



The Implementation of Artificial Intelligence in Managing Multi-Functional Conglomerate

Groups of Companies

A Dissertation Presented To

The Faculty Members

SBS SWISS BUSINESS SCHOOL

In Partial Fulfilment of the Requirements

For The Degree Doctor of Business Administration

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Abstract

This dissertation investigates the transition from traditional Enterprise Resource Planning (ERP) systems to Artificial Intelligence (AI)-enabled management within multi-industry conglomerates along with addressing the gap in understanding how AI implementation impacts managerial efficiency, decision-making, and strategic agility. The researcher has adopted pragmatic and mixed-methods approach combined quantitative surveys from 200 mid-to-senior-level managers and qualitative thematic interviews to gain comprehensive understandings. The key findings of this research indicate unanimous agreement among managers that AI significantly improves departmental efficiency, accelerates informed decision-making, and enhances cross-functional coordination compared to legacy ERP systems. Remarkably, AI integration fostered organisational agility with the help of enabling proactive and predictive management. Additionally, despite initial concerns regarding resistance and inadequate training, the findings revealed robust acceptance facilitated by structured upskilling and communication strategies. The primary statistical formula utilised was the regression equation: $Y = \beta_0 + \beta_1 X_1 + \epsilon$. The research concludes that AI adoption transforms enterprise management by providing real-time, integrated decision support, which significantly advances theoretical understanding of ERP-to-AI transitions in conglomerates.

Keywords: *Artificial Intelligence, ERP Integration, Strategic Agility, Conglomerate Management, Mixed Methods*

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Sample

Chapter 1: Introduction

1.1. *Background of the Study:*

The rapid advancement of Artificial Intelligence (AI) is transforming the business landscape, allowing organizations to leverage intelligent systems to streamline complex operations and foster innovation (Santhosh et al., 2024). This shift is particularly impactful for conglomerates—large corporations composed of diverse business units operating across multiple industries and geographies. Managing such multifaceted entities poses significant challenges, from coordinating disparate operations and efficiently allocating resources to maintaining strategic alignment across subsidiaries. For decades, conglomerates have relied on Enterprise Resource Planning (ERP) systems as the backbone for integrating core processes. However, as global markets become increasingly dynamic and competitive, traditional ERP solutions are struggling to meet evolving business demands. In response, many conglomerates are looking to AI-driven management tools to address these emerging challenges, boost operational efficiency, enhance decision-making, and cultivate greater agility in a rapidly changing environment (PC Social, 2023).

Diversification provides conglomerates with benefits such as risk reduction and multiple revenue streams (Maduka & David, 2024). Yet this very diversity also introduces volatility and complexity: each subsidiary may operate under different conditions, regulations, and market pressures. Traditional management approaches (e.g. paper-based processes or siloed IT systems) cannot adequately cope with such complexity. While ERP implementations have long unified processes and data within large organisations, even these systems are becoming insufficient as business needs evolve. AI, with its ability to process vast volumes of data and discern complex patterns, is increasingly seen as an indispensable tool for overcoming the limitations of legacy systems (PC Social, 2023). By augmenting or integrating with ERP, AI can help conglomerates manage their diverse operations more effectively.

AI can contribute to conglomerate management at operational, tactical, and strategic levels. For example, AI-driven software can automate and consolidate financial reporting across numerous subsidiaries, reducing manual effort and errors beyond the capabilities of standard ERPs. Advanced analytics improve demand forecasting, inventory management, and supply chain

optimisation, enabling conglomerates to detect market trends early and respond proactively. At a strategic level, cognitive AI applications (such as decision-support systems and predictive analytics tools) help managers evaluate potential investments, assess risks, and identify synergies between different business units. By realising these capabilities, conglomerates can achieve higher operational efficiency and sustain competitive advantages in their industries (Maduka & David, 2024).

A key advantage of AI over conventional ERP systems is its capacity to integrate data from disparate sources and break down organisational silos. In traditional environments, each business unit might use independent systems and performance indicators, limiting interdepartmental integration and holistic planning. AI platforms equipped with modern data integration and analytics can unify these diverse datasets into a cohesive framework, providing leaders with a comprehensive, enterprise-wide view of the organisation's performance. With this big-picture perspective, management can make more informed decisions based on holistic insights rather than fragmented information. For instance, a conglomerate spanning the automotive and renewable energy sectors could deploy AI analytics to identify cross-sector opportunities—such as leveraging advances in electric vehicle technology to benefit clean energy initiatives—uncovering synergies that would be difficult to spot using traditional systems (Chen, 2025).

Despite its promise, the implementation of AI in conglomerate management is not without challenges. Deploying AI at scale requires substantial investment in technology, skilled human capital, and organisational development. Firms must also address concerns around data privacy, security, and compliance with legal and ethical standards (Beernink, 2024). Moreover, successfully adopting AI demands an organisational culture that embraces innovation and change; employees need to be prepared and willing to adapt to new AI-driven processes, otherwise resistance and fear of job displacement may hinder progress (Santhosh et al., 2024). To manage these risks, conglomerates often take a phased approach to AI implementation. For example, stakeholders might begin with pilot projects in select departments or subsidiaries and gradually extend AI use across the conglomerate, allowing time to learn and adjust before full-scale rollout (Maduka & David, 2024). Anticipating and planning for such challenges is crucial to ensure that the transition to AI-driven management delivers its intended benefits.

The potential applications of AI in conglomerate strategy are expansive. AI tools can simulate complex scenarios to help conglomerates prepare for events like economic recessions, regulatory changes, or technological disruptions, thus guiding proactive countermeasures and building organisational resilience (PC Social, 2023). Advanced algorithms may even assist in high-level strategic decisions—for instance, by identifying promising merger or acquisition targets and projecting the long-term value of such moves (Iansiti & Lakhani, 2020). Notably, many large conglomerates have already reported significant gains from early AI adoption. Global technology firms, for example, use AI to redesign products, reduce energy consumption, and improve production quality. Financial conglomerates leverage AI to detect fraud more effectively, enhancing security and customer trust. Retail-focused conglomerates employ AI to personalise customer experiences, streamline supply chains, and boost sales. These successes in diverse sectors underscore the transformative potential of AI-driven management for complex multi-business organisations (van der Vlist, Helmond, & Ferrari, 2024). This context sets the stage for the present research, which delves into how AI can be strategically implemented to improve the management of conglomerate groups.

1.2. Problem statement:

Conglomerate groups, with their diversified portfolios and multi-industry operations, face persistent difficulties in coordination, resource optimisation, and strategic alignment across subsidiaries (Beernink, 2024). Traditionally, ERP systems have been the backbone for managing such complexity by streamlining workflows, centralising data, and standardising processes enterprise-wide. Yet as the business environment becomes more volatile and competitive, conventional ERP solutions are increasingly inadequate for supporting the real-time decision-making and adaptability that modern conglomerates require (Fountaine, McCarthy, & Saleh, 2019). The limitations of legacy ERP systems—such as rigidity, delayed data updates, and one-size-fits-all processes—can hinder a conglomerate’s agility and responsiveness, potentially undermining performance in fast-moving markets.

AI has emerged as a promising avenue to address these shortcomings, offering capabilities in automation, big-data analytics, and predictive insight that can introduce real-time adaptability and

proactive decision-making across a conglomerate's operations (Chen, 2025). However, the transition from an ERP-centric management model to an AI-driven one remains underexplored and fraught with questions. Conglomerates must determine effective strategies for integrating AI with existing systems, ensure compatibility and customisation for diverse subsidiary needs, and overcome practical hurdles such as high implementation costs, the need for specialised AI expertise, data privacy and cybersecurity concerns, and ethical issues surrounding algorithmic decision-making (Lakshmi et al., 2024). Without clear guidance, firms risk ad hoc or misaligned AI adoptions that fail to deliver expected benefits—or worse, introduce new operational risks. There is a clear need for a structured framework to guide conglomerates in successfully adopting AI-driven management. This study responds to that need by analysing how AI can be leveraged to overcome the limitations of ERP, enhance enterprise-wide coordination, and establish a more adaptive and competitive management paradigm for multi-business enterprises. In doing so, it will also explore the potential risks and best practices associated with implementing AI, ensuring that the shift from traditional ERP systems to intelligent, data-driven processes is both effective and sustainable.

1.3. Aim:

The primary aim of this study is to examine the transformative role of AI-driven management in multi-functional conglomerates, particularly focusing on how the implementation of AI can facilitate the transition from traditional ERP systems to more intelligent and adaptive management processes. In essence, the research seeks to determine the extent to which AI applications and methodologies can address the challenges of managing highly diversified business groups—optimising resource allocation, improving decision-making quality, and enhancing strategic agility across various subsidiaries. By concentrating on this ERP-to-AI transition, the study intends to develop a strategic understanding (or framework) of how conglomerates can effectively integrate AI into their management practices, ensuring these organisations become more innovative, responsive, and efficient in the face of evolving business demands.

1.4. Objectives:

To fulfill the above aim, the research has outlined the following key objectives:

- **Evaluate the current state of AI–ERP integration in conglomerates:** *Assess the extent to which AI technologies have been incorporated into existing ERP systems within conglomerate businesses, and identify the primary AI tools in use (such as machine learning, natural language processing, robotic process automation, and AI-driven analytics).*
- **Assess the impact of AI on operational efficiency:** *Analyse how AI implementation enhances core business functions (e.g. financial reporting, demand forecasting, supply chain management, human resources) and quantify its effects on productivity, cost reduction, process automation, and error minimisation, in comparison to traditional ERP-based management.*
- **Examine AI-driven improvements in decision-making:** *Explore the role of AI-powered tools—such as predictive analytics, decision support systems, and risk assessment models—in supporting strategic decision-making, and determine how AI can integrate and synthesise data across multiple subsidiaries to enable more informed and cohesive decisions by top management.*
- **Analyse the challenges of AI implementation:** *Investigate the organisational, technical, and ethical barriers encountered when transitioning from ERP to AI-driven management. This includes examining issues related to data security and privacy, regulatory compliance, workforce preparedness (skills and training), and resistance to change among employees or leadership.*
- **Explore future opportunities and formulate a roadmap:** *Examine emerging AI innovations that could further enhance conglomerate management beyond current ERP capabilities (e.g. advanced predictive modelling, AI-driven strategic planning tools). Based on the findings, propose a structured roadmap or set of strategic recommendations for successfully embedding AI-driven management practices within conglomerate organisations.*

1.5. Research Question:

On the basis of afore-mentioned problem statement and objectives, the central research question in this dissertation is:

How can the implementation of Artificial Intelligence (AI) enhance management efficiency, decision-making, and strategic agility in conglomerate groups operating across diverse industries and geographies, particularly in the transition from traditional ERP systems to AI-driven management?

This question is addressed through the detailed objectives and analysis outlined above, while helping to focus the research on the critical aspects of AI integration in conglomerate management.

1.6. Key Definitions:

To ensure clarity, several key terms used throughout this dissertation are defined below:

- **Enterprise Resource Planning (ERP).** *ERP is an integrated software system that centralises and streamlines core business processes across an organisation (Iansiti & Lakhani, 2020). It enables the efficient management of functions such as finance, supply chain, human resources, procurement, and customer relations by consolidating data into a unified platform. ERP systems enhance operational efficiency by automating workflows, improving data accuracy, and facilitating real-time decision-making (Fountaine, McCarthy, & Saleh, 2019). In conglomerates, ERP platforms have been instrumental in coordinating activities across multiple subsidiaries. However, as market dynamics evolve, traditional ERP systems are increasingly being supplemented or replaced by AI-driven solutions to achieve greater adaptability and strategic agility.*
- **Artificial Intelligence (AI).** *AI refers to computer systems designed to perform tasks that typically require human intelligence, such as learning, reasoning, problem-solving, and understanding language or vision (Chen, 2025). AI encompasses a range of technologies including machine learning, natural language processing, computer vision, and neural*

networks. In the context of conglomerate management, AI contributes to more informed decision-making, greater organisational effectiveness, and improved strategic planning. For instance, AI systems can monitor performance across different subsidiaries, forecast future trends, and provide data-driven recommendations on how to optimise resources or strategies to achieve better outcomes (Beernink, 2024).

- **Conglomerate.** A conglomerate is a large business organisation formed by the integration of multiple distinct companies or business units, often operating in various industries under one corporate group. Diversification in a conglomerate offers advantages such as minimising risk and creating multiple revenue streams (Maduka & David, 2024). However, it also introduces complex managerial challenges: coordinating diverse operations, ensuring that all subsidiaries align with overarching strategic objectives, and maintaining compliance with a range of industry regulations. Effectively managing a conglomerate requires robust systems that can handle large-scale data integration, optimise reporting, and facilitate communication across subsidiaries (van der Vlist, Helmond, & Ferrari, 2024).
- **Machine Learning (ML).** Machine Learning is a subfield of AI in which algorithms learn from historical data to improve their performance on tasks, without being explicitly programmed with specific instructions for every scenario. Instead of following fixed rules, ML models identify patterns in data and use those patterns to make predictions or decisions. In conglomerates, ML techniques can be applied to a variety of functions, including predictive maintenance (e.g. forecasting equipment failures), customer segmentation for targeted marketing, fraud detection, and supply chain optimisation (Nagaraju et al., 2024). For example, an ML system in a logistics division might analyse past shipment records to predict and preempt potential delivery delays, while an ML-driven marketing tool in a retail subsidiary could tailor promotions to individual customers based on their purchasing behaviour (Iansiti & Lakhani, 2020).
- **Predictive Analytics.** Predictive analytics involves using statistical methods, data mining techniques, and machine learning algorithms to develop models that can forecast future events or trends. This approach is especially valuable in conglomerates, where strategic

decisions often involve large-scale investments and high uncertainty. By analysing historical data alongside current market indicators, predictive analytics can help managers anticipate market trends, optimise inventory levels, forecast customer demand, or estimate the potential outcomes of strategic initiatives. Utilizing predictive models enables conglomerates to reduce risks and capitalise on opportunities—for instance, entering a new market or adjusting product strategies based on predicted changes in consumer behaviour (Joshi et al., 2024).

- **Robotic Process Automation (RPA).** *RPA is an AI-driven technology that uses software “bots” to automate repetitive, routine tasks that would otherwise be performed manually. It is particularly useful for structured tasks such as data entry, invoice processing, compliance checks, or payroll operations. In a conglomerate setting—where many administrative processes are centralised and handled at high volume—RPA can significantly reduce labour-intensive work, minimise human error, and improve processing speed. For example, an RPA system could gather and reconcile financial data from multiple subsidiaries to generate consolidated reports, freeing up human employees to focus on more complex analytical or strategic tasks (Lakshmi et al., 2024).*
- **Strategic Agility.** *Strategic agility refers to an organisation’s ability to rapidly and proactively adapt its strategies and operations in response to changes in the business environment. In the context of conglomerates, which operate in dynamic and often highly competitive markets, strategic agility is crucial for sustaining long-term success. AI can enhance strategic agility by continuously monitoring relevant data (such as market trends, competitor moves, and customer feedback) and identifying emerging patterns or anomalies. By providing early warnings and forward-looking insights, AI systems enable leaders to adjust course quickly—whether that means pivoting to address a new market opportunity or mitigating a looming risk. This ability to anticipate and respond to change helps conglomerates remain resilient and competitive over time.*

1.7. Rationale/Significance of Study:

The significance of this study curtails from the wide-ranging benefits that effective AI integration could bring to conglomerate management, as well as the need to understand how to realise these benefits in practice. First, AI has the potential to enhance strategic planning and decision-making in diversified companies by aggregating and analysing information from across different business units. This means that conglomerate leaders can base their decisions on a richer and more comprehensive set of insights, considering factors from multiple industries and markets simultaneously. AI systems also promise improvements in operational efficiency and cost reduction by automating routine, repetitive tasks—such as scheduling, data entry, and report generation—thereby freeing up human resources for higher-value activities (Chen, 2025). In areas like customer relations, AI-driven analytics can personalise products, services, and marketing efforts to different customer segments, improving the customer experience and satisfaction across the conglomerate's varied businesses. These capabilities suggest that AI implementation could directly address some of the key pain points in managing complex organisations, leading to more efficient operations and better strategic outcomes.

