 1998. “Resistance: A Constructive Tool for Change Management.” Management Decision 36 (8): 543–48. https://doi.org/10.1108/00251749810232628.

Wang, Chenxing, Sayed Fayaz Ahmad, Ahmad Y.A. Bani Ahmad Ayassrah, Emad Mahrous Awwad, Muhammad Irshad, Yasser A. Ali, Muna Al-Razgan, Yasser Khan, and Heesup Han. 2023. “An Empirical Evaluation of Technology Acceptance Model for Artificial Intelligence in E-Commerce.” Heliyon 9: e18349. https://doi.org/10.1016/j.heliyon.2023.e18349.

Warrick, D.D. 2023. “Revisiting Resistance to Change and How to Manage It: What Has Been Learned and What Organizations Need to Do.” Business Horizons 66 (4): 433–41. https://doi.org/10.1016/j.bushor.2022.09.001.

West, Darrell M., and John R. Allen. 2021. “How Will AI Affect Productivity?” Brookings Institution, November 15, 2021. Available at: https://www.brookings.edu/articles/how-will-ai-affect-productivity/ (accessed November 30, 2024).

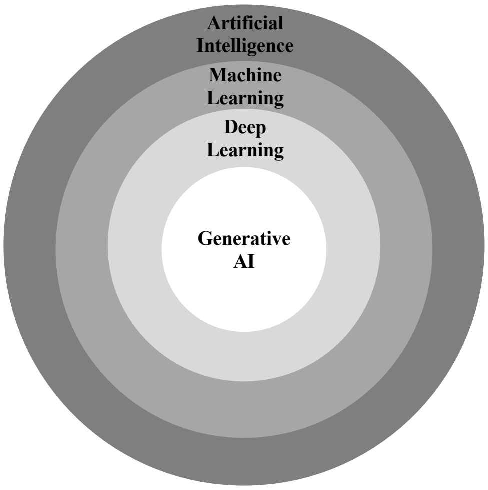
Xie, Xiang, and Jiaqin Yan. 2024. “How Does Artificial Intelligence Affect Productivity and Agglomeration? Evidence from China’s Listed Enterprise Data.” International Review of Economics and Finance 94: 103408. https://doi.org/10.1016/j.iref.2024.103408.

Zalando. 2024. “Zalando Brings Its AI-Powered Assistant to All Markets and Adds Four New Cities to Its Trend Spotter.” Accessed November 7, 2024. https://corporate.zalando.com/en/technology/zalando-brings-its-ai-powered-assistant-all-markets-and-adds-four-new-cities-its-trend.

8 Appendix

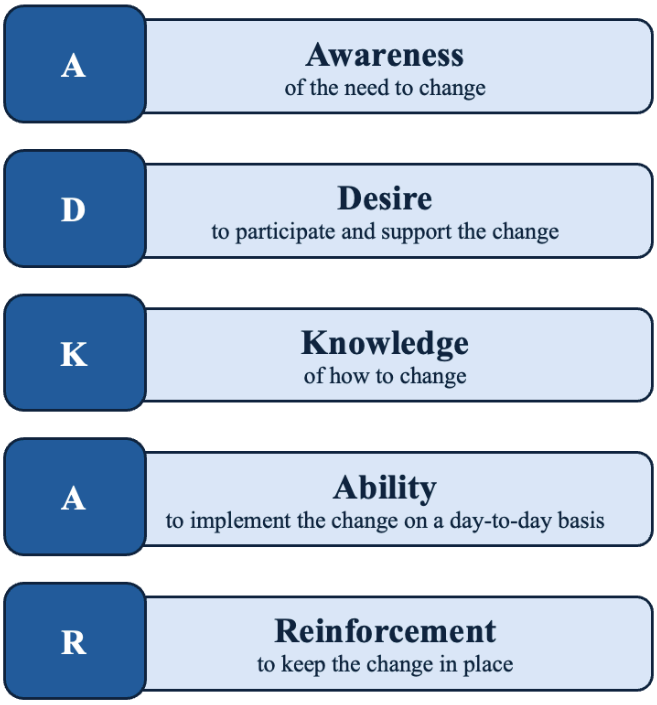
Appendix A: Figures

Figure 1: Layers of AI



Source: McKinsey & Company (2024b).