Furthermore, AI can strengthen a conglomerate's ability to manage risk and compliance in an increasingly complex regulatory and security landscape. Advanced AI algorithms are capable of sifting through large datasets to detect early signs of potential risks—such as cybersecurity threats, financial irregularities, or market disruptions—allowing management to take preventative action before such issues escalate (Beernink, 2024). Embracing AI can also drive innovation and competitive advantage: by leveraging tools like predictive analytics and machine learning, conglomerates can identify emerging market gaps and technological trends, informing the development of new or improved products and services. In addition, AI platforms that integrate data across traditionally siloed divisions encourage greater cross-division collaboration and synergy, enabling different subsidiaries to work together more effectively and share insights in real time. A unified, AI-enabled data environment not only improves internal coherence but also contributes to greater strategic agility. With real-time dashboards and predictive foresight, conglomerates can respond swiftly to changing customer preferences or sudden market shifts,

adapting their strategies to maintain or improve their competitive position (van der Vlist et al., 2024).

By investigating these areas, the study will yield practical insights into how conglomerates can harness AI to improve their management practices and outcomes. The findings are expected to benefit business practitioners by highlighting best practices and potential pitfalls in AI adoption within large, diversified firms. At the same time, the study will contribute to the academic understanding of technology-driven organisational transformation, particularly in bridging the gap between traditional management systems (like ERP) and new AI-enabled paradigms. In sum, this research is significant because it addresses a contemporary challenge at the intersection of technology and management, offering guidance on leveraging AI for enhanced efficiency, innovation, and strategic responsiveness in complex organisational settings.

1.8. Methodology Overview:

This research employs a **mixed-methods approach** to examine the transition from ERP-based management to AI-driven management in conglomerates, ensuring a comprehensive analysis that captures both quantitative trends and qualitative nuances. The study design combines quantitative and qualitative methods in a complementary way. Quantitative data were collected through structured surveys administered to key managers in the conglomerate context (including, where applicable, surveys conducted before and after AI implementation to observe changes over time). These surveys gathered measurable data on aspects such as operational performance metrics, decision-making efficiency, and user acceptance of AI tools. To gain deeper insight beyond the numbers, qualitative data were gathered via in-depth **interviews** with management executives and stakeholders. The interviews explored experiences, perceptions, and challenges related to implementing AI in their organisational processes.

In addition to primary data, the study incorporated secondary data from sources like internal company reports, industry white papers, and relevant case studies or academic literature. These secondary sources provided context and helped validate the primary findings by offering baseline information and external perspectives on AI adoption in similar settings.

For data analysis, the quantitative survey results were processed using statistical techniques. Descriptive statistics and graphical analyses were used to summarise the data, while inferential statistics (including correlation and regression analysis, performed with tools such as Microsoft Excel's Analysis ToolPak) were applied to test relationships and measure the impact of AI adoption on various performance indicators. On the qualitative side, the interview transcripts were analysed using thematic analysis. This involved coding the transcripts to identify recurring themes, patterns, and insights regarding how AI integration affected managerial work, decision processes, and organisational dynamics within the conglomerate. By triangulating findings from both the quantitative and qualitative analyses, the research derives a robust understanding of the phenomena under study. This mixed-methods approach provides both the breadth of evidence (through numeric data on outcomes) and the depth of understanding (through personal accounts and detailed observations), which together strengthen the validity and richness of the study's conclusions.

1.9. Structure of the Dissertation

This dissertation is organised into six chapters, following a logical progression from context-setting to analysis and conclusions. Chapter 1 (the current chapter) has introduced the research topic, outlined the problem statement, aim, objectives, and research question, provided necessary definitions, and explained the significance and methodological approach of the study. Chapter 2: Literature Review will critically review relevant literature, including theoretical frameworks and prior studies on ERP systems, AI in business management, and technology adoption in conglomerates. This chapter will identify key themes and gaps in existing knowledge that the present research will address. Chapter 3: Research Methodology will detail the research design, data collection methods, and analysis procedures used in the study, justifying why a mixed-methods approach was appropriate for the research question. Chapter 4: Data Analysis and Results will present the findings of the study, including the results from the quantitative surveys and qualitative interviews, supported by tables, figures, and direct quotations as needed. Chapter 5: Discussion will interpret and discuss these findings in the context of the research objectives and the literature review, highlighting how the results answer the research question, what implications they have for theory and practice, and how they align or contrast with existing studies. Finally,

Chapter 6: Conclusion will conclude the dissertation by summarising the key insights and contributions of the research, acknowledging its limitations, and offering recommendations for practitioners as well as suggestions for future research avenues. This structured approach ensures a coherent flow from the identification of a problem through to the generation of conclusions and recommendations, guiding the reader through each stage of the inquiry.

Chapter 2: Literature Review

2.1. *Introduction:*

Artificial Intelligence AI is viewed as a new revolution that is transforming the business management across all the fields. The ability to process large and often complicated data to understand the underlying patterns in time, helps decision-making regarding AI a key enabler of both operational and strategic improvement (Iansiti and Lakhani, 2020). It has been seen that the businesses increasingly rely on AI not only to enhance routine processes but also to develop competitive advantages that allow them to adapt to rapidly evolving market conditions. While AI was earlier a separate solution, which people tried to apply individually, it has turned into one of the critical elements of complex management systems, especially impactful for massive and differentiated organisations (Fountaine, McCarthy, and Saleh, 2019).

In regards to the conglomerates, which are characterised by their ownership and management of valorous business units functioning across several industries, AI adoption presents unique challenges and opportunities. Conglomerates are typically associated with significantly different business profiles, structure, and geographical distribution and industry specifics (Chen, 2025). These organisations need complex solution to enhance their resource management; integrate strategies across business divisions; and sustain corporate vision and goals. AI has therefore come out as a solution that can be geared towards providing enhanced approaches such as; predictive analytics, machine learning, natural language processing and more. They help conglomerates to reduce complexity, and get insights about the organisation that are otherwise not possible when managing organisations using traditional management methods (Fountaine, McCarthy, and Saleh, 2019).

Although the topic of AI in management is well explored in the extant literature, this paper is particularly relevant as it demonstrated the value of AI in improving administration tasks. As per the past studies AI has redefined the scope and scale of administrative operations, starting from automation of repetitive tasks to enabling the advance analytics for decision making (Beernink, 2024). In conglomerates, this shift is even more apparent as AI is the key to addressing internal issues with operating divisions as well as issues with data systems, while achieving consistent performance across subsidiary companies. For example, an AI-based enterprise resource planning (ERP) solution can gather data from all the subsidiaries within an organisation and allow heads of a conglomerate to oversee the performance of the organisation. Such a high level of integration is required for critical alignment at the strategic level and receiving actual and timely data for decision-making (Nagaraju et al., 2024).

Moreover, AI technologies such as machine learning and predictive analytics have proven instrumental in addressing the complexities of managing diverse organisational structures. Machine learning algorithms can learn from an ever-increasing amount of data, come up with new patterns, and forecast outcomes that conglomeration allow firms to predict future changes in a market, and improve their supply chain and customer relations (Iansiti and Lakhani, 2020). Among them, one should mention that predictive analytics helps foresee certain risks and opportunities, which is very helpful when managing organisations' businesses, given the volatility of the current economic environment for various industries. Likewise, the application of NLP technologies is transforming the customer relations and intranet communication by instantaneous language translation, analysis of meaningful emotions and self-service queries.

However, the use of AI in conglomerates has its challenges as explained in this paper. Complex solutions can be implemented across several subsidiaries in which data is exchanged; this always entails massive investments in infrastructure, staff, and change programs. Fear of change within the organisation, alongside data protection issues, ethical concerns, and supply issues make the process more challenging (Marr, 2019). The challenges notwithstanding, the advantages associated with AI includes among others reduced costs and increased efficiency as well as better strategic decision making processes making it a must for conglomerate management. This chapter

presents a critical discussion on the place of AI in business management with emphasis on the conglomerates.

There are certain key areas that are explored by this literature review including, administrative functions in relation to AI, how AI can be useful for the management of complex hierarchies, and finally AI technologies that have been implemented. Moreover, the chapter includes further development of theoretical knowledge concerning the support of AI implementation, summarises the benefits and drawbacks of applying AI, as well as tendencies and development in the application of AI. Furthermore, the study proposed on critically reviewing the literature in order to approach the subsequent more methodological chapters with knowledge of what is probably missing or not well explained in the current literature. In this regard, this paper aims at presenting a systematic review of the literature to enhance understanding on how AI can help to manage the diversified conglomerate organisations.

2.2. ERP in Business Administration and Business Management

ERP systems were once vital for business administration and management because of offering integrated solutions that streamline operations across various departments (Chen, 2025). However, looking at the research by Ranjan, Jha, and Pal (2016), it is identified that ERP systems presents numerous challenges that can impede organisational efficiency, such as: organisational resistance to change, inadequate training, and misalignment between the ERP system and existing business processes. These challenges lead to project delays and budget overruns thus indicate towards the need for planning and stakeholder engagement during implementation. Moreover, identification of critical success factors is also essential for the successful deployment of ERP systems. Systematic review by Butarbutar et al. (2023) highlights that top management support, clear project objectives, and effective communication are important for successful implementation of ERP. They also added that a strong commitment from leadership and a well-defined project scope significantly enhance the likelihood of successful ERP adoption.

Though customisation of ERP systems to fit specific organisational needs is a common practice, it has certain challenges. Literature review by Wijaya and Utomo (2021) discusses the complexities associated with ERP modifications. They discussed increased costs, extended

implementation timelines, and potential system instability. It is implied that organisations should carefully assess the necessity of customisations and consider the long-term implications on system performance and maintainability. The literature has also shown the post-implementation phase of ERP systems that is critical for realising anticipated benefits. Butarbutar et al. (2023) examined factors that affect ERP success after implementation. They found that continuous user training, system usage, and business process reengineering play significant roles in enhancing business process performance. Thus, ongoing support and periodic assessments to ensure the ERP system continues to align with organisational objectives is needed.

Some recent developments have indicated a shift towards cloud-based ERP solutions and process-centric business platforms. Böhme et al. (2023) explores the transition from traditional ERP systems to more flexible, cloud-native platforms that offer scalability and real-time data processing. The transition or evolution addresses some limitations of conventional ERP systems, such as high entry barriers and lack of adaptability. Thus, for dynamic business environments ERPs are seem to be not suitable enough. Therefore, the literature highlights the complexity of ERP implementation and the critical factors influencing success. While ERP systems offer substantial benefits in integrating business processes, organisations must navigate implementation challenges carefully, prioritise critical success factors, and stay abreast of emerging trends to fully leverage ERP capabilities in business administration and management.

2.3. AI in Business Administration and Business Management:

It has been observed in the current study is that the AI has revolutionised the business administration and management by handling the automations of the routine work, improving the data – based decision making and analytics (van der Vlist, Helmond, and Ferrari, 2024). Artificial Intelligence (AI) has become a crucial element in business administration and management because it has changed how organisations work and make choices. The implementation of AI systems in business processes has profoundly changed the traditional approach to evaluating administration and coordination of activities, optimisation, and automation of monotonous work, transition to the prevention of organisational decision making. By using attributes such as deep learning, real-time analysis, and predictions, AI has changed several aspects of business

administration functions offering the prospect of operational optimisations and business development (Fountaine, McCarthy, and Saleh, 2019).

One of the extremely critical area where AI has made a crucial influence is the modernisation and automation of routine administrative tasks. Operations that once demanded a lot of resource, including time and effort to execute – for instance, payroll processing, employee on boarding, and financial accounts management – benefit from intelligent ERP systems. Beernink (2024) argued that because of AI's ability to learn deeply and analyse data in real time executives and managers are able to move from slow administrative bureaucratic processes to active, information-based decision making processes. For example, AI can help determine leave patterns and turnover, assisting human resource departments in taking measures before nurturing their employees to leave their organisation. Likewise, both management and financial reporting systems supported by AI do not only produce proper and efficient financial reporting but also highlight compliance issues and risks (Lakshmi et al., 2024).

AI has also made it easier to make good decisions based on data on issues of strategic planning and operations management. According to Iansiti and Lakhani (2020), AI improves decision making for managers by applying predictive modelling. It helps the businesses to predict market movements, measure the risks and to act accordingly. In conglomerates, where its operation processes are considered more complex because of the variety of the business units involved, AI systems can easily coordinate and process big data in different subsidiaries. This integration ensures that leaders have a central view of the organisational performance and actualisation of goals to ensure the subsidiaries' strategies are in tune with the general corporate goals (Chen, 2025). For instance, in a supply chain, the use of artificial intelligence will mean that supply management is made intelligent in that it can analyse supply demands based on history and current trends. Purchasing products from local suppliers also keeps costs low while also guaranteeing the efficient delivery of merchandise, customer satisfaction, and organisational effectiveness.

Additionally, it is also important that many industries such as healthcare and retail, shows the benefits of AI implementation that can be later transferred to conglomerate structures (Fountaine, McCarthy, and Saleh, 2019). This reflects that in the health-care institutions AI enabled systems are capable of estimating the number of patients to be treated, resource utilisation, and appropriate

and optimal human resource planning. Similarly to that, in retail, the use of Machine Learning (ML), as well as Natural Language Processing (NLP) to examine consumers and predict their behaviour to individualise their purchasing processes. These insights can help various business functioning under conglomerates to align and act based on available data letting the top management unite the conglomerates under one unified strategy (Joshi et al., 2024).

When it comes to the AI capability of business, it is not only about automation and analytics-based prediction. It also has a very significant function of strategic positioning in conglomerates that are commercial undertakings (van der Vlist, Helmond, and Ferrari, 2024). AI tools make it easier to synchronise business departments due to real-time performance indicators and performance assessment. This foster collaboration and makes it possible that individual organisational segments have corporate objectives in mind. For instance, a company that is involved in manufacturing, transportation, and sales of goods can benefit from AI by integrating the manufacturing timetable, the delivery routes, and the supply with the consumer turnover waves. This integration helps in elimination of what may be referred to as implied waste within organisations thus helping to increase organisational performance (Beernink, 2024).

Despite its numerous benefits, the implementation of AI in business administration and management also presents challenges. It is significant that implementing of AI technologies requires notable investments into infrastructures, talent development, and change management. Also, the issues, like data privacy, cybersecurity, and ethical issues are the major challenges that may hinder the process. However, as it was mentioned earlier, AI brings many long-term benefits to the organisation such as boosting the costs, overall performance, and decision-making abilities as well as facilitating strategic planning (Fountaine, McCarthy, and Saleh, 2019).

2.4. *AI in Managing Conglomerate Structures:*

According to the past study, Conglomerates are complex entities characterised by their diverse business portfolios, extensive operational geographies, and the need for cohesive management practices (Iansiti and Lakhani, 2020). It positioned differently from any single industry organisation which is faced with the traditional issues and advantages of one sector while operating in another sector of the economy. The diversity naturally leads to results in silo operations,

misaligned strategic objectives and disparate data streams creating efficient and effective management for a daunting task. To address these complexities, traditional management approaches that involve a huge dependence on paper-based works and analysis of documenting materials fail to meet desired goals. Conglomerate operations are often viewed as complex problem spaces that require a new organisational interface; Artificial Intelligence (AI) has risen as the calculator tool to streamline conglomerate operations and ensure the establishment of a communal vision both for the conglomerate and its subsidiary firms (Lakshmi et al., 2024).

AI's ability to integrate and process vast amounts of data from various sources has made it a cornerstone technology for conglomerates. The key technologies empowering such a change are AI emphasised ERP systems, such systems aggregate financial, operational and customer information from all subsidiaries in one place, thereby giving the decision-maker a complete picture of organisational performance. Joshi et al. (2024) explain that while the AI capability of ERP systems enables such mundane activities to be handled digitally, it also delivers vital analytical information necessary for several managerial resources and strategic alignment. For example, Tata Group of which deals in manufacturing, IT services, and products among others has applied AI when using ERP to great success in improving cross-organisational relations for efficiency. Through consolidation of information from various sub companies of Tata group, the organisation has been able to detect systematic failures, anticipate and control for disruptions, and optimise assignments towards creating organisational rhythm across a broad spectrum of operations (van der Vlist, Helmond, and Ferrari, 2024).

The other obvious advantage of AI in managing conglomerates is the analysis of the predictive nature of the system. Predictive analytics refers to the kind of data processing that involves historical data analysis, application of machine learning algorithms as well as real time data analysis to give a prediction of the future trend and result (Chen, 2025). This predictive capability allows conglomerates to implement preventive measures and develop contingency plans, minimising the impact of adverse events. For example, AI used by Mitsubishi Corporation to predict arise or drop in prices of commodities has been useful in the management of risk and safeguarding profitability.

In addition, the capability of AI on generating innovation and agility cannot be ignored. This is particularly the case due to increased competition among conglomerates in the current business environment (Beernink, 2024). As a result, using natural language processing NLP and computer vision, conglomerates can discover new opportunities, design new products, and improve customer experience. For instance, Google's parent company Alphabet Inc. applies AI in its subsidiaries: Waymo for the production of self-driving cars and in Verily for enhancement of health technologies (Iansiti and Lakhani, 2020).

However, the present study identifies that the introduction of AI in conglomerates is not without its problems. Some of the limitations that were obtained include; high initial costs, specialised talents, and issues of data privacy or security. Also, AI deployment in LCS is challenging and may take time to execute because it has to work hand in hand with the older systems. However, the advantages of this approach in the form of improved efficiency, improved decision making, and better alignment at the strategic level outweigh these challenges which are why AI is a critical tool to managing conglomerate structures (Lakshmi et al., 2024).

2.5. Types of AI in Conglomerates:

Different AI technologies are different in terms of the functions they serve and automation levels and provide numerous benefits for conglomerates. In this section, the study described three primary subtypes of AI: predictive analytics, machine learning, and NLP, and describe their transformative roles in handling the complexities of conglomerates. All these technologies make conglomerates to have operation efficiency, strategic consistency, and market sensitive making them vital in present day management.

2.5.1. Predictive Analytics:

It's a branch of artificial intelligence which involves forecasting based on data mining, statistical analysis and machine learning (Fountaine, McCarthy, and Saleh, 2019). While most decision-makers understand that predictive analytics is all about predicting trends and patterns in data, there is often a misunderstanding of the benefits that come with the results generated by it. In conglomerates, predictive analytics is a key enabler for the organisations to effectively handle the

various operations and to make right decisions in various industries and locations (Nagaraju et al., 2024).

2.5.1.1. Applications in Conglomerates:

Predictive analytics is a business solution that is useful in variety of ways for conglomerates including forecasting demand, managing risks, preparing financials and allocate resources. For instance, manufacturing conglomerate Unilever, with a bundle of brands and products possesses a reputable image and extensive brand portfolio, uses AI predictive models to influence consumer behaviour and subsequently manage everything effectively starting from supply lines to marketing strategies (Beernink, 2024). These models work on enormous amounts of data from operations across the world such as sales data, customer feedback, and market trends where they provide precise forecasts that support the firm's strategic direction.

One of the most impactful applications of predictive analytics in conglomerates is demand forecasting. With help of historical sales data, seasonality and trends, conglomerate organisations can use such models to identify future demand for their products and services (van der Vlist, Helmond, and Ferrari, 2024). For instance, Procter & Gamble (P&G) applies artificial intelligence in predictive analytics in an effort to build schedules that help its subsidiaries hold right stocks, free of waste. This not only improves operational efficiency but also enhances customer satisfaction by reducing stock outs and delivery delays (Iansiti and Lakhani, 2020).

Another important area of concern risk management in supply chains. IT has seen seen that the conglomerates functioning in volatile markets often encounters a heavy multitude of risks that includes regulatory changes, supply chain disruptions and economic fluctuations (Lakshmi et al., 2024). Predictive analytics can be used to address concerns before struggling or failing, thus saving troubled companies and organisations. For example, the large multinationals such as GE utilises AI risk management systems in evaluating the company's operations across the world and likely disruptions of its supply chains. These tools process information about suppliers, transportation systems, and unrests to supply real-time risk notifications allowing GE adapt to change and avoid negative effects on its operations (Fountaine, McCarthy, and Saleh, 2019).

2.5.1.2. Enhancing Strategic Decision-Making:

The use of predictive analytics also helps conglomerate organisations to enhance strategic decisions and to improve performance. The predictive models enable executives to make right decisions in the organisation based on information that will be provided through the forecast (Beernink, 2024). For instance, Samsung employ proactive statistics to understand and forecast growing customer preference and technology trends and in this way the conglomerate to direct capital in productive sectors such as 5G and AI (Chen, 2025).

Moreover, predictive analytics helps conglomerates to identify likely performance consequences in implementing strategies including mergers, acquisitions, diversification and new product introductions. Predictive models allow decision-makers to estimate the potential consequences by testing different situations and, thus, increase resources utilisation efficiency. For example, Tata Group's use of Artificial Intelligence in generating first level scenarios of business scenarios necessary for approving new products or acquisition opportunities minimises the rate of failed risky decisions (Marr, 2019).

2.5.1.3. Operational Efficiency and Cost Savings:

Apart from the strategic benefits, predictive analysis also plays a vital role in delivering operational efficiencies and cost reduction for conglomerates. In terms of resource optimisation and efficiency, by employing and applying different predictive models, productivity enhancement at reduced cost is possible. For example, Mitsubishi Corporation had applied artificial intelligence to predict energy consumption of its units and save millions of dollars, cutting unnecessary costs and at the same time environmental harm (Iansiti and Lakhani, 2020).

In addition, it enhances workforce management since it factors in logistical data and the trends of operation to give a probable workforce demand. For example, Walmart employs the algorithmic approach of a machine to forecast staff requirements in all its stores depending on consumer traffic. This not only has the effect of lowering a major expense – labour – but also it improves the quality of service to clients eliminated long waiting periods.

2.5.1.4. Challenges and Limitations:

While predictive analytics offers numerous benefits, its implementation in conglomerates is not without challenges. There is a key obstacle in quality and access to data. In its application, many prediction models depend on large accurate and complete datasets and any lack of unity or even lacuna in the data affects the prediction. The problem is especially acute for conglomerates owning plants and facilities throughout different regions and industries and having so many different databases that integrating them into a single system may take lots of time and will be more costly (van der Vlist, Helmond, and Ferrari, 2024).

One more problem is connected with interpretability of the results gained with the use of predictive models. Higher level models like deep learning model, often operates black boxes, and makes it difficult for decision makers to easily understand how predictions are generated. This lack of transparency can hinder trust and adoption among stakeholders. Thus, in response to the problem, more firms apply explainable AI (XAI) practices that can give users information about how the predictive models work (Joshi et al., 2024).

Furthermore, IT investments hold the key proportionate to moving predictive analytics successful, as does hiring skilled talents. The use of predictive analytics requires conglomerates to spend in platforms of analytics, cloud infrastructure, and data scientists. However, it is clear that investing in the predictive analytic systems reaps long-term organisational benefits such as better decision making, operations, and competitive advantage for conglomerates (Lakshmi et al., 2024).

2.5.2. Machine Learning:

Machine learning is a part of AI that uses statistical techniques to give to the systems the ability to learn, make decision and improve their performance over a period of time without being corrected by users. Because Machine Learning is capable of change upon receiving experience of usage it is highly recommended for conglomerates since they are composed of numerous or diverse business units (Beernink, 2024). This paper outlines the use of ML applications throughout the business operation and strategy including fraud, customer profiling, asset health monitoring, supply chain management, and manufacturing.

2.5.2.1. Optimising Supply Chain Management:

The most useful field in which the ML approach is applied in conglomerates is supply chain management. The machine learning algorithms scan through huge data such as the production data, logistics data, and sales data to judge when disruptions are likely to happen, when the system is suboptimal or when a different approaches are better. This capacity of making forecasts can help conglomerates to reduce possible tardiness and over expenses while enhancing the use of resources (Iansiti and Lakhani, 2020).

For instance, Siemens is a global business firm that deals with sectors of manufacturing, energy and health care and has developed efficient using of the ML approach in the production line to schedule processes. Machine learning approaches conduct data mining of real-time data collected from sensors placed on machines and equipment, helps in finding out possible chocking points, probable failure or wear and tear of machinery and suggest the best course of action to be taken for preventive maintenance (Chen, 2025). Reducing time spent on unscheduled events yields increased productivity, while assuring continuity to production around the different plants owned by Siemens across the globe.

Furthermore, the application of ML in the inventory helps in demand forecasting, avoiding the pitfalls of holding or running low on stock. Some firms such as the General Electric (GE) use ML for demand prediction to achieve optimal inventory. Using sales data, customer behaviour, and other variables like weather or other political factors, ML models for conglomerates help to stock and manage items in such a way that holding costs are minimised and customer satisfaction is maximised (Fountaine, McCarthy, and Saleh, 2019).

2.5.2.2. Enhancing Fraud Detection and Risk Management:

Machine learning plays a critical role in risk management and fraud detection, specifically for conglomerates functioning in financial services or any other industry to fraudulent activities. And the principles of Machine Learning allows evaluating transactional data in real time with highlighting possible deviations from the norm and manifestations of fraudulent intent. Such

algorithms continuously learn from new data. Enhancing their accuracy and minimising the negativity over time (van der Vlist, Helmond, and Ferrari, 2024).

For instance, large diversified firms such as Mitsubishi Corporation apply machine learning techniques to analyse financial transactions performed by subsidiaries, looking for suspicious activity suggesting fraud or regulatory violation (Nagaraju et al., 2024). Likewise, (Insurance or Banking) companies like Berkshire Hathaway uses ML based fraud detection system to understand the claims data and flag suspicious activities. Use of automated tools on fraud detection enable conglomerates to save a lot of resource, loss minimisation and reputation (Iansiti and Lakhani, 2020).

In addition to fraud prevention, machine learning is invaluable for credit risk assessment and decision-making. The credit scores, market trends, customer's buying behaviour and many more things, all such aspects are analysed by the ML algorithms for credit risks or loan defaults. This capability is specifically significant for the conglomerates with financial divisions, as it allows them to take credible informed lending decisions by minimising risk exposures (Lakshmi et al., 2024).

2.5.2.3. Improving Operational Efficiency and Automation:

Machine learning leads to improve efficiency by modernising and automating routine tasks and optimising complex processes across conglomerate structure (Beernink, 2024). In manufacturing, artificial vision technologies automatically examines production line data and provide suggestions for optimisation of the process and improvement of the quality of the end product. For instance, 3M a diversified conglomerate which deals in various industries inclusive of manufacturing, healthcare and electronics use ML to help it minimise resources used, time taken and material wasted while producing its products (Marr, 2019).

Apart from process optimisation, ML makes it possible for conglomerates to conduct predictive maintenance on the equipment. In the analysis of the various machineries' data acquired by sensors, ML paves way in flagging structures which are likely to break down and schedule for repair before total failure. It also leads to minimise the downtime, enhances the equipment lifespan and reduces the rapier costs. Companies such as Honeywell, uses embedded ML predictive

maintenance solutions that help cut costs across Honeywell's industrial and building solutions business units (van der Vlist, Helmond, and Ferrari, 2024).

Other examples of using machine learning are also in the sphere of workforce optimisation because it predicts the staff number depending on organisational history and necessities. For instance, mammoth conglomerates such as Walmart adopt the use of ML to accomplish changes of staff schedules with due consideration of costs of labor and quality services (Fountaine, McCarthy, and Saleh, 2019).

2.5.2.4. Driving Innovation and Competitive Advantage:

Machine learning enables the conglomerate companies to promote innovation and achieve a competitive edge in growing markets. It allows the companies to integrate detailed analysis and selective control regarding the latest trends and estimate future advancement of technologies and potential growth fields. For instance, to advance its consumer electronics division, Samsung employs ML. The process of learning concerning methods for new product designs in R&D, customers' feedbacks or competitors' performance (Chen, 2025).

Conglomerates operating in healthcare also use machine learning to advance medical research and improve patient care. For example, Johnson & Johnson uses algorithms for the evaluation of clinical trials data, for selection of drug candidates, and for the prognosis of the patients' outcomes. All these tools shorten the process of development and produce the drug at a cheaper cost and make available the essential medicine in the marketplace (Iansiti and Lakhani, 2020).

2.5.2.5. Challenges of Implementing Machine Learning:

Despite of many advantages, it reveals that the use of machine learning has huge potential and this study also unmasks some of the problems in applying it in conglomerates. One major hindrance in the data integration across various subsidiaries and industries. It has been seen that the conglomerates encounters data silos, where information is stored in independent systems, creating it more difficult for ML algorithms to access and analyse the robust datasets (Lakshmi et al., 2024). One another major challenges is the lack of skilled personnel. Machine learning essentially means that there is need for data scientists, software data analysts, and machine learning engineers and

artificial intelligence specialists, who will put into practice the idea of machine learning. A number of conglomerates report the deficiency of talent; it makes it difficult to optimise ML capacities (Chen, 2025).

Moreover, ML framework can rarely produce findings that are more difficult to interpret, specifically in cases including deep learning techniques. This problem, where one is unable to see how a model arrives at a particular decision, is referred to as the black-box issue, for it may hamper trust and embrace by stakeholders. This problem affects conglomerates, and they have to weigh in on explanations for AI (XAI) to cater for the needs of decision makers on the validation of information from ML models (Beernink, 2024).

2.5.3. Natural Language Processing:

Natural language processing (NLP), which is essential division of Artificial intelligence interface, deals with the use of text or speech by human beings. Enabling an environment where machines can comprehend, evaluate, understand, and reply to textual and spoken language information (Nagaraju et al., 2024). Within conglomerates, NLP has revolutionary features that revolutionise communication, customer relations, and internal work (Lakshmi et al., 2024). Through NLP technology conglomerates helped to save cost, operational time also provide greater and necessary correlation of business insight from large unstructured data.

2.5.3.1. Improving Customer Engagement:

The most notable area where NLP is profoundly used is customer interfacing using artificial intelligence in form of chatbots and virtual assistants. All these tools are aimed at the natural dialogue with consumers and on the handling of general questions without involving company's staff. This automation is particularly important for conglomerates since many offer goods and services to almost every sector and geographical location. Chatbots powered by Artificial Intelligence are available at all times to give customers a prompt response at any time of the day (van der Vlist, Helmond, and Ferrari, 2024).

For instance, Reliance Industries involved in operating in the telecom sector, retail, and digital that utilises NLP reliant chatbots for holding questions, answering them, and sorting out basic issues

and concerns from the user. Likewise, Amazon uses NLP in customer service where customers can speak to chatbots who can manage to recommend products, track orders, and complaint quickly (Iansiti and Lakhani, 2020). Through the use of such interactions, conglomerates enhance the quality of customer experience, release human labor for higher level tasks, and ensure customers receive a high quality support.

Besides, the customer service, NLP helps to personalisation which is the important element to retain the customer. Electronic communication and purchasing activities, as well as sentiments, content, and other consumption-related data, all make it possible for NLP to help companies provide and fine-tune suggestions, offers, and messages based on each client. These levels of personalisation assist conglomerates to develop closer relations with its clients, and not only enable brands to be well-recognised but also create brand-entity affiliations (Beernink, 2024).

2.5.3.2. Facilitating Cross-Border Communication:

Language is key component for any organisation due to globalisation leading to differences in regions, languages can be a big barrier for multinational conglomerates organisations. NLP for this reason utilises AI translation tools that translate, speech and text, to different languages in real time. These tools take care of language differences thus facilitating interactions among different subsidiary companies in the different countries (Chen, 2025).

For instance, massive corporations including Samsung and General electric incorporate the NLP powered translation software in communication across the global teams. Through the use of platforms, issues that may require meetings, provision of documents and even disapproving of issues, all can be addressed effectively despite barriers in speaking or writing the same language. It does not only foster organisational relations, but also optimize organisational operations on the international level (Fountaine, McCarthy, and Saleh, 2019).

2.5.3.3. Automating Documentation and Insights:

With NLP, documentation is done automatically involving summarizing reports, extracting useful information, and working with unformatted textual data. The extent of papers, consumer feedback, and performance reports that large conglomerates prepare make it cumbersome to sieve out

pertinent information by hand (Marr, 2019). Traditional text analysis creates such a schedule because the detailed review often takes more time than the standard workweek to complete. Analyzing text data using NLP tools can reduce the time spent reviewing for trends and important aspects and provide a view of which areas demand more attention.

For instance, text mining for example can analyse customer feedback and feedback on their social media pages to determine the reputation of the brand and the needful. This way conglomerates are able to analyse and decide what products to launch and market, along with what promotional activities to conduct and many customer engagement programs. Furthermore, they used NLP for text mining of legal papers, contracts, and financial statements, for fast decision-making and compliance check (Nagaraju et al., 2024).