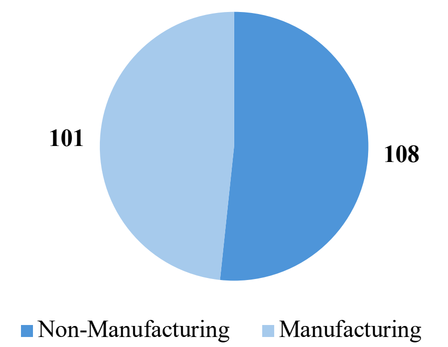
Figure 2: ADKAR Model by Jeff Hiatt



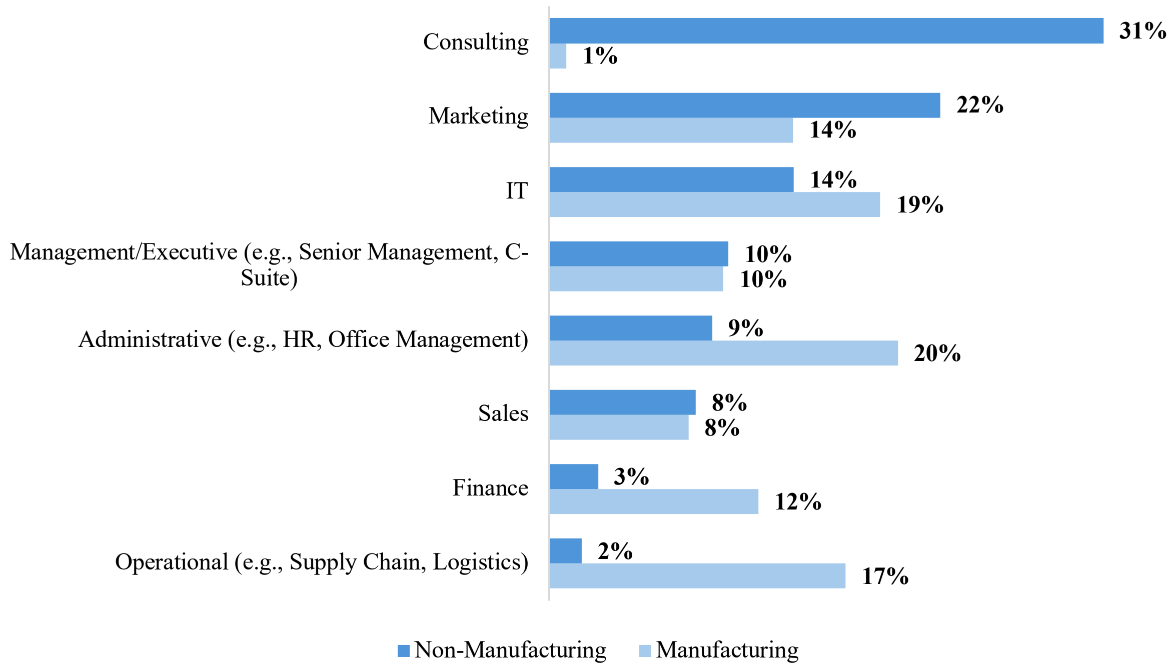
Source: Generated by the author based on Goyal and Patwardhan (2018).

Figure 3: Survey Results

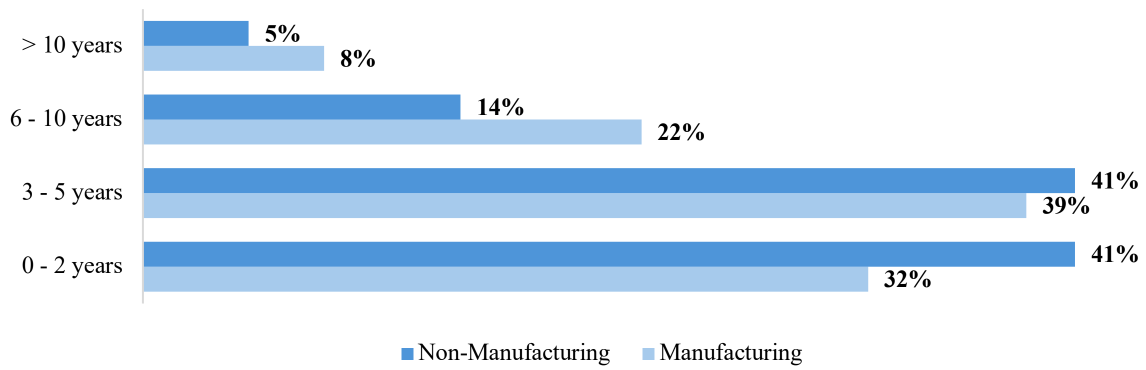
Question 1: How often do you use generative AI tools (e.g., ChatGPT, Copilot) in your daily work?



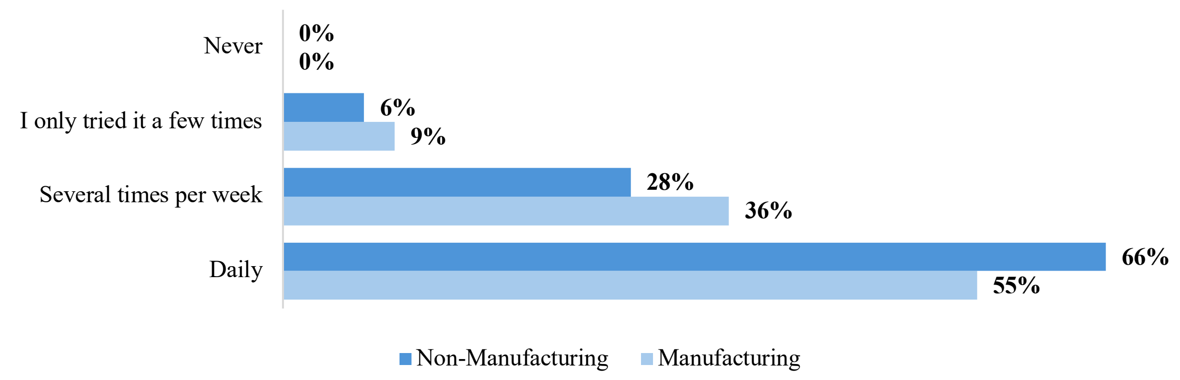
Question 2: What is your primary role within your organisation?



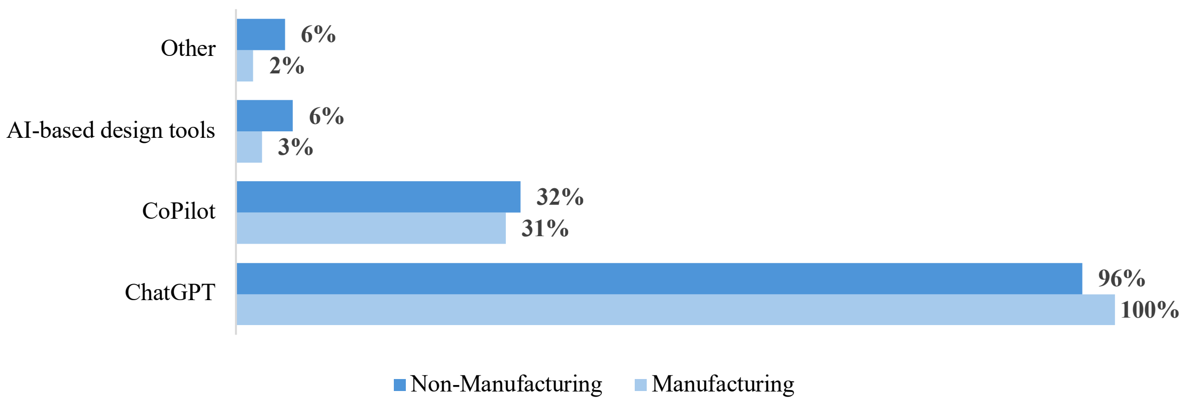
Question 3: How many years of professional experience do you have?



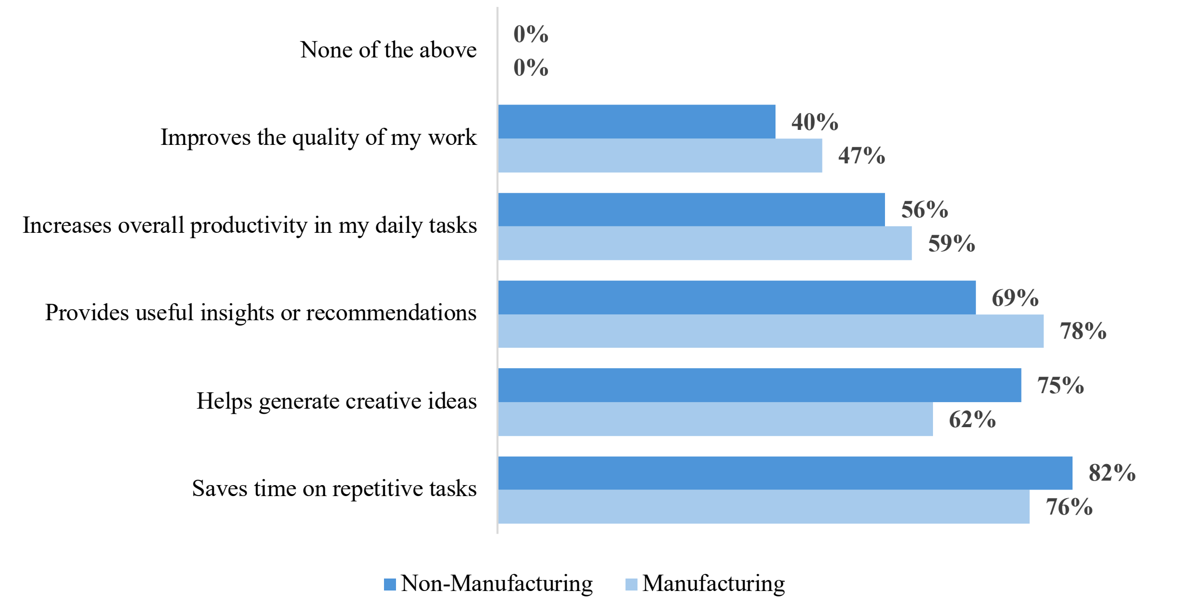
Question 4: How often do you use generative AI tools (e.g., ChatGPT, Copilot) in your daily work?



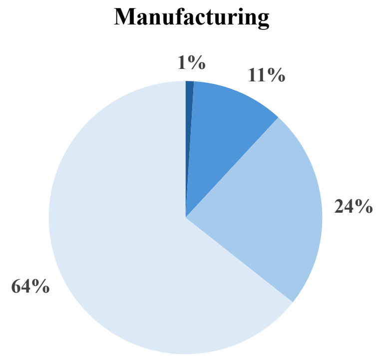
Question 5: Which generative AI tools have you used at work?