2.6. Theoretical Frameworks:

2.6.1. Enterprise Architecture Frameworks:

Enterprise Architecture (EA) frameworks help support the implementation and integration of AI in organizations as essentially highlighted in this paper. These frameworks provide a formal way of developing the technological and business aspects on how an enterprise should be constructed and operated. Within conglomerates which business activities cover different industries, zones and branches EA frameworks play a crucial role in AI technology governance to capture common, scalable and compatible approaches for their adoption (van der Vlist, Helmond, and Ferrari, 2024)

2.6.1.1. TOGAF: A Comprehensive Framework:

Currently, one of the most employed framework for enterprise architecture is TOGAF (The Open Group Architecture Framework). TOGAF was developed to provide sound foundation on how its implementers can align the technology related undertakings like AI to the business strategic plans. This is highly relevant to conglomerates because there are integrated subsidiaries and operational divisions that must collectively drive organizational goals. TOGAF can guide conglomerates in a structure manner to develop their AI strategies by using Architecture Development Method (ADM) (Iansiti and Lakhani, 2020).

TOGAF pays significant attention to how AI systems become a part of a company's structure of IT, so that they improve the existing work processes. For instance, when a conglomerate is implementing AI-embedded (ERP) systems, TOGAF offers decision-making criteria and framework on how best to integrate these new platform into its other subsidiaries and platforms, obtain data coherence and other process interconnectivity. It is a structural approach to AI and its implementation reduces the prevalence of individual department or team information technology and AI implementation.

2.6.1.2. Consistency and Interoperability in Conglomerates

In this case, the use of AI when implemented presents a major challenge of consistency especially when the conglomerate has many unrelated business units, but which are part of the same bigger whole with similar goals and objectives. EA frameworks guarantee that the AI systems are created to work similarly across the units, so as to allow for exchange of data, working in set methods and processes, and the same reporting structures. This is particularly important in conglomerate decision making whereby integrated data from all subsidiaries is required. Furthermore, integration flexibility is an important factor for conglomerates organizations with diverse IT environments. The EA frameworks guarantee that an AI solution, for example, predictive analytics platform or machine learning algorithms, are ready to integrate with the existing tools and systems. Through the formulation of these frameworks, technical integration barriers and corresponding risks are reduced, and AI solutions achieve optimal returns (Lakshmi et al., 2024).

2.6.1.3. Enhancing Governance and Risk Management:

The next benefit of applying EA frameworks, including TOGAF is that their focus is mainly on the proper governance and risk management. They offer recommendations for evaluating how well that organization is operating AI systems and maintaining its security. For example, EA frameworks used by conglomerates executing in health or financial sector can help avoid legal and ethical pitfalls with the AI planning (Beernink, 2024).

2.6.2. Innovation Management:

Concerning the dissemination of ITs like the innovative AI, organizational professions have reflected on diverse theories we can identify as the Diffusion of Innovations theory developed by Rogers (1962). These theories highlight the importance of organizational culture, leadership support, and stakeholder engagement in facilitating AI adoption. AI adoption and use increases in various organizations and the same is true in multinational organizations to provide easy services to employees and enhance organizational performance (Patnaik & Bakkar, 2024). The AI used in organizations for various functions includes innovation management, creating new opportunities for optimization, efficiency, and market competitiveness. AI can facilitate better decision-making processes by analyzing vast amounts of data in real time, thus helping companies make more informed and timely strategic decisions. By automating routine tasks and utilizing predictive analytics, AI drives efficiency across different business functions, from supply chain management to marketing strategies, thereby enabling conglomerates to focus on innovation and be more concerned for productivity and growth. With the use of AI marketing, HRM activities including payroll processing, employee attendance, and financial records are automated, and employee productivity and ease increases (Ali, Hamdan & Alareeni, 2021).

AI is used by organizations to support and enhance innovation strategies as being a key defining focus area for large corporations. It helps to ensure that different departments work together; it provides better understanding of customers; it triggers the creation of new products and services. By adopting AI management and organizations achieve faster product life cycle since it is easier to predict what the customer needs better than traditional program. The technology also allows for the personalization of services, creating more targeted customer experiences and improving satisfaction, the use of AI helps the management to design an effective strategy for growth and development and alignment with strategy (Sharma et al., 2022).

The use of AI has increased in many manufacturing organizations including the automobile sector, food, and beverages, and the Textile industry with automation of technology, time scheduling, inventory management personalized services to consumers provided by AI to customers, hence customer satisfaction also increased. Identifying key areas where AI can add value, ensuring that leadership and employees are adequately trained, and embedding AI within the company's culture to promote innovation across all levels. The use of AI-enhanced Innovation Management becomes

even more significant in multi-functional conglomerates, where different business units need to integrate processes and share knowledge. AI contributes to decreasing the degree of separate departments' autonomy, increase cooperation, and strive for a coherent approach to problem solving in different conglomerates' sectors. AI as the source of innovation can provide efficient opportunities for conglomerates, namely, the ability to adapt to the shifting customer demand and achieve long-term sustainability by positive changes resulting from competitive advantages for long-term orientation (Antosz, Pasko & Gola, 2020).

The diffusion innovation theory highly explains the concept of innovation and with the use of the Technology acceptance model and AI implementation organizations gain huge growth and development. Multinational organizations and conglomerates can facilitate a smoother transition to AI adoption. Further, compatibility with the AI system, for instance, modernizing the infrastructure and technological culture within the organizations is crucial in the development and growth of organizations with the right customer satisfactory rate as well as the higher employee retention (Patnaik & Bakkar, 2024).

2.6.3. Urban Digitization Frameworks

The process of digitization has been increased to a dramatic shift in technological innovations. There are many frameworks associated with AI that provide services to organizations including Big Data Analytics, the use of the Internet of Things (IoT), and the use of AI services. The AI and tools are used for resource allocation, connectivity for customers, suppliers, and managers, and along with increase the business profitability to increase business growth of conglomerate business organizations (Davenport & Ronanki, 2018). Various Multinational organizations and manufacturing companies are operating in urban contexts and various sectors leveraging such frameworks can significantly boost the impact of AI implementation. Urban digitization frameworks prioritize data-driven decision-making and smart city initiatives, which align closely with AI's strengths in data analysis and real-time processing. In organizations from production and logistics, customer care support, marketing support, management of online inventory and operations along with many supply chain and production activities are managed through the use

of AI and organization gains the benefit of framework in different contexts (Al Mansoori, Salloum & Shaalan, 2020).

The AI provides the different frameworks for digital infrastructure, ensuring that AI adoption aligns with organizational goals, addresses regulatory concerns, and incorporates innovation at the base level and managing operations with AI enhances efficiency and effectiveness within organizations (Choudhuri & et al., 2022). Urban digitization also involves coordination with others key players including local government, private firms, and knowledge institutions, something similar to the conglomerates' need for integration of functions. By integrating the urban digitization measures conglomerates should embrace the future of urban smart systems and sustainability for organizations and large organizations to achieve growth sustainably in a competitive world (Doroshuk, 2021).

2.7. Challenges and Opportunities in AI Adoption:

While AI offers significant benefits, its adoption in conglomerates is not without challenges. Key obstacles include data integration, organizational resistance, and the need for skilled talent.

2.7.1. Challenges:

Thus, Artificial Intelligence (AI) has changed business significantly and brought unique opportunities for improvements and increased competitiveness. However, the firm adoption of AI within conglomerates is not without a hitch. The opportunity for AI to unlock optimization and growth is huge, however there are several challenges that conglomerates face arising from technological, organizational and human resource issues. This sections leads to determine three major challenges in AI adoption, data integration, organisational resistance and talent gap, and also highlight strategies to address these hurdles while representing the opportunities that can take birth from overcoming them.

2.7.1.1. Data Integration:

Different databases within the firm might employ diverse data formats, naming conventions, and diverse data formats. These inconsistent data formats and legacy systems further complicate integration efforts. Incompatible data schemas or formats could build harmonisation, transformation, and mapping issues (Mishra and Konidala, 2023). This procedure becomes increasingly intricate as data sources progress, making it challenging to maintain accuracy and consistency across integrated data. In addition, siloed data secured in disparate systems makes it challenging to merge a coherent dataset. Data silos stem when data is secured in isolated databases, applications, and systems, often in distinct business units or departments (Ullah et al., 2024). These silos frequently restrict data sharing or access, resulting in inconsistencies, inadequate apprehension of the business, and redundancies. For instance, customer details might be secured within a separate system for distinct departments such as customer support, sales, or marketing, making it challenging to receive a 360-degree view of the consumer. AI models demand huge amounts of high-quality, structured data to operate optimally. If the data secured in the legacy system is incomplete or fragmented, it would ultimately hinder the AI's capability to provide considerable insights (Sinha and Lee, 2024). Moreover, there are no sole data standards for Internet of Things (IoT) devices, which adds more complications to data integration (Alahi et al., 2023). A few of the other AI data integration challenges include security, latency, duplication, and fragmentation. These issues, whether combined or alone, could pose operational setbacks, lost revenues, and dated insights. Nedopil, Yue, and Hughes (2024) found that organisations lose around \$12.9 million yearly from poor data quality. Furthermore, increasing concerns regarding data compliance and security is another key data integration issue which is challenging to integrate AI solutions. It is essential to assure that the sensitive data is adequately shielded or managed during integration.

2.7.1.2. Organizational Resistance:

It has been revealed that organizational acceptance is the greatest administrative challenge associated with AI usage due to resistance which main source the fear because of change and future

consequences of the executive of the AI technologies. It comes in a package that some managers may reject it outright, employees may feel that it is a threat that will cost them their jobs, and the institutional factor that will not allow rapid uptake of this style of management (Fountain, McCarthy, and Saleh, 2019).

- ***Fear of Job Displacement***

Automation is one of the common areas in which technologies based on artificial intelligence cause concern among employees. Employees particularly clerk have concerns because they believe that the AI systems are likely to take over their positions, especially where responsibilities involve following patterns, for example, entering data, responding to customer inquiries, or restocking products (Joshi et al., 2024). This fear can result in active or passive resistance, where employees either openly oppose AI adoption or fail to fully engage with new technologies. For instance if a conglomerate has a large manufacturing department, the use of robots with artificial intelligence is likely to make the assembly line workers feel that they are next in line for termination. This resistance can lead to situations where employees will be unwilling to support training or may even go further to implement the process (Iansiti and Lakhani, 2020).

- ***Lack of Understanding of AI's Benefits***

Because AI adoption may not be well understood, some managers and employees may be against its implementation. This can be especially so in organizations that have conventional or 'old economy' corporate environments where they may not consider the application of technology as relevant. Another factor is that there are a lot of misconception about AI like that AI is complicated or AI is unreliable etc. For instance, directors in a conglomerate retail arm may shy away from AI based demand forecasting software if they cannot easily see how such systems could reduce excess stocks. Where value is not demonstrated overtly then resistance can start to develop (van der Vlist, Helmond, and Ferrari, 2024).

- ***Institutional Inertia***

Large organizations often feature institutions that make them bureaucratic; that is, the companies use long-established policies in making decisions. Some of such structures can prevent or hinder the progress of integrating AI in organizations. Different departments have different agendas, which is why an agreement on the optimal approach to AI use is difficult to achieve. In particular, the IT department would always be in support of AI integration, while the finance or HR departments may always be against it since they believe there are many risks involved in AI integration or that it may not be financially feasible to integrate AI (Lakshmi et al., 2024).

2.7.1.3. Talent Gap:

Moreover, another significant challenge that is encountered while adopting AI is the talent gap. The effective implementation of AI necessitates skilled professionals in areas like machine learning, data sciences, AI system design and natural language processing. However, these requirement for these skills often outpaces the supply, developing a prominent barrier to AI adoption.

- ***Shortage of AI Talent:***

AI is a unique branch of study that needs computer science skills, mathematical skills, and skills related to the specialized field. The problem is that most of the conglomerates have difficulties finding specialists who can both design and implement AI systems and then maintain them. It is the exact deficit is especially significant in the emerging markets as the availability of AI education and training at the advanced levels is also rare (Nagaraju et al., 2024). For instance, companies in Southeast Asia or Africa will struggle to find data scientists or machine learning engineers simply because there aren't many in those areas. This leads to a kind of dependency on international talent, especially when such talents are highly paid therefore not sustainable.

- ***High Competition for Talent***

The international demand for AI professionals has caused an intense competition amongst organizations. Companies that work in the technology industry such as Google, Amazon, and

Microsoft often try to attract those individuals who possesses AI backgrounds by offering them high end compensation or by giving them an access to great resources and interesting projects. That may make it challenging for conglomerates to match such offers, becoming an issue in developing strong AI teams (Beernink, 2024).

- ***The need for cross functional expertise:***

AI integration in conglomerates also needs professionals that not only comprehend AI technologies but also have good insights about industries relevant to the conglomerate company. For instance, using AI in a pharmaceutical division of a company will need someone with knowledge in both AI and in pharmacology. It is not easy to look for individuals that have this kind of cross functional experience (Iansiti and Lakhani, 2020).

2.7.2. Strategies to Address These Gaps:

2.7.2.1. Organizational Resistance:

Highlighting the organizational resistance requires a multifaceted technique which include change management, communication and training.

- **Change Management**

Effective change management strategies are essential for overcoming resistance. They also need to involve the employees and managers of the conglomerates right from the time the adoption of artificial intelligence is being planned since it will penalize them. Communications should cover advantages of AI and how it will transform work; implications for roles, and emphasizing that AI will enhance people's work, not replace it. For example, GE used AI for predictive maintenance for assets; thus, the process involved the following steps: It meant that people bought into change since this approach created confidence and little resistance (Fountaine, McCarthy, and Saleh, 2019).

- **Education and Training**

Employee and manager awareness of AI technologies must be informed and educated on AI technologies. Authoring training programs must allow participants to understand what AI is, what it can do, the ways in which it can complement and improve human performance. Presentations in the form of workshops, training sessions, use of case studies, can sometimes give employees a glimpse of how AI can make their work easier (van der Vlist, Helmond, and Ferrari, 2024).

- **Incentivizing Adoption**

There is always a way that the organizations can be persuaded to adopt AI and some of them are; For instance, the performance incentives can be frozen to the proper adoption of the AI measures or the achievement of the intended objectives that AI technologies seek to realize.

2.7.2.2. Talent Gap:

To overcome the talent gap, conglomerates can adopt several strategies:

- **Investing in Training and Upskilling:**

Conglomerates can address talent shortages by investing in upskilling programs for existing employees. AI training for employees can thus be acquired from affiliation with universities, online learning, and training institutes. For example, leading Indian company Tata Group's subsidiary TCS conducts internal AI courses for its workers, so it always has enough AI professionals on staff (Marr, 2019).

- **Leveraging Outsourcing and Partnerships:**

Reducing talent supply gap can be accomplished by contracting the AI development to specialized firms or by partnerships that can be done with technology firms. Due to this social capital, conglomerates can obtain the professional knowledge required for artificial intelligence initiatives without direct recruiting of the necessary talent.

- **Building a Talent Pipeline:**

Conglomerates can establish long-term strategies to build a pipeline of AI talent. Sponsoring AI research, funding scholarships, and creating internship programs can attract young talent. For example, conglomerates like Siemens collaborate with universities to offer internships and projects in AI, fostering future professionals (Lakshmi et al., 2024).

- **Adopting Low-Code and No-Code AI Tools:**

The rise of low-code and no-code AI platforms enables businesses to develop AI solutions with minimal technical expertise. These tools democratize AI development, allowing employees without formal AI training to create and deploy AI applications.

2.7.3. Opportunities in AI for Conglomerates:

AI is now emerging as a phenomenon in the business world, it is changing the face of many organizations and competition in general. With conglomerates having several business units operating in various industries, AI provides the perfect way to enhance overall organizational performance, cut costs, improve the understanding of business operations, and provide new opportunities to unlock value. AI helps conglomerates to solve a variety of issues, optimize work processes, improve their employees' performance in fulfilling their primary value added tasks, and achieve competitive advantages in the context of highly unstable markets. This short paper features a breakdown of how conglomerates benefit from it, real-world examples, and analysis of the key takeaways (Chen, 2025).

2.7.3.1. Streamlining Operations:

Large conglomerates are known to undertake various and sometimes complicated operations as this leads to drive expected efficiency. AI technologies are ways of creating approaches and techniques that reduce technical costs and time wastage, thereby improving efficiency.

- ***Automation of Routine Tasks:***

Some of the areas like data entry, invoice processing, and inventory, among others, are well suited to use of AI automation tools. This cuts down the use of human interaction thus making the activities more efficient free from human interferences. For example, General Electric (GE) used artificial intelligence in robotic technique in their factories where it has automated processes of assembling various items reducing drastically the amount of time required for production and at the same time delivers high quality end product (van der Vlist, Helmond, and Ferrari, 2024).

- ***Predictive Maintenance:***

In industries like manufacturing, automotive, and energy, predictive maintenance powered by AI has become a game-changer. Analyzing pieces of equipment information through machine learning enables determining when the equipment is likely to have a breakdown to plan for maintenance without incurring more loss. For example, Siemens introduced AI in its industrial branches to track equipment so that production remains constant and expenses are greatly reduced.

- ***Supply Chain Optimization:***

AI improves supply chain through real time information tracking, optimizing logistical routes, and demand prediction. Data, weather condition, and market trends patterns can be quantified so that conglomerates are ready to make accurate predictions, based on algorithm analysis. P&G employs AI to ensure efficient delivery of its products throughout the world while cutting costs of logistics (Beernink, 2024).

2.7.3.2. Cost Reduction:

One of the most critical driver of cost reduction for conglomerates is AI-driven efficiency. By enhancing resources allocation and fostering processes, AI tend to reduce operational expenses across different business units.

- ***Energy Efficiency:***

Smart systems based on AI functions helps the factories, offices and data centers to manage the power consumption in an efficient manner which in turn brings a lot of savings. The advancement Google and its DeepMind AI in cutting energy usage in the firm's data centers by forty percent demonstrate how AI is capable of producing great outcomes on energy saving (Iansiti and Lakhani, 2020).

- ***Dynamic Pricing Models:***

In retail goods sector and in the e-commerce sector, AI is used in pricing that provides examinations that ensure that firms capture the highest possible price while ensuring competition does not force a firm to reduce the price. Computing abilities analyse market environment, competitors' strategies, and customers' attitudes toward particular price levels. Many conglomerates such as Reliance Industries use AI within its retail business units to gain more customers with reasonable profitability.

- ***Fraud Detection and Prevention:***

It found that the utilization of AI systems in financial operations have been continually rising especially in identifying fraud. It predicts various transactions and alerts users of any strange behaviour and therefore minimizes on fraud. For instance, the insurance section of Berkshire Hathaway uses artificial intelligence for fraud detection which help save the company a lot of money (Chen, 2025).

2.7.3.3. Enhanced Decision-Making:

AI makes conglomerates to perform faster, reduce their error rate and work more based on the data collected hence enhancing their strategies. Thus, relying on the massive volume of available information, AI comes up with tangible conclusions that give direction to many key decisions.

- ***Business Intelligence and Analytics:***

Business intelligence translates the large volumes of data into useful knowledge that can guide issued-based decisions. They also use AI to analyse the performance of their portfolio companies, and the broader market, and evaluate risks. For example, Tata Group has been implementing AI analytics within its segments to analyse potential trends and conditions on the market (Nagaraju et al., 2024).

- **Real-Time Decision-Making:**

With real-time processing of data, AI systems are best suited for real-time decision making. It is especially useful in industries like telecommunication since early identification can lead to quick reaction to network problems. Tata group uses artificial intelligence to manage its networks and provide reliable service to millions of its clients globally.

- **Scenario Simulation and Risk Assessment:**

It has been observed that AI enables scenario modelling, allowing conglomerates to assess the impact of various strategies and make informed choices. A recipe of being prepared is to use scenarios of markets or possible disturbances to prepare for them. To be prepared for global uncertainties Johnson & Johnson adapts AI to acknowledge supply chain risk (Marr, 2019).

2.7.3.4. Empowering Employees for Strategic Initiatives:

By implementing AI in the workplace, the companies can release their employees from mundane or monotonous tasks, enabling to emphasis on more creative and strategic responsibilities. This not only increases the rate of satisfaction in the workplace but also increases the rate of innovations among organizations.

- **Enhancing Man's Intelligence**

According to the past studies, AI assistance supports and provide recommendations to employees in order to facilitate their decisions. For instance, an AI-reinforced customer relationship

management (CRM) system predicts the strategies for selling on the basis of customer response and helps the sales department to seal the sale (Beernink, 2024).

- **Fostering Innovation**

The daily repetitive functions being undertaken by employees are mechanized, thereby freeing up the individuals' time, which they can use to think creatively. Subsidiary corporations such as in the case of Samsung, the integration of intelligent machinery for automation especially in the production lines have enabled the engineers to come up with spirited innovation designs of the products (Fountaine, McCarthy, and Saleh, 2019).

- **Upskilling Opportunities**

The use of AI always leads to changes in human capital, so this process requires the implementation of reskilling and upskilling initiatives. These programs help the workers acquire specialist skills on the new technologies at the workplace to advance their careers. Companies such as IBM leads to deliver extensive training programs in the area of AI for their employees, so that the Human Capital would stay pertinent in the context of the information age (Joshi et al., 2024).

2.7.3.5. Competitive Advantage in Market Dynamics:

In today's volatile markets, the conglomerates that incorporate AI give themselves a competitive advantage by being more adept at adjusting to its creep than its counterparts.

- ***Customer Experience Personalization:***

The customer preference trends are best understood and leveraged through the help of AI-based personalization tools. Technological giants such as Amazon then deploy this kind of AI mechanism to produce recommendations on products, customers' satisfaction and loyalty. There is a great deal of competitive advantage, when it comes to customer retention as well as attracting new customers (Iansiti and Lakhani, 2020).

- ***Agility and Scalability***

AI can be used in businesses to help them address change quickly in the market. From meeting increased demand rates to expanding into new markets, the shift-to-speed tools are provided by AI. The application of AI in marketing campaigns makes sure that Unilever stays relevant to the consumer's preferences by taking action as they happen.

- ***Sustainability Initiatives***

AI helps in sustainability by achieving maximum output while minimizing the utilization of resources. Those conglomerates, which seriously consider sustainability and the principles of assessing sustainable performance, have an advantage since the public is gradually paying attention to the ecological footprint made by the brands they support. Similarly, Nestlé is using an AI system to ensure an efficient provision of its supply chain while reducing its overall negative impact on the environment (Chen, 2025).

2.7.3.6. Cross-Industry Innovation and Synergy:

Conglomerates, by their very nature, operate across diverse industries, providing a unique opportunity to leverage AI for cross-industry innovation

- **Shared AI Platforms**

It may also be important for conglomerates to build common AI infrastructures that will serve all the different business lines. For instance, one particular AI system for manufacturing division that focuses on routine maintenance can also be deployed within energy divisions of a business entity, generating both cost saves and innovation (Lakshmi et al., 2024).

- **Knowledge Transfer:**

With AI in between, cross-business unit knowledge and the sharing of benchmarks are made easy. For instance, analytics tools, applicable in the retail division can inform and add value in the logistics or healthcare division, as such increasing organizational performance.

- **New Revenue Streams:**

AI-powered innovations often lead to the creation of entirely new products or services, opening up additional revenue streams. Alphabet Inc. has successfully used AI to enter into transport (with Waymo) and home automation technologies (with Nest), demonstrating that conglomerates can successfully look at reinventing their structures.

2.7.3.7. Opportunities for Global Impact:

AI integration helps conglomerates to solve problems facing the world today such as poverty, education, and health all while being profitable and responsible.

- ***Healthcare Advancements***

AI is revolutionizing healthcare sector, from diagnosis to particular therapy, as well as in the discovery of new medications. Many conglomerates with healthcare sector like Johnson and Johnson with its health division, apply the AI advancements in efforts to enhance patient condition and support the efforts towards the betterment of worldwide health recognition. However, these opportunities can be implement in practice with a help of vision, using right strategic investments and overcoming difficulties including organizational one and the problem of talents. As conglomerates expand their applications of AI in various business sectors, they will gain immense value and generate a new form of market and economy worldwide (Nagaraju et al., 2024).

- ***Education and trainings***

Learner management systems promoted through AI advances improve the accessibility of education particularly in developing countries. Mega education technology investors, such as Tata Group's Tata ClassEdge, then use artificial intelligence technologies. In addition, it enhances cross

functionality between various departments, becomes a tool to maintain sustainable business, and develops new income-generating possibilities. Companies adapting AI are more prepared to be ahead of competitors around the world as well as tackling key societal issues (Fountaine, McCarthy, and Saleh, 2019).

- ***Disaster Management***

AI systems assist in the prediction and tackling of disasters to enable conglomerates make their contribution to humanitarian causes. For instance, IBM has created its proprietary AI solution called the Weather Company that generates important weather data used in designing a response to emergencies. AI offers conglomerates tremendous and diverse possibilities for profit-making as well as helping them become more efficient, reduce costs, make better decisions, and thus change the world. In this manner, AI enhances the generality of employees by allowing them to engage in innovativeness in organizational development, not by repetitive tasks. By so doing it assists conglomerate companies to growth effectively and rapidly within the market place and thus is a great source of competitive advantage (Iansiti and Lakhani, 2020).

2.8. Comparative Case Studies of AI Adoption in Conglomerates:

This element of artificial intelligence is revolutilizing industries by improving communication and processes, promoting innovation and delivering customized customer experiences. Global industries and corporations that span across various industries and industries are in the best place to apply AI in improving on performance and profitability (van der Vlist, Helmond, and Ferrari, 2024). The following part of the paper contains two comparative case studies dedicated to the implementation of AI in conglomerates, specifically in the field of automotive industry and financial services. These case studies pointed out where AI has been implemented and become a part of operational processes to manage issue and unleash potential.

2.8.1. Automotive Industry: Optimizing Production with AI-Driven Predictive Analytics:

The automotive industry that has been defined as one of the most vibrant and especially competitive is in the ever-changing process in order to fulfill market needs and solve the problems of low efficiency of operations. In this regard, predictive analytics as a form of AI has become a powerful instrument to change the balance in favor of automotive conglomerates and satisfy the customer needs effectively and decrease waste (Beernink, 2024). Based on the prior general study, this research aims to investigate the specific instance of how a global automotive conglomerate has embraced AI-driven predictive analytic technology in handling some issues and realizing meaningful operational and strategic advantages.

2.8.1.1. Case Study Overview:

The automotive conglomerate that needs to be considered to promote innovation is the company that is among the global top players in this industry offering unique solutions to production and integrating hi-tech novelties into the car manufacturing process. Existing in many countries, it experienced urgent issues in supply chain management, unstable customer needs, and manufacturing constraints. Such problems not only raised costs but also hindered timely delivery of vehicles damaging customer satisfaction. Understandably appreciating what the AI is capable of doing for its operation, the conglomerate used the AI in the form of a predictive analysis of production. Benchmark logistics and supply chain, Production line and sensor data, and patterns of market demand were utilized to make more real-time decisions. This change direction not only resolved current issues, but also made the organization outlook as an industry leader in smart manufacturing (Fountaine, McCarthy, and Saleh, 2019).

2.8.1.2. Implementation Strategy:

To achieve goals of implementing and integrating AI relevant to predictive analytics into the production lines of the conglomerate, it embraced some order and structure. The implementation strategy focused on three core components: the use of the IoT sensors, supply chain data analysis and demand forecasting.

1. Integration of IoT Sensors:

The first measure concerning the actual implementation was to introduce IoT sensors to the production lines. These sensors were installed with a purpose of measuring many attributes within the production line such as the performance of the machines, rate of production and their comparative maintenance needs.

- **Data Collection at Scale:** IoT sensors created a persistent stream of data, capturing significant metrics such as equipment efficiency, temperature variations, and wear-and-tear indicators. This data provided a foundation for analytical tools through which information relating to production activities could be processed to near real-time capabilities.
- **Proactive Maintenance:** It could oversee how the equipment was performing in matters of real time and assess mechanical breakdowns as to schedule for maintenance. This cut the incidence of non-scheduled production stoppages, increased the durability of the machines, and maintained the continuity of production.
- **Granular Visibility:** The fusion of IoT sensors gave detailed insight into every section involved in the line of production. Managers and engineers could track performance metrics at the level of individual machines or entire production units.

2. Supply Chain Data Analysis

The second part of the strategy was to employ AI data algorithms to analyse the supply chain information. Due to the integrated nature of Global Supply Chain, stock outs, substandard suppliers and planned transportation lapses were some of the common problems encountered in Global Supply Chain (Chen, 2025).

- **Real-Time Inventory Monitoring:** algorithms used inventory data to monitor stock conditions across different sites so that it was always possible to have the right stock in the right amount. The system pointed out such conditions as shortage or over stock conditions that allowed the managers to make necessary corrections.

- **Supplier Performance Insights:** Supplier reliability and delivery time information were reviewed at the Company to recognize areas of possible delay. Through integrating with the best suppliers and responding to concerns with low performing ones the supply chain became more reliable.
- **Dynamic Scheduling:** The AI systems used real time insights in the supply chain networks to adapt shift production schedules. For instance if raw materials were to be delayed, the system was able to indicate another string of production processes to be followed in order to prevent time loss (Iansiti and Lakhani, 2020).

3. Demand Forecasting:

The last and final component of the implementation strategy was demand forecasting. When it comes to production planning it is crucial to make correct forecasts of the market tendency in order not to produce too much unsold merchandise or too little to meet customers' demand.

- **Machine Learning Models:** The conglomerate used specific machine learning models to analyse past sales data, as well as market and buyers' behaviours. These models helped recognize trends and make useful recommendations about changes in demand.
- **Seasonal and Regional Variations:** AI algorithms assigned a relevancy factor to seasonal sales and regional preferences for a specific type of product. For example, the demand for specific types of vehicles or specific features within specific regions and the AI was ensuring the right production occurred.
- **Collaboration with Marketing and Sales:** The forecasting system was connected with marketing and sales data to provide a loop to boost the result of accurate predictions. Promotional appeals were advanced to match anticipated demand, thus increasing the probability of a better fit with manufacturing schedules.

2.8.2. Financial Services: Enhancing Customer Experience with AI-Powered Chatbots

2.8.2.1. Case Study Overview:

The use of AI chatbots has been felt across different organizations across the world. Scientists have noted that organizations embraced applying the services of AI chatbots for increasing the

effectiveness of the consumer services and for the better incorporation of the innovative marketing solutions that would help in retaining the consumers and eventually create the new ones (Wang et al., 2022; Zhang et al., 2023). Likewise, other global firms, Sephora a global market leader in cosmetics and beauty retail have introduced AI chatbots for better consumer experience. Tadimarri et al., (2024) have defined that the use of AI-powered chatbots in Sephora has significantly enhanced consumer engagement because all the purchasing processes are streamlined which has significantly increased consumer satisfaction. Vrublevskaia (2021) has also defined that Sephora has introduced “Sephora Virtual Artist” in which the combination of AR (Augmented Reality) and AI (Artificial Intelligence) used by customers based on their preferences have product recommendations and it also provides consumers with a virtual makeup trial.

2.8.2.2. Implementation Strategy:

It is for this reason that Sephora has used a multiple approach towards the integration of the AI chatbots in the organisation. Prasad (2023) has mentioned here that the use of AI chatbots has been made by Sephora in four levels including the plan level, development level, and integration level and optimise level. The author has analysed that the integration of AI chatbots is strategic for Sephora because it provides that the adopted strategy is formulated based on the company’s objectives. Nguyen et al., (2022) have defined that the primary focus of Sephora’s implementation strategy was to address the key issues faced by their consumers and they have designed AI chatbots in such a manner that these issues can be addressed efficiently. Researchers while analysing Sephora’s implementation strategy for AI chatbots have defined that the firm was focused on providing their consumers with tailored choices based on their preferences. This approach will provide ease for the consumers to select their desired products from a diverse product range (Rebière & Mavoori, 2021; Lele, 2021). PAWAR & PAWAR (2023) have also examined the implementation strategy of Sephora which defines that a large capital was invested in the development of machine learning algorithms by which AI-chatbots ability can be enhanced and AR can be used to provide consumers with an engaging shopping experience.

2.8.2.3. Outcomes and Benefits

As highlighted by Oanh (2024) Sephora following the integration of the AI chatbots has booked several advantages. There were not only sufficient organisational benefits but the consumers also gained enough benefits for their welfare. It has been emphasized by scholars that Sephora has experienced a boost in consumer interaction due to real-time recommendation and personalization elements, arguably being the major factors which led to an increase in consumer interaction rates (Deshmukh et al., 2024, Mohapatra et al., 2024). This factor has been further defined by Moussaddak (2024), consumers due to the AI chatbots have shown a high level of engagement with Sephora which has resulted positively due to higher sales and consumer conversion rates. One of the major benefits of implementing AI chatbots was cost savings in Sephora. According to Dang (2022), Sephora with the use of AI chatbots have significantly reduced work pressure on its consumer support agents and they were transferred to work on other complex tasks. Based on all these facts, AI chatbots have significantly increased the operational efficacy of Sephora and a high level of consumer satisfaction was also witnessed (Eyada & Ahmed, 2022).