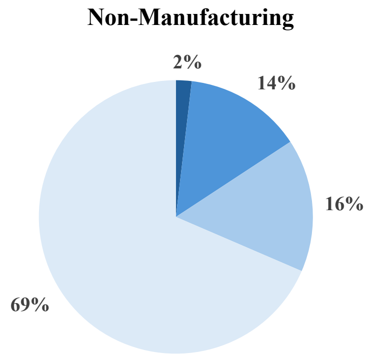


Question 6: What benefits have you experienced from using generative AI?



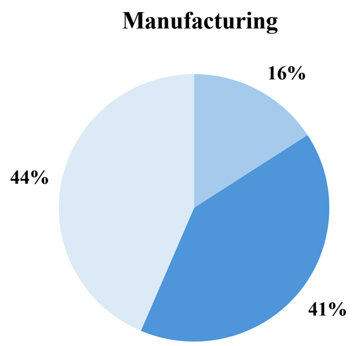
Question 7: Have you noticed an improvement in your productivity since using generative AI (GenAI)?

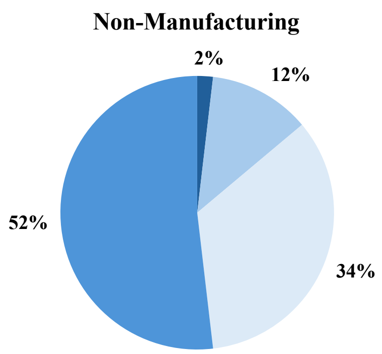




- I feel significantly less productive
- I feel somewhat less productive
- GenAI has had no noticeable impact on my job productivity
- I feel somewhat more productive
- I feel significantly more productive

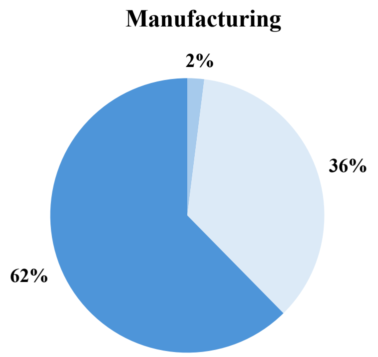
Question 8: How has GenAI impacted your engagement or motivation at work?

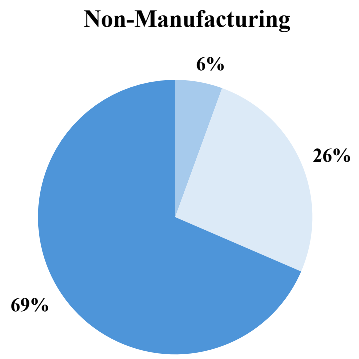




- I feel significantly less engaged and motivated
- I feel somewhat less engaged and motivated
- GenAI has had no noticeable impact on my engagement and motivation
- I feel somewhat more engaged and motivated
- I feel significantly more engaged and motivated

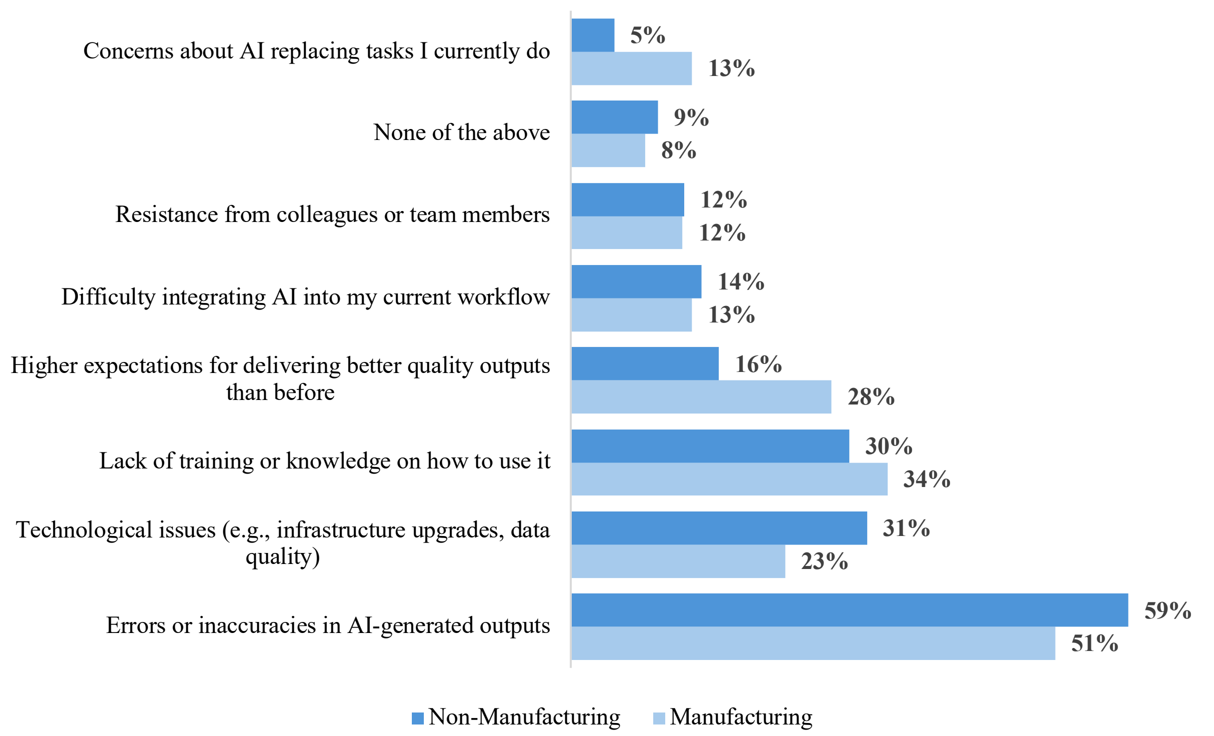
Question 9: Since the implementation of GenAI in your company, how has your job satisfaction changed?