2.8.2.4. Challenges Faced:

Sephora besides various benefits, numerous challenges were also reported during the implementation of AI chatbots. The key challenge that was observed due to the AI chatbots in Sephora was to ensure that accurate product recommendations were being provided to the consumers. The machine learning algorithms were designed in such a manner by which personalised suggestions could be provided to the consumers but various initial iterations were observed in which inaccurate or wrong recommendations were observed by the consumers (Liew, 2021). On the other hand, Sephora has significantly invested in algorithm optimisation and data cleaning. This has resulted in various challenges because of the integration of more feedback loops by which the system can develop an understanding of consumer interaction. To ensure that all consumer demands are fulfilled accordingly with the use of AI chatbots, Sephora has to deal with the challenge of rapid changes in the product catalogue to ensure that all the product information is updated and accurate (Rangert, 2024). NLP (Natural Language Processing) was another

challenge faced by Sephora due to the implementation of AI chatbots. The initial system was unable to develop an understanding regarding human nuances specifically in the ways when consumers interact and the system is not trained in these aspects. This has negatively affected consumer satisfaction levels and a training feedback loop was implemented for chatbot training to improve on its NLP characteristics (Rana et al., 2024).

2.8.3. Comparative Analysis: Lessons from Both Industries.

2.8.3.1. Chatbots in the Beauty Industry:

For clear appreciation of the impact of AI and particularly chatbots, it is evident that beauty organisations' consumer base has expanded. As Moreira pointed in 2024, AI chatbots enable organisations from the beauty industry to offer their customers superior and efficient consumer service, sales help, virtual beauty consultations and thus, AI-recommended beauty products. Current trends for conversation AI reveals that beauty giants such as Mecca, Sephora, and scores of others have complemented their online consumer engagement systems with AI chatbots. The new breed of intelligent machines has been adopted across beauty conglomerates to augment a 24x7 client-organisation relationship that has raised the organisations' consumer proficiency rates (Ghosh et al., 2024).

Masnita et al., (2023) have also defined that the integration of AI chatbots in the beauty industry has provided various new features for the consumers like virtual consultations in which differentiated skincare products are recommended for the consumers based on their preferences, conditions and skin types. Popular examples include Sephora Virtual Artist which are basically an artificial intelligence chat-bot consumer interface which not only suggests the appropriate skincare product for the consumers but also allows them to try out the makeup virtually before purchasing these products (Khanna & Yadav, 2024). AI chatbots have also helped in improving the after-sale services whereby consumers can solve any issue at their convenience without any influence from the beauty industries. This has to enhance the consumer operation efficiency while human resources are employed for other complex tasks (Chandel, 2024).

2.8.3.2. Chatbots in Healthcare Industry:

AI chatbots are also integrated into the healthcare sector. As noted by Xu et al., (2021), there are several services that are executed in the health sector by AI chatbots in which major ones entail appointment parlays, telemedicine, and patient enunciation. The primary aim of AI chatbots in the healthcare industry is to provide assistance to doctors in dealing with different medical conditions in which information is provided to the consumers regarding medications (Shahsavari & Choudhury, 2023). A noticeable evolution of AI chatbots has been witnessed in the healthcare industry during the era of the global pandemic. During this time, patient screening and virtual consultations were performed to prevent human interaction (Balasubramanian et al., 2023). A noticeable influence of AI chatbots was observed in the NHS (National Health Service) in the UK in which patient symptoms were examined through this system and advice was provided to the patients whether they were required to seek medical attention or not (Miles et al., 2021). The implications of AI chatbots in the healthcare industry have significantly improved the initial diagnostic services specifically in the underserved areas where limited healthcare facilities are present. A series of questions are asked by AI chatbots and the algorithm is designed in such a manner by which immediate actions can be taken for addressing serious patient conditions and the burden on healthcare providers can be reduced to a sufficient extent (Reis & Lenz, 2024).

2.8.3.3. Lessons Learned:

AI chatbots have been introduced in both the healthcare and beauty industries. A noticeable difference has been observed in the impact, challenges and application between these two industries. According to Dassouli et al., (2024), one of the major differences in the integration of AI chatbots in both industries is the regulatory requirements. The healthcare industry is required to have strict regulatory requirements considering the ethical considerations and importance of securing patient confidential data. On the other hand, the healthcare industry with the integration of AI chatbots was focused on having no errors because it could lead towards severe consequences (Basharat & Shahid, 2024). Besides this, the beauty industry had significantly low regulatory

requirements for the integration of AI chatbots because the primary concern for this integration was to enhance consumer satisfaction.

Moreover, the complexity level of AI chatbot integration in both the healthcare and beauty industries was significantly different. The AI chatbots in the healthcare industry had to deal with high-stakes and complex situations because direct consultation was being provided to the patients without any human involvement. To ensure this a high level of efficacy was required by which risks associated with errors can be mitigated effectively. On the other hand, the use of AI chatbots in the healthcare industry was different and they were required to be focused on accuracy, privacy and security of the consumers. The beauty industry heavily relies on AI chatbots, whereas, the use of AI chatbots is still evolving in the healthcare industry ensuring that no errors are present as it could lead towards severe consequences of wrong medical treatment and patients can suffer adverse consequences (Xiao et al., 2023; Thapa & Camtepe, 2021).

2.9. Emerging Trends and Future Directions:

2.9.1. Machine Learning and Deep Learning

ML and deep learning are evolving and becoming the necessary tools in the technological setting since they have transformative solutions to offer across the industries. These technologies are essentially the subsets of AI that enable machines to learn from data, identify patterns, and make decisions with minimal human intervention. In conglomerate management, ML and deep learning are found to be reshaping their operational efficiency, predictive analysis, and decision-making processes.

ML is being extensively applied in conglomerates for tasks such as demand forecasting, supply chain optimization, and fraud detection. For example, predictive ML models are being utilised to analyse historical data, seasonal trends, and market fluctuations so to generate precise demand forecasts. As a result, conglomerates like Procter & Gamble (P&G) efficiently maintain optimal inventory levels and reduce wastage (Maduka & Alheri David, 2024). Similarly, ML algorithms are being used in optimizing supply chain networks by identifying bottlenecks, assessing supplier reliability, and dynamically adjusting production schedules based on real-time data (Santhosh et al., 2024).

Fraud detection and risk management are some other critical applications of ML, found in the literature. Algorithms are frequently used in evaluating transactional data in real time and flagging the anomalies that could indicate fraudulent activities. As example, Mitsubishi Corporation conglomerate has used these systems to safeguard financial transactions, reduced risks and enhanced customer trust (Santhosh et al., 2024).

On the other hand, deep learning is also a specialized branch of ML that basically uses artificial neural networks to process large volumes of unstructured data, including images, videos, and text. The emerging trends have shown that it is very transformative for those conglomerates that operate in healthcare, manufacturing, and retail sectors. For instance, computer vision systems based on deep learning are frequently being used in manufacturing to inspect products on assembly lines that ensures quality and minimizes defects (PC Social, 2023). In healthcare, its models aid in medical imaging and diagnostics that significantly improve patient outcomes while reducing diagnostic errors (Maduka & Alheri David, 2024).

The integration of ML and DL with Internet of Things (IoT) and Edge Computing is another emerging trend noted in the literature that allows conglomerates to process data closer to its source. As a result, latency gets minimized and speed of decision-making gets enhanced in supply chain and logistics operations (Ullah et al., 2024). Additionally, the rise of Explainable AI (XAI) addresses the “black-box” issue in deep learning models as the new trend and promotes greater trust among stakeholders by providing transparency into how decisions are made (Sinha & Lee, 2024).

As ML and DL continue to advance and their role will only be expanding in autonomous decision-making and innovation for conglomerates. For example, conglomerates could adopt reinforcement learning models to optimize resource allocation dynamically across diverse subsidiaries. Furthermore, advancements in quantum computing hold the potential to revolutionize ML and deep learning and offer exponential increases in computational power and enabling the processing of previously intractable datasets (Alahi et al., 2023). However, challenges such as data privacy, skill shortages, and infrastructure requirements must be addressed to fully ripe the benefits of these technologies (Mishra & Konidala, 2023). In this way, ML and deep learning trends and the future of AI applications in conglomerates are driving efficiency, innovation, and competitiveness. Their

continued evolution and integration will undoubtedly redefine organizational capabilities in a rapidly changing global market.

2.9.2. AI Innovation in Companies:

As AI is revolutionizing companies across industries, it is bringing transformative changes in their operations, decision-making, and innovation strategies. AI technologies, such as machine learning, natural language processing (NLP), and robotics, are not streamlining processes that open the ways for ground-breaking advancements in products and services.

1. **Hyper-Personalization and Customer Experience:** AI is reshaping customer engagement through providing hyper-personalized experiences. Companies like Amazon and Reliance Industries are incorporating AI-driven recommendation engines and chatbots to modify products, services, and interactions according to the preferences and behaviours of their individual customers. Thus, the companies are noticing the trend of enhanced customer satisfaction, fostered brand loyalty, and driven revenue growth (Santhosh et al., 2024).
1. **AI-Driven Sustainability Initiatives:** Sustainability is also becoming a core focus for businesses, and AI (in this regards) is playing a very important role that allows the companies to achieve environmental goals. For instance, Nestlé is using AI to optimize supply chains, reduce waste, and minimize carbon footprints. Smart systems analyse resource consumption, thus helpg companies in meeting sustainability targets while also letting them maintain the profitability (Maduka & Alheri David, 2024).
2. **Cross-Industry Collaboration:** AI platforms are fostering collaboration across diverse industries within conglomerates. Shared AI systems integrate data and processes across business units, enabling cross-industry innovation and synergies. For example, predictive analytics tools used in manufacturing may inform strategic decisions in logistics or retail divisions (PC Social, 2023).

3. **Integration with IoT and Smart Systems:** The convergence of AI with the Internet of Things (IoT) is transforming industries by enabling real-time data analysis and automation. AI-powered IoT systems in smart factories optimize production lines, reduce downtime through predictive maintenance, and improve operational efficiency (Ullah et al., 2024).
4. **Ethical AI and Regulatory Compliance:** As AI adoption grows, companies are prioritizing ethical AI practices and compliance with global regulations. Explainable AI (XAI) is emerging as a critical trend, ensuring transparency in decision-making processes and fostering trust among stakeholders. Companies are investing in frameworks to mitigate bias, enhance accountability, and align AI systems with societal values (Sinha & Lee, 2024).

AI innovation is poised to drive even more significant changes in companies as the technology evolves.

1. **Autonomous Decision-Making:** Advanced AI models, such as reinforcement learning, will empower companies to implement autonomous decision-making systems. These systems can dynamically optimize operations, resource allocation, and market strategies without human intervention (Mishra & Konidala, 2023).
2. **Quantum AI Integration:** The advent of quantum computing is expected to revolutionize AI capabilities. Quantum-enhanced AI will enable companies to solve complex optimization problems and process vast datasets at unprecedented speeds, unlocking new opportunities for innovation (Alahi et al., 2023).
3. **AI in R&D and Product Development:** Companies are increasingly using AI to accelerate research and development (R&D). From drug discovery in healthcare to material design in manufacturing, AI algorithms are shortening product development cycles and reducing costs. This fosters innovation and ensures competitiveness in fast-paced markets (Maduka & Alheri David, 2024).
4. **Enhanced Collaboration Through AI Platforms:** AI-driven collaborative platforms will facilitate seamless communication and knowledge sharing across teams and subsidiaries. These platforms will enable remote work optimization, real-time data integration, and cross-functional innovation (Santhosh et al., 2024).

5. **Focus on AI Talent and Upskilling:** To fully harness AI's potential, companies must address the talent gap by investing in upskilling and reskilling initiatives. Collaborations with educational institutions, internal training programs, and the adoption of low-code AI tools will democratize AI adoption and empower employees to contribute to AI-driven transformations (Mishra & Konidala, 2023).

AI innovation is redefining the operational and strategic paradigms of companies, driving efficiency, enhancing customer experiences, and fostering sustainability. By embracing emerging trends and addressing associated challenges, companies can position themselves at the forefront of technological advancement, ensuring long-term growth and resilience in an increasingly competitive global market.

2.9.3. Sustainability Initiatives:

Sustainability has emerged as a key strategic priority for businesses, particularly in the wake of increasing environmental concerns, regulatory pressures, and shifting consumer expectations. Enterprise Resource Planning (ERP) systems and Artificial Intelligence (AI) are playing a pivotal role in enabling organizations to achieve sustainability goals by optimizing resource utilization, minimizing waste, and reducing carbon footprints. Recent literature highlights how AI-integrated ERP solutions are transforming traditional business practices into eco-friendly, data-driven, and sustainable operations.

One of the critical areas where ERP and AI contribute to sustainability is energy efficiency and resource optimization. Studies indicate that AI-enhanced ERP platforms leverage predictive analytics and IoT (Internet of Things) integration to monitor energy consumption patterns, detect inefficiencies, and provide recommendations for reducing energy waste (Maduka & Alheri David, 2024). Companies such as Siemens and General Electric have integrated AI-driven predictive maintenance within their ERP systems, reducing energy consumption by optimizing the performance of industrial machinery and equipment (Santhosh et al., 2024). This proactive approach not only enhances operational efficiency but also contributes to long-term environmental sustainability by reducing carbon emissions.

Additionally, AI-powered ERP systems play a crucial role in sustainable supply chain management by enhancing visibility across procurement, logistics, and distribution. Advanced AI models analyse data related to supplier sustainability compliance, transportation emissions, and inventory management, enabling companies to select eco-friendly suppliers and optimize delivery routes to minimize fuel consumption (Sinha & Lee, 2024). For example, Unilever and Nestlé utilize AI-driven ERP solutions to track and reduce supply chain emissions, ensuring adherence to global sustainability standards such as the Science-Based Targets initiative (SBTi) (Ullah et al., 2024). Another emerging trend is the adoption of circular economy models within ERP frameworks. AI-powered ERP systems help organizations implement waste reduction strategies, product lifecycle assessments, and recycling initiatives by analyzing product usage patterns and recommending sustainable alternatives (Mishra & Konidala, 2023). The automotive industry, particularly firms like Tesla and BMW, has embraced AI-driven ERP solutions to enhance battery recycling programs and optimize raw material utilization, leading to significant reductions in industrial waste (Alahi et al., 2023).

Furthermore, sustainability reporting and compliance have gained prominence in corporate governance. AI-driven ERP platforms facilitate automated tracking and reporting of environmental, social, and governance (ESG) metrics, ensuring that companies remain compliant with sustainability regulations such as the EU Green Deal and the Global Reporting Initiative (GRI) (PC Social, 2023). By integrating real-time data analytics and blockchain technology, AI-powered ERP systems enhance transparency and accountability in sustainability efforts, allowing businesses to make informed, responsible decisions.

While AI-integrated ERP solutions offer transformative potential in sustainability, challenges remain, including high implementation costs, data privacy concerns, and the need for skilled talent (Santhosh et al., 2024). Future research should explore scalable AI-driven sustainability models that align business profitability with environmental responsibility, ensuring that sustainability remains a core pillar of ERP and AI-driven business management strategies.

2.10. *Literature Gap:*

While the literature review in this chapter provides extensive information about the role of ERP systems and AI in business administration and business management, there are some gaps that require more investigation. These gaps primarily emerge due to evolving business complexities, technological advancements, and organizational resistance to transitioning from traditional ERP systems to AI-enhanced ERP frameworks. The first research gap is lack of research on ERP and AI Convergence in multi-industry conglomerates. Most studies analysed in the chapter focus on ERP implementations within single-industry enterprises, such as manufacturing, retail, healthcare, and finance, but fail to comprehensively examine how ERP functions within conglomerate structures that operate across multiple industries and geographies. Given the diverse business operations of conglomerates, ERP systems often struggle with integration challenges across different sectors with unique regulatory requirements, operational models, and market dynamics. Another identified gap is the insufficient research on how AI-driven ERP can provide a centralized yet adaptable management solution for conglomerates that operate in multiple industries. Likewise, there is limited analysis available in the literature for the role of AI-based decision making and predictive analytics in improving the operations when transitioning from ERP. While the chapter acknowledges ERP's contributions to business process automation, its potential in strategic decision-making remains underexplored. Many ERP systems still rely on historical data analysis rather than predictive analytics, limiting their ability to offer real-time, data-driven strategic insights.