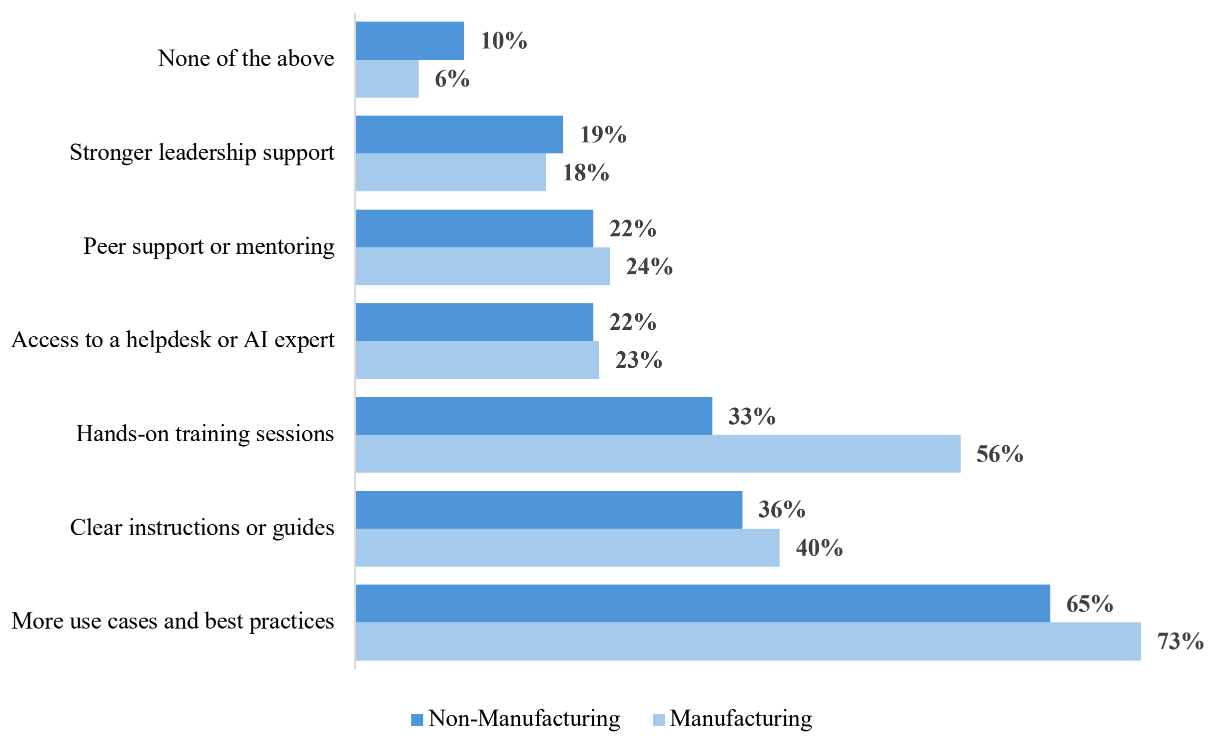


- I feel significantly less satisfied with my job
- I feel somewhat less satisfied with my job
- GenAI has had no noticeable impact on my job satisfaction
- I feel somewhat more satisfied with my job
- I feel significantly more satisfied with my job

Question 10: What challenges have you faced when using GenAI?



Question 11: What types of support would help you better use GenAI?



Source: Generated by the author based on primary survey data.

Appendix B: Tables

Table 1: Applications and Adoption of Generative AI Tools Across Manufacturing and Non-Manufacturing Sectors

Sector	Industry	GenAI Tools Used (Examples)	Applications of GenAI	Adoption Highlights
Manufacturing	General Manufacturing	ChatGPT, Copilot	Product design and rapid prototyping	Yamaha: Optimised EV design using GenAI tools
			Predictive maintenance	Siemens: Predictive maintenance to minimise downtime
			Workflow optimisation	GE Vernova: Improved supply chain efficiency via predictive analytics
	Automotive	ChatGPT, MidJourney, Autodesk Fusion 360	Component design refinement	BMW: Personalised car designs
			Customisation	BMW: Dynamic exterior colour changes through E-ink wraps
			Workflow optimisation	Toyota: Streamlined workflows and production processes
Non-Manufacturing	Retail (Fashion)	ChatGPT, OpenAI Codex, DALL-E, Shopify Magic AI	Personalised product & recommendations	Zalando: Outfit personalisation, AI-driven outfit suggestions
			Inventory optimisation	Amazon: Real-time inventory management
			Customer engagement	Nike: AI-enhanced product recommendations to improve customer interaction
	Marketing	Jasper.ai, ChatGPT, Adobe Firefly	Content creation & campaign optimisation	Jasper.ai: Efficient content strategies
	Healthcare	ChatGPT, IBM Watson Health, DeepMind AlphaFold	Drug discovery	Pfizer: Molecule development
			Personalised treatment plans	Johns Hopkins: Predictive patient care
			Patient data analysis	Mayo Clinic: Leveraging AI for real-time patient data insights and diagnostics
	Consulting	ChatGPT, DataRobot, Tableau GPT	Strategic insights generation & decision making	McKinsey: Increased use of AI for advanced analytics

Sources: Multiple industry reports and corporate websites (full details available in the References).

Table 2: Interview Questions

Chapter	Section	Question
Introduction Questions	**1. Background and Role**	Can you describe your role and responsibilities?
		How are generative AI tools relevant to your position or company? *Follow-up: What are your personal views on the use of generative AI in the workplace?*
Section 1: Generative AI Integration and Productivity	**1. AI Implementation and Usage**	Which generative AI (ChatGPT, Copilot, ...) tools has your organisation implemented, and how do these impact employee roles and productivity? *Follow-up: When did your organisation first start integrating these AI tools? Could you walk us through the timeline of your AI adoption—what steps were taken?*
		What was your company's main reason for adopting generative AI? *Follow-up: What new skills or knowledge have you or your team had to acquire due to AI integration?*
	2. Pre-AI Versus Post-AI Processes	What processes were in place before AI integration, and how have they evolved since
		In which specific workflows or tasks have AI tools been most impactful? *Follow-up: Can you give specific examples of how AI has changed or improved processes within your team or department?*
	3. Sector-Specific Differences	Can you identify specific challenges or benefits associated with generative AI adoption in your company's sector?
Section 2: AI's Influence on Employee Performance and Engagement	**1. Impact on Performance and Engagement**	How has generative AI influenced performance and engagement levels, being it your own or those of colleagues and other employees?
		Has the adoption of AI tools created more engagement or, conversely, challenges? Please provide specific examples. *Follow-up: Have there been any changes in key performance indicators (KPIs) or other metrics of performance after AI adoption?*
		In what ways do you believe generative AI enhances creativity or innovation in your role? *Follow-up: Can you give an example of how AI has enabled employees to innovate or work more creatively*
	2. Employee Reactions and Satisfaction	How did you and your colleagues initially react to the introduction of AI tools, and has this sentiment changed over time?
		Are there feedback mechanisms to gauge employee satisfaction with AI tools? *Follow-up: On a scale of 1 to 10, how would you rate the general satisfaction of employees with AI tools in your department?*
Section 3: Change Management Strategies for AI Integration	**1. Strategies for AI Integration**	What types of training or support were provided to help employees adjust to

		the AI tools, as part of your company's change management strategies?
		When your company introduced generative AI tools, how was the process managed?
		Were there specific actions like communication from leadership or other forms of support, and what were the key considerations in choosing these strategies?
	2. Ongoing Change Management	What ongoing support exists to address any challenges related to AI tools?
		How does the company gather and act on employee feedback about the AI tools?
		In your view, which strategies have been most effective in maintaining engagement and a positive outlook towards AI?
	3. Challenges and Lessons Learned	What were the primary challenges in change management and how did the organisation address these issues? *Follow-up: What unexpected challenges did you encounter in implementing AI, and how did you overcome them?*
		If you're familiar with change management, what best practices can you share from your company's AI integration? If not, how did the company support employees during the transition?
		How do you think the company could have better managed the introduction of generative AI?
Section 4: Broader Impact on Processes and AI Strategy	**1. Influence on Other Processes**	Have generative AI tools affected other business processes outside of the immediate area where they were implemented? *Follow-up: Has the adoption of AI tools led to any changes in the company's overall business strategy or goals?*
		Are there strategies or policies in place to expand AI usage or adapt other processes accordingly?
		Overall, how would you describe the impact of generative AI on your company's performance?
	2. Future AI Integration Plans	How do you envision the future of AI tools within your company and industry?
		Are there any plans to enhance, replace, or further expand AI integrations? I.e., do you see any areas where the company plans to increase AI adoption in the near future, or will the focus shift toward optimising current tools?

Source: Author's own compilation of interview questions used for the study.