There is also a lack of research on how ERP, combined with AI-driven predictive analytics, can be used for forecasting business trends, risk mitigation, and strategic agility in decision-making. In future, studies can focus on how ERP, integrated with AI, can enhance decision-making through machine learning models that predict economic fluctuations, supply chain risks, and consumer behaviour. There is also minimal research on how organizations can ethically implement AI-driven ERP solutions without compromising data privacy, security, or workforce stability. Therefore, it requires studies that investigate AI governance frameworks and ensure ERP compliance with international data protection laws (e.g., GDPR, CCPA) while addressing employee concerns over job displacement due to automation.

The literature review touches on cloud-based ERP solutions but fails to address the transition challenges from on-premise ERP to cloud-based or hybrid ERP models in large-scale organizations. Many large enterprises and conglomerates hesitate to adopt cloud ERP due to data security concerns and the complexities of migrating from legacy systems. There is limited research on the strategic transition from traditional ERP to cloud-based or hybrid ERP solutions, particularly in large conglomerates. Best practices should be explored for hybrid ERP adoption, including cost-benefit analyses, security measures, and migration strategies for multi-national corporations.

2.11. *Chapter summary:*

This chapter provided a comprehensive literature review on the integration of Enterprise Resource Planning (ERP) systems and Artificial Intelligence (AI) in business administration and business management, with a particular focus on their role in optimizing decision-making, operational efficiency, and strategic agility in conglomerates. The review explored how ERP systems, once the backbone of enterprise management, are evolving through AI-driven enhancements to meet the complexities of modern multi-industry business structures. While ERP remains a vital tool for resource planning and workflow standardization, its traditional limitations—such as rigidity, high implementation costs, and lack of real-time adaptability—have driven the need for AI augmentation.

The discussion highlighted the role of AI in enhancing ERP's capabilities, including predictive analytics, machine learning (ML), natural language processing (NLP), and robotic process automation (RPA). These AI technologies address key challenges in data integration, business intelligence, risk management, and workforce optimization. Studies reviewed indicated that AI-powered ERP models enable conglomerates to synchronize diverse subsidiary operations, optimize supply chains, and enhance financial and HR planning through real-time analytics. However, the review also identified organizational resistance, data privacy concerns, and the need for AI-skilled personnel as barriers to successful AI-ERP implementation.

A significant portion of the literature was dedicated to AI's role in strategic decision-making within conglomerates. Traditional ERP systems primarily provide historical data insights, whereas

AI enables real-time forecasting, risk assessment, and prescriptive analytics. AI-integrated ERP systems have been adopted by global firms such as Siemens, Tata Group, and General Electric, allowing top management to make data-driven decisions with higher precision. Moreover, AI-driven scenario modeling has proven essential in industries like manufacturing, healthcare, and finance, where dynamic market conditions require proactive rather than reactive decision-making approaches.

The review also delved into the transition from on-premise ERP to cloud-based and hybrid ERP models, reflecting a major trend in enterprise technology. While cloud ERP solutions offer scalability, lower infrastructure costs, and enhanced security, large conglomerates still face challenges in migrating legacy systems due to data security risks, regulatory constraints, and integration complexities. AI plays a crucial role in overcoming these barriers by automating migration processes, detecting security vulnerabilities, and ensuring seamless interoperability across cloud environments.

Another key theme examined was AI's role in sustainability initiatives within ERP frameworks. AI-driven ERP models enable energy-efficient operations, optimized supply chains, and ESG (Environmental, Social, and Governance) compliance tracking. Companies like Unilever and Nestlé use AI-powered ERP tools to monitor carbon footprints, manage waste reduction programs, and implement circular economy principles. The integration of AI with blockchain technology further enhances transparency in sustainability reporting and compliance with international standards.

While the literature underscores AI's transformative impact on ERP-driven management, significant research gaps remain in areas such as AI-ERP integration for multi-industry conglomerates, ethical challenges in AI decision-making, and AI-enhanced ERP user experience. Future research must explore scalable AI-driven ERP models that balance business performance with sustainability, regulatory compliance, and workforce adaptability to create truly intelligent enterprise ecosystems.

Chapter 3: Methodology

3.1. Research Philosophy:

In any research, its philosophical foundation has a significant role in the formulating of its approach, methods, and outcomes. For this study, pragmatism was chosen as the guiding research philosophy, since it emphasizes practical knowledge and seeks to bridge theoretical inquiry with real-world solutions (Creswell & Creswell, 2017). In this research, pragmatism is best suited because research aims to generate practical understanding of a complex issue: the implementation of AI in the management of large multi-functional conglomerates.

As a research philosophy, pragmatism prioritizes solving actionable problems through practical approaches. This aligns with the study's aims, which go beyond theoretical exploration of AI to deliver tangible strategies for improving management effectiveness in conglomerates. Embracing the principle of "what works" ensures the study remains focused on practical insights rather than abstract theory (Morgan, 2014). Pragmatism also supports the use of diverse methodologies so that the central research question can be answered comprehensively. Given this study's wide-ranging objectives – from evaluating AI integration to investigating operational and decision-making improvements – a pragmatic stance enables the researcher to utilize multiple tools (surveys, case studies, statistical analysis, etc.) to address these complex goals. This flexibility is especially important when studying conglomerates, as they span various industries and locations, which calls for adaptable, context-sensitive methods.

Ontologically, pragmatism embraces a pluralistic view that reality is dynamic and can be interpreted in numerous ways depending on the observer and context (Maarouf, 2019). This is particularly relevant when researching AI's impact on conglomerates, where the outcomes and efficacy of AI implementation can vary widely based on organizational culture, technological readiness, and industry-specific conditions. A pragmatic ontology thus accommodates the inherent diversity in a topic like this. Epistemologically, pragmatism postulates that knowledge is best understood when applied practically to real-world concerns (Patton, 2014). This perspective aligns with the focus of this research on identifying how AI can be implemented in practical, strategic ways to address challenges such as resource allocation, decision-making, and adaptability in

conglomerates. The pragmatic philosophy ensures the research remains solution-oriented by emphasizing actionable knowledge that is directly relevant to practitioners in the field.

Furthermore, pragmatism allows for a critical examination of both the opportunities and challenges of AI, fostering a balanced view of AI implementation. For instance, while this study investigates how AI can improve operational efficiency and decision-making, it also explores organizational, ethical, and technical barriers that conglomerates might face. This balanced perspective reflects the pragmatic focus on achieving practical outcomes. Overall, pragmatism encourages iterative inquiry, where findings inform ongoing adjustments to both research methods and real-world practices (Shan, 2022). This iterative approach is crucial in the rapidly evolving field of AI, where new methodologies and technologies continuously emerge.

3.2. Research Approach:

This study employs an inductive approach, which correlates with its pragmatic philosophy. An inductive approach involves formulating research questions on the basis of existing frameworks and theories, then using empirical findings to confirm, refute, or refine those concepts (Bougie & Sekaran, 2019). This method is well-suited to the present work because it focuses on analyzing how existing AI methodologies apply to conglomerate management, providing a systematic way to assess the degree of organizational transformation.

For exploring the study's primary research question—how AI can be used to improve management productivity and inform strategic options in a diversified conglomerate—the inductive approach is appropriate. It begins with a theoretical understanding of various AI applications such as machine learning, natural language processing (NLP), and robotic process automation (RPA) (Russell & Norvig, 2016). These concepts are then examined against the data; by evaluating the empirical results, the study can determine how these AI tools assist conglomerates in increasing operational efficiency and enhancing decision-making.

Epistemologically, the inductive approach aligns with pragmatism's focus on real-world applicability and actionable knowledge. It offers a framework that facilitates some level of generalization and provides structured methodologies to present AI-driven strategies for conglomerates. In addition, this approach helps identify the strengths and weaknesses of applying

AI technology, allowing a more objective view of its positive and negative impacts (Bryman, 2016). Beyond its structured nature, the inductive approach also encourages empirical assessment and iterative refinement of the research process. By incorporating findings back into addressing the problem, it ensures the research stays solution-focused and yields practical benefits for industry practitioners. Thus, the inductive approach provides a solid conceptual foundation for realizing the aims of the study and for effectively addressing the research question.

3.3. Research Design:

This study uses a mixed-method research design and incorporates quantitative and qualitative approaches to assess the impact of AI-driven management that transitioned from ERP. The methodology is structured into two primary phases: pre- and post-surveys among employees, followed by in-depth interviews with management. It offered a comprehensive evaluation of the effectiveness, challenges, and strategic benefits of AI-ERP integration within an organization.

The first phase consists of pre- and post-surveys administered to employees across various departments. The pre-survey is conducted before AI-enhanced ERP implementation to gauge employees' existing experiences with traditional ERP systems, including their efficiency, usability, and limitations. Questions are focused on workflow efficiency, ease of use, perceived challenges, and adaptability to AI-driven enhancements. Following the implementation of the AI-driven ERP system, a post-survey is conducted to assess changes in employee perceptions, usability, and operational effectiveness. This comparative analysis will help quantify efficiency improvements, user satisfaction levels, and potential barriers to adoption.

The second phase involves in-depth interviews with management personnel, including department heads, IT specialists, and senior executives, to gain qualitative insights into the strategic implications of AI-ERP integration. These interviews explored decision-making processes, resource optimization, risk management, and long-term business impact. Management's perspectives provide a detailed view of AI-driven ERP adoption, including organizational resistance, investment considerations, data security concerns, and future scalability.

This sequential explanatory design—where quantitative data from surveys informs the qualitative interviews—ensures that both employee experiences and strategic leadership insights are systematically analysed. The combination of statistical survey analysis and narrative interview data strengthens the study’s validity, offering a comprehensive evaluation of AI-ERP’s impact from both operational and managerial perspectives. The research is conducted within a single organization that ensured consistency in implementation variables. However, the findings are foundation for broader applications of how AI-driven ERP systems can be optimized across various industries and conglomerate structures.

Furthermore, the study focuses on a single large conglomerate (pseudonymously referred to as “Alpha Group”) for both the survey and interview phases, effectively making the qualitative component an in-depth case study of that organization. By concentrating on one case, the research controls for variations in context and ensures consistency in implementation variables (such as organizational culture, structure, and technology infrastructure). A case study approach allows an in-depth, multi-faceted exploration of this complex issue within its real-life setting, which is ideal for examining how the ERP-to-AI transition unfolds in a real organizational environment. This strategy yields rich contextual insights that complement the broader trends identified through the surveys. While the analysis is rooted in a single case, the insights gained provide a foundational understanding of AI-driven ERP implementation that can inform similar initiatives in other conglomerates or industry contexts.

3.4. Data Collection Method:

Pre- and Post-Surveys (Quantitative Data Collection)

The first phase of data collection involves conducting structured surveys before and after the implementation of the AI-driven ERP system. These surveys target employees across different departments, including operations, finance, supply chain, human resources, and IT, to assess their perceptions, challenges, and experiences with ERP usage before and after AI integration.

Pre-Survey	Post-Survey
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Conducted before the implementation of the AI-driven ERP system	Conducted after the AI-driven ERP has been fully implemented and used for a specified period (e.g., three to six months)
Aims to measure current user experience, efficiency levels, perceived barriers, and usability challenges of the traditional ERP system	Measures improvements in workflow efficiency, ease of use, productivity, and strategic insights compared to the previous ERP system
Uses Likert-scale questions (e.g., satisfaction with ERP functions, ease of use, decision-making support)	Evaluates employee satisfaction levels, adaptability to AI features, and perceived limitations
Includes open-ended responses to capture employee concerns and expectations regarding AI-enhanced ERP	Compares results with the pre-survey data to quantify changes in operational efficiency, AI adoption challenges, and user experiences

Survey Administration and Sampling:

Surveys is distributed electronically via Google Forms. Random sampling is used to select participants across departments that ensured representation of different functional areas and job roles. The sample size was deliberately capped at 200 employees. This cap was set to ensure a sufficient number of responses for statistical reliability while keeping the data collection and analysis manageable. In other words, 200 responses were deemed an adequate representation to yield meaningful quantitative insights (exceeding common minimum guidelines) without exceeding the project's time and resource constraints.

In-Depth Interviews (Qualitative Data Collection)

The second phase of data collection involved conducting semi-structured in-depth interviews to gather qualitative insights. These interviews targeted key stakeholders in Alpha Group, including senior management and IT leadership, who had direct involvement in or oversight of the AI-ERP implementation. By focusing on this single organization, the interviews form part of the case study analysis, offering context-rich information on the implementation process and its outcomes.

Interview Objectives: The interviews were designed with several objectives in mind: To explore management's perspectives on the ERP-to-AI transformation, including perceived efficiency gains, improvements in strategic alignment, and considerations around investment (cost vs. benefit), to understand decision-making improvements, risk assessment enhancements, and AI's role in predictive analytics, and to assess barriers to adoption, including resistance to AI, infrastructure challenges, and data security concerns.

- **Interview Sample and Procedure:**

Interviews were conducted with 10-15 key stakeholders, including C-level executives, IT directors, ERP managers, and department heads. A purposive sampling method was used to select participants based on their involvement in ERP implementation and strategic planning. All interviews were conducted in person, which facilitated a deeper conversation and enabled the interviewer to observe non-verbal cues. Each interview lasted roughly 30 minutes. With the consent of participants, interviews were audio-recorded to ensure accuracy of data. The recordings were later transcribed for analysis.

3.5. Data Analysis Technique:

The pre- and post-surveys generate numerical data that is analysed using statistical methods to assess changes in employee perceptions, operational efficiency, and user satisfaction.

- **Descriptive Statistics:**

Basic descriptive statistics were calculated to summarize the survey responses. For key measures (such as perceived system efficiency, user satisfaction, etc.), the mean, median, and standard deviation were computed to understand central tendencies and variability in responses. Additionally, frequency distributions were used to determine the percentage of employees selecting each response option on Likert-scale items, which helped in identifying overall trends (for example, the proportion of users reporting improvements post-implementation).

- **Comparative Analysis (Pre- vs. Post-Survey):**

To assess whether any observed changes between the pre-implementation and post-implementation survey responses were statistically significant, inferential tests were performed. Specifically, paired t-tests (for approximately normally distributed response data) and Wilcoxon

signed-rank tests (for non-normally distributed data) were conducted to compare employees' responses before and after the AI-ERP implementation on key metrics. These tests determine if the mean differences in responses (pre vs. post) are likely due to the intervention (AI integration) or just random variation. Additionally, an ANOVA test was used to compare post-implementation perceptions across different groups (e.g. across departments or job levels) to see if certain groups experienced significantly different outcomes or not.

- **Correlation and Regression Analysis:**

Further analysis was done to examine relationships between the extent of AI-driven ERP adoption and various outcome metrics. Correlation analysis was used to see if there were significant associations between, for instance, the degree of AI usage and improvements in efficiency, error reduction, or decision-making support. Building on this, regression analysis (using linear regression models) was performed to assess the impact of specific AI features (such as predictive analytics or automation components) on outcomes like employee productivity. The regression models helped isolate the effect of AI features while controlling for other factors, providing insight into which aspects of the AI integration had the strongest influence on performance improvements.

- **Qualitative Data Analysis (Interview Data)**

The qualitative data from management interviews were analyzed using a thematic analysis approach, which is well-suited for identifying patterns and insights in textual data. Given that this is effectively a case study of Alpha Group, the thematic analysis helps synthesize individual viewpoints into broader themes that describe the AI implementation experience.

Transcription and Coding: All interview recordings were transcribed verbatim to create accurate textual data. Using qualitative analysis software (such as NVivo or ATLAS.ti), the transcripts were then coded. Coding involved labeling segments of text with codes or tags that represent specific topics or concepts. An initial codebook was developed based on the research questions and interview guide (including expected topics like strategic alignment, adoption barriers, decision-making improvements, cost-benefit considerations, etc.), but coding remained open to new themes emerging from the data. For example, if multiple managers mentioned issues about change

management or training, those segments would be coded under those themes. This systematic coding organized the qualitative data into categories for further analysis.

Thematic Analysis: Following Braun & Clarke's (2006) six-step framework for thematic analysis, the study then identified key themes across the coded data. This involved: (1) familiarization with the data, (2) generating initial codes (as described above), (3) searching for themes by collating codes into potential themes, (4) reviewing those themes against the data, (5) defining and naming the themes, and (6) producing the report. Through this process, recurring patterns and managerial insights were distilled into major themes that characterize the AI-ERP implementation at Alpha Group. Examples of themes that emerged include the impact of AI on strategic agility, workforce resistance and change management, and long-term scalability and infrastructure challenges. These themes were analyzed for internal consistency and against one another to construct a coherent narrative of the case. The qualitative findings (themes and representative quotes) thus provide depth and context, illustrating how and why the AI integration achieved certain outcomes, which complements the quantitative results.