Table 3: Survey Questions

Section	Question
Section 1: Your Role and Industry	1. Which industry does your company primarily operate in? Select one (Required). • Manufacturing (e.g., Automotive) • Service/Non-manufacturing (e.g., Consulting, Marketing Agency)
	2. What is your primary role within your organisation? Select one (Required). • Administrative (e.g., HR, Office Management) • Finance • IT • Marketing • Sales • Operational (e.g., Supply Chain, Logistics) • Consulting • Management/Executive (e.g., Senior Management, C-Suite)
	3. How many years of professional experience do you have? Select one (Required). • 0 - 2 years • 3 - 5 years • 6 - 10 years • 10 years
	4. How often do you use generative AI tools (e.g., ChatGPT, Copilot) in your daily work? Select one (Required). • Daily • Several times per week • I only tried it a few times • Never
	5. Which GenAI tools have you used at work? Select all that apply (Required). • ChatGPT or similar text-generation tools • Copilot • AI-based design tools (e.g., Adobe Firefly) • Other
Section 2: Your Experience with GenAI at Work	6. What benefits have you experienced from using GenAI? Select all that apply (Required). • Saves time on repetitive tasks • Helps generate creative ideas • Provides useful insights or recommendations • Improves the quality of my work • Increases overall productivity in my daily tasks • None of the above
	7. Have you noticed an improvement in your productivity since using generative AI? Select one (Required). • I feel significantly less productive • I feel somewhat less productive • GenAI has had no noticeable impact on my job productivity • I feel somewhat more productive • I feel significantly more productive 8. How has generative AI impacted your engagement or motivation at work? Select one (Required). • I feel significantly less engaged and motivated • I feel somewhat less engaged and motivated • GenAI has had no noticeable impact on my engagement and motivation • I feel somewhat more engaged and motivated • I feel significantly more engaged and motivated
	9. Since the implementation of GenAI in your company, how has your job satisfaction changed? Select one (Required). • I feel significantly less satisfied with my job • I feel somewhat less satisfied with my job • GenAI has had no noticeable impact on my job satisfaction • I feel somewhat more satisfied with my job • I feel significantly more satisfied with my job
	10. What challenges have you faced when using GenAI? Select all that apply (Required). • Lack of training or knowledge on how to use it

	• Concerns about AI replacing tasks I currently do • Errors or inaccuracies in AI-generated outputs • Difficulty integrating AI into my current workflow • Technological issues (e.g., infrastructure upgrades, data quality) • Resistance from colleagues or team members • Higher expectations for delivering better quality outputs than before • None of the above
	11. What types of support would help you better use GenAI? Select all that apply (Required). • Hands-on training sessions • Clear instructions or guides • Access to a helpdesk or AI expert • Peer support or mentoring • More use cases and best practices • Stronger leadership support • None of the above

Source: Author's own compilation of survey questions used for the study.

Table 4: Identified Themes from the Interviews

Theme	Description	Codes	Cited Supporting Quotes (Manufacturing)	Cited Supporting Quotes (Non-Manufacturing)
GenAI-Induced Organisational Change	Examines how the adoption of generative AI drives significant organisational change across industries	External Pressures, Innovation, Competitive Urgency, Phased Scaling	"If you're not integrating these tools in the automotive industry, you're already falling behind." "largely employee-driven, with tools being championed by specific teams interested in their application. Leadership provided access but not structured guidance."	"The main reason is because we like to be at the forefront of innovation." "We started small to gather insights and build confidence in the tools before scaling further."
Resistance to Change	Investigates the origins and manifestations of resistance to generative AI, including fears, training gaps, and compliance concerns	Fear of Job Loss, Scepticism, Training Gaps , Expectation Management	"People still don't fully understand how to use tools like ChatGPT effectively, leading to hesitancy."	"The idea of meeting transcription being used for evaluations raised significant concerns with our workers' council."
CM Strategies – Communication	Explores the role of tailored and transparent communication strategies in facilitating AI adoption	Tailored Messaging, Stakeholder Engagement, Consistency	n.a.	"The biggest risk is not segmenting your audience. If you don't tailor communication to each team, they won't see the value, and that leads to no usage."
CM Strategies – Leadership	Explores the role of tailored and transparent communication strategies in facilitating AI adoption	Leadership Advocacy, Trust Building, Resource Allocation, Role Modeling	"When managers started using the tools in team meetings, it motivated others to do the same." "ensuring the smooth operation of AI tools and addressing any challenges employees face."	"I would have loved to see a sponsor or leader say, 'This is how I'm using Copilot. Why don't you give it a try?' Even a short video would have been impactful."
CM Strategies – Skill Development through Training	Highlights the importance of structured training to equip employees with the skills needed to effectively use generative AI tools	Tailored Training, Knowledge Sharing, Compliance Training, Peer Learning	n.a.	"with clear use cases aligned with business goals and expanding from there"
CM Strategies – Continuous Feedback and Monitoring	Examines the role of real-time feedback mechanisms and usage monitoring in refining AI adoption strategies	Feedback Loops, Real-Time Monitoring, Employee Surveys	"Feedback loops [are] critical for refining use cases."	n.a.
Success Factors and Best Practices	Identifies the key practices and obstacles in implementing generative AI, emphasising employee inclusion, pilot projects, and flexibility	Employee Inclusion, Change Champions, Change Agents, Flexibility, Pilot Projects, ADKAR	n.a.	"Just do it. Start small, get a pilot team, and then decide if it works. But you need to start somewhere."

Adoption of GenAI	Examines how organisations integrate GenAI tools into workflows, focusing on employee reactions, training, and tailored change management strategies	Initial Scepticism, Tailored Training, Managerial Advocacy, Productivity Gains, Data Privacy Concerns	"Predictive maintenance applications enabled our team to pre-emptively address equipment failures, saving time and resources."	"A 60% increase in productivity within the team was achieved by automating mundane, time-intensive activities like transcription and document drafting."
Efficiency, Creativity, and Employee Satisfaction	Examines how GenAI enhances productivity, fosters creativity, and influences job satisfaction	Productivity Gains, Creative Tasks, Task Enrichment, Operational Efficiency, Strategic Innovation	n.a.	"By automating repetitive tasks, we've achieved a significant time reduction in daily workflows, freeing up capacity for innovation." "GenAI is a great partner for creativity, amplifying human ideas rather than replacing them." "Meeting minute creation, previously a labour-intensive process requiring one to two weeks, is now completed within a single day using tools like Otter.ai and ChatGPT."
Resistance and Engagement in GenAI Adoption	Examines how tailored strategies mitigate resistance and foster engagement with GenAI tools in addressing job security concerns, training gaps, and communication	Resistance Management, Tailored Training, Psychological Engagement, Transparent Communication, Competency Building	"There's always this lingering question of whether the AI is here to help or to replace us."	"Seeing senior managers actively use these tools made the whole team feel confident about their relevance and impact."
Feedback and Employee Engagement	Explores the role of feedback mechanisms in fostering employee engagement, with a focus on how formal and informal feedback loops differ between sectors	Feedback Mechanisms, Peer Mentoring, Satisfaction Tracking, Personalised Communication, Adaptive Feedback	n.a.	"Usage analytics were leveraged to optimise tool deployment and license allocation, indirectly reflecting employee engagement with GenAI tools."
AI's Role in Talent Retention and Development	Investigates GenAI's role in fostering career growth and retaining talent, contrasting non-manufacturing's optimism with manufacturing's apprehensions about automation	Talent Development, Career Enhancement, Automation Fears, Skill Enhancement, Innovation Support	"AI feels like a tool designed to phase out workers rather than support us."	"Working with AI gives me a sense of being at the forefront of my industry."
Strategic Alignment with Organisational Goals	Examines how AI adoption aligns with organizational strategies to enhance business value, drive innovation, and support leadership objectives	Strategy-Driven AI, Enhancing Business Value, Supporting Innovation	"AI aligns with our 'speed to business value' strategy pillar." "It supports the company vision of combining technology and innovation to drive market leadership."	"Our AI initiatives align with the strategic pillar 'speed to market,' allowing us to stay ahead in competitive industries." "It supports the organisation's vision of combining technology and innovation to drive market leadership."

Cost-Benefit Analysis of GenAI Integration	Explores the challenges of balancing significant investments in AI with measurable productivity outcomes and justifying ROI	Cost-Benefit Analysis, ROI Concerns, Optimism, Cost Concerns	“The high costs for licenses are not yet justified by the current productivity gains.” “AI tools are promising, but their high cost sometimes leaves me questioning the value.”	“Licenses are expensive, so we are working to justify ROI through productivity measurement.”
Measuring Productivity Gains	Investigates the lack of clear KPIs and infrastructure to systematically measure productivity improvements achieved through AI adoption	Undefined KPIs, Lack of Tracking Tools, Infrastructure Gaps, Systematic Tracking	“Measurement frameworks are still under development, so many AI-automated or augmented processes remain manually assessed.” “If certain functions, such as the ‘copy button,’ are used, we assume that added value has been generated.”	“We want an efficiency measurement system, but there’s a risk it might turn into a monitoring mechanism that discourages employees.”
Productivity Gains Dependence on the Application	Analyses how productivity gains vary depending on specific AI use cases, with administrative tasks benefiting more than strategic or operational areas	Use Case Dependency, Task-Specific Gains	“Efficiency varies; tools like that work well for repetitive tasks, but we don’t see comparable gains in higher-level processes.”	“The biggest productivity gains come from individual use, not yet from processes.”
Perceived versus actual Productivity Gains	Explores the gap between employees’ perceptions of AI as a time-saver and the reality of time lost due to prompt refinement or output validation	Perception vs. Reality, Reviewing Outputs	“Overestimating AI capabilities leads to inefficiencies, especially when the tools are applied in ways they weren’t designed for.” “AI is useful, but employees often waste time correcting outputs when the tool isn’t used correctly.”	“AI saves time on repetitive tasks, but reviewing outputs or handling hallucinations can take longer than expected.”
Balancing Quantitative versus Qualitative Gains	Examines how time savings are more easily measured in quantitative tasks, while qualitative benefits like reduced workload stress and creativity enhancement remain harder to assess	Quantitative Outcomes, Qualitative Benefits	“It helps reduce stress by automating tedious tasks, but we don’t track these softer impacts formally.”	“While we don’t track qualitative improvements, employees report feeling less overwhelmed and more creative.”

Source: Author’s own analysis of interview data collected for the study.