3.6. Ethical Consideration:

This study adheres to strict ethical guidelines to ensure participant protection, data integrity, and compliance with research ethics standards. Given the involvement of human participants, ethical considerations are crucial in maintaining confidentiality, voluntary participation, and unbiased data collection.

1. Informed Consent

All participants, including employees and management personnel, received a detailed consent form outlining the purpose and objectives of the study, their voluntary nature of participation, ensuring they can withdraw at any time without consequences, the data collection process, including how survey responses and interview data will be used, and the assurance that participation will not impact their employment status or job security.

2. Confidentiality and Anonymity

To protect participant identities, all survey responses were anonymized and any identifiable information was removed. Also, the interview transcripts were coded to replace names with participant IDs. Data was securely stored in encrypted files, with access restricted to authorized researchers only.

3. Non-Coercion and Voluntary Participation

No participants were pressured to take part in the study. Management involvement did not influence employee responses thus it prevented bias or perceived obligation. The presence of company management in the study was handled carefully. Managers did not directly solicit subordinates to participate, and their involvement in overseeing the research did not influence any employee's decision to participate or their responses. This separation helped prevent any perception of obligation or fear of reprisal, thereby avoiding bias. During both the survey and interviews, participants were reminded that they could skip any question or stop the interview at any point if they felt uncomfortable. This ensured that participants only provided information they were comfortable sharing, further underscoring the voluntary nature of the research.

4. Data Protection and Security

Survey data are stored on a password-protected cloud server. Interview recordings and transcripts are encrypted and deleted after analysis. Compliance with GDPR and institutional data protection policies are maintained.

5. Avoiding Research Bias

The survey was designed with neutral wording for all questions. Care was taken to avoid leading questions or loaded terms that might sway respondents toward a particular answer. The survey went through a review process (and a pilot test, if applicable) to ensure clarity and neutrality. The interviews were conducted in a semi-structured format, which allowed participants to express their views in their own terms. The interviewer used an interview guide with open-ended questions and followed up for clarification without imposing personal opinions. This approach gives respondents the freedom to highlight what they felt was important, reducing the chances of the interviewer's perspectives shaping the conversation. During analysis, especially of qualitative data, a conscious effort was made to let themes emerge from the data itself (grounded in participants' actual words) rather than fitting the data into preconceived categories. Peer

debriefing and review of themes (with a supervisor or colleague) were utilized to ensure that the interpretations of the data were reasonable and not solely reflective of the researcher's biases.

Sample

Chapter 4 – Data Analysis, Results, and Findings

The research was conducted using a sequential mixed-methods approach, combining a pre- and post-implementation survey with qualitative interviews to explore the effectiveness of integrating AI into ERP systems within Alpha Group. The implementation began with the distribution of structured surveys to employees across various departments, aimed at assessing user experience with the legacy ERP system. Following the rollout of the AI-enhanced ERP platform, the same participants were invited to complete a post-survey after a three-month usage period, allowing for comparative analysis. Simultaneously, semi-structured interviews were conducted with senior managers and department leads to gain strategic insights into the integration process, challenges encountered, and the perceived value of AI functionalities.

While the overall research process progressed smoothly, a few practical issues emerged. The deliberate cap of 200 survey respondents was implemented to maintain data manageability and ensure focused, representative analysis within project constraints. However, participant follow-up for the post-survey phase posed challenges, with some delays arising due to scheduling conflicts and limited engagement in certain departments. Additionally, coordinating interviews with senior stakeholders required flexibility and repeated rescheduling, particularly during quarterly business review periods. Despite these constraints, all essential data were successfully collected within the planned timeframe, and ethical safeguards—such as informed consent and data confidentiality—were rigorously maintained throughout.

The aim of this study is to examine and analyse the transformative role of AI in transitioning from traditional ERP systems to AI-driven management in multi-functional conglomerates. Following this aim, this particular chapter has presented the results from primary data. To begin with, the chapter first shed light on descriptive statistics from quantitative data, i.e., survey. In this section of this chapter, particular details about participants have been unfolded. Their role, their experience, and the industries they belong to are presented. The next sub-section in descriptive statistics from quantitative data is results and analysis of pre-implementation survey and post-implementation survey. Next in line are inferential statistics from quantitative data where regression and correlations are estimated. The latter part of this chapter contains thematic analysis from qualitative data.

4.1. Descriptive Statistics from Quantitative Data

4.1.1. Demographic Aspects

1.1.1.1. *Role of Participants*

Table 1: Role of Participants

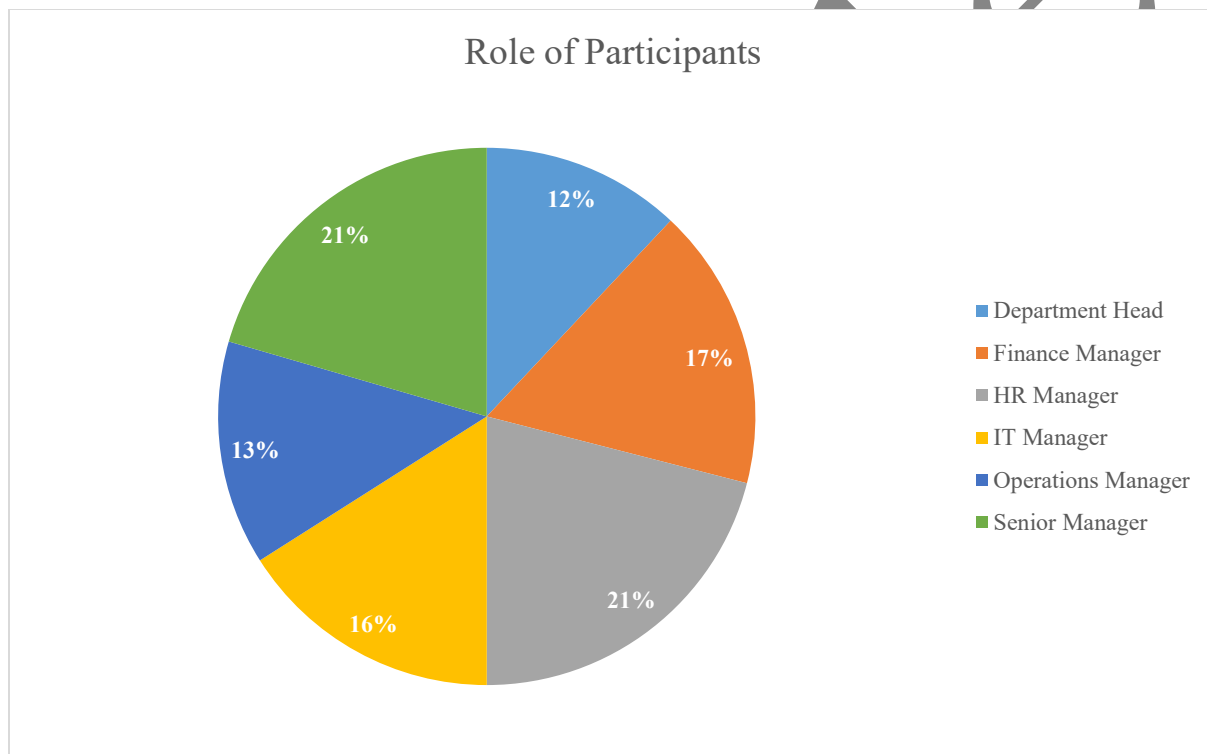
Role	No. of Participants
Department Head	24
Finance Manager	34
HR Manager	42
IT Manager	32
Operations Manager	27
Senior Manager	41
Grand Total	200

The provided table no. 1 above and accompanying pie chart in figure no. 1 below illustrate the distribution of participant roles among the total of 200 survey respondents. The largest share of participants comes from HR Managers, making up 21% (42 participants). It is closely followed by Senior Managers, who also constitute a substantial 21% (41 participants). Finance Managers represent 17% of the respondents and account for 34 individuals. IT Managers also form a notable segment that comprises of 16% of the total participant pool with 32 individuals. Operations Managers represent 13% (27 participants) and reflect a moderate yet significant group. The smallest group of respondents are Department Heads, who stands at 12% (24 participants) in total participants representation.

The pie chart visually strengthens these proportions and offers a cleared depiction of role distribution. The figure no. 1 highlights the prominence of HR and Senior Managers among participants. It also demonstrates balanced representation from critical business areas (such as finance and IT) that ensures diverse managerial perspectives. The overall distribution presented in the pie chart (figure no. 2) indicates that an all-inclusive range of mid-to-senior-level management

viewpoints are collected in this survey. As a result of such balanced involvement from multiple managerial positions in the survey, the relevance and applicability of the findings get enhanced for understanding organizational transition from ERP to AI-based systems. This variety is beneficial in understanding complex yet critical managerial perceptions and attitudes related to strategic management decisions within conglomerate structures.

Figure 1: Role of Participants



1.1.1.2. Number of Year of Participants' Experience

Table 2: Number of Year of Participants' Experience

No. of Experience	Role(s)						Grand Total
	Department Head	Finance Manager	HR Manager	IT Manager	Operations Manager	Senior Manager	
1	0	3	2	3	2	1	11

2	1	1	3	1	2	3	11
3	2	3	1	3	2	0	11
4	2	2	3	0	2	3	12
5	2	0	1	1	1	2	7
6	2	0	1	0	1	4	8
7	1	1	2	2	3	0	9
8	1	2	0	1	0	7	11
9	2	0	1	2	1	4	10
10	0	2	4	1	3	0	10
11	1	4	4	1	1	3	14
12	2	2	1	3	0	1	9
13	2	5	4	2	1	1	15
14	0	2	3	0	0	1	6
15	0	1	3	1	3	2	10
16	1	1	3	0	1	2	8
17	2	1	2	4	0	1	10
18	2	1	0	3	2	3	11
19	0	0	2	1	2	2	7
20	1	3	2	3	0	1	10
Grand Total	24	34	42	32	27	41	200

The table no. 2 presented above provides a detailed overview of the distribution of participants' years of professional experience across six key managerial roles within the surveyed organizations. As a total of 200 individuals participated in the survey, their roles are categorized into Department Heads, Finance Managers, HR Managers, IT Managers, Operations Managers, and Senior Managers. The table no. 2 shows data across a span of twenty years of experience and offered information about the seniority as well as the diversity of the respondent pool.

The cumulative totals at the bottom of the table show that HR Managers constitute the largest group with 42 participants, followed closely by Senior Managers with 41 individuals. Finance

Managers account for 34 respondents, while IT Managers make up 32. Operations Managers and Department Heads are slightly fewer in number, representing 27 and 24 participants respectively. This balanced distribution across functional roles highlights the multi-disciplinary representation within the dataset, supporting the study's focus on conglomerate organizations.

Examining the experience levels, it becomes evident that participants are spread across a broad range of career tenures. Notably, the experience bracket with the highest number of respondents is 13 years, with 15 participants. This is followed by 11 years of experience with 14 individuals and 4 years of experience with 12 participants. Several other experience levels, including 2, 3, 8, and 10 years, show a frequency of 10 or more respondents, suggesting a relatively even spread. Such a distribution implies that the survey includes both mid-level professionals and individuals with more senior tenures, offering a layered perspective on AI implementation across different stages of managerial maturity.

A closer look at role-specific experience reveals that HR Managers are represented across nearly all years of experience, ranging from 1 to 20 years. This indicates a diverse mix of early-career and seasoned professionals within HR. In contrast, Senior Managers appear more frequently in the higher experience brackets, such as between 10 to 20 years, reflecting their elevated roles within the organizational hierarchy. Similarly, IT and Finance Managers are consistently distributed across the mid to senior experience ranges, suggesting steady career progression within technical and financial departments. Operations Managers and Department Heads, though fewer in number, also show a relatively even distribution across the years, further reinforcing the dataset's inclusivity.

Hence, the table no. 2 above has shown that the survey contained well-rounded and varied participant base in terms of role as well as experience, which strengthens the reliability and depth of understandings that can be drawn from the study.

1.1.1.3. Industry of Participants

Table 3: Industry of Participants

Industry	No. of Participants
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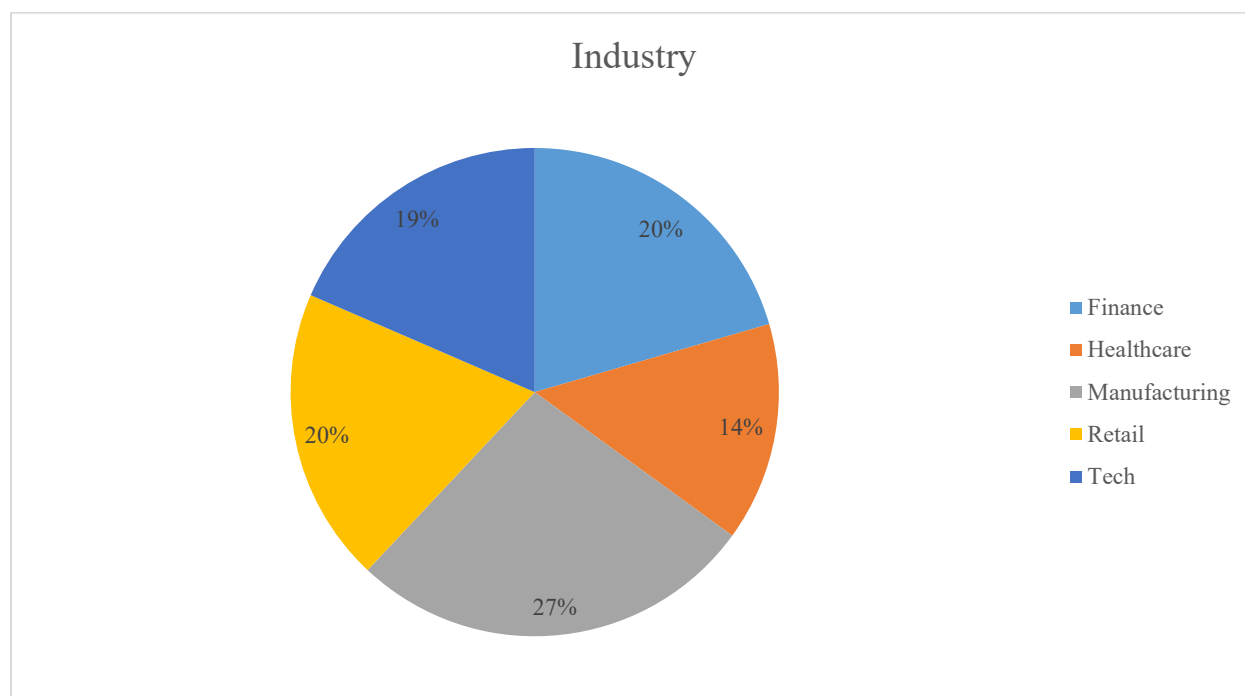
Finance	41
Healthcare	29
Manufacturing	54
Retail	39
Tech	37
Grand Total	200

The table no. 3 and pie chart shown in figure no. 2 display the industry-wise distribution of the 200 participants who took part in the study. The five industries that are represented include Finance, Healthcare, Manufacturing, Retail, and Tech. Among these industries, Manufacturing emerges as the most represented sector, since it has 54 participants and constituted approximately 27% of the total sample. It suggests a strong engagement from manufacturing-based organizations, which is consistent with the growing interest in AI implementation for process optimization and automation in that industry.

Both the Finance and Retail sectors contribute equally to the participant pool, each with 41 and 39 individuals respectively, representing 20% and just under 20% of the total. This balanced representation between operational and consumer-facing industries indicates a diverse sample composition. Tech sector participants make up 37 of the total, amounting to 19%, while the Healthcare sector, with 29 respondents, comprises the smallest segment at 14%. Despite being the smallest, the healthcare sector's involvement is notable given the growing role of AI in medical diagnostics, records management, and operational efficiencies.

The pie chart visually complements the table by presenting these proportions in a clear and digestible format. Each segment is distinctly color-coded, allowing for easy comparison across industries. The chart confirms that although Manufacturing has the largest share, the other four sectors are also well-represented and fairly balanced in terms of participation. This cross-sectoral representation enriches the study by incorporating varied organizational needs, challenges, and readiness levels for AI adoption. It also ensures that the findings reflect a holistic view of AI implementation trends across multiple verticals within conglomerate settings.

Figure 2: Industry of Participants



1.1.1.4. ERP in Use

Table 4: Currently using an ERP system (Yes/No)

ERP in Use	No. of Participants
Yes	184
No	16
Grand Total	200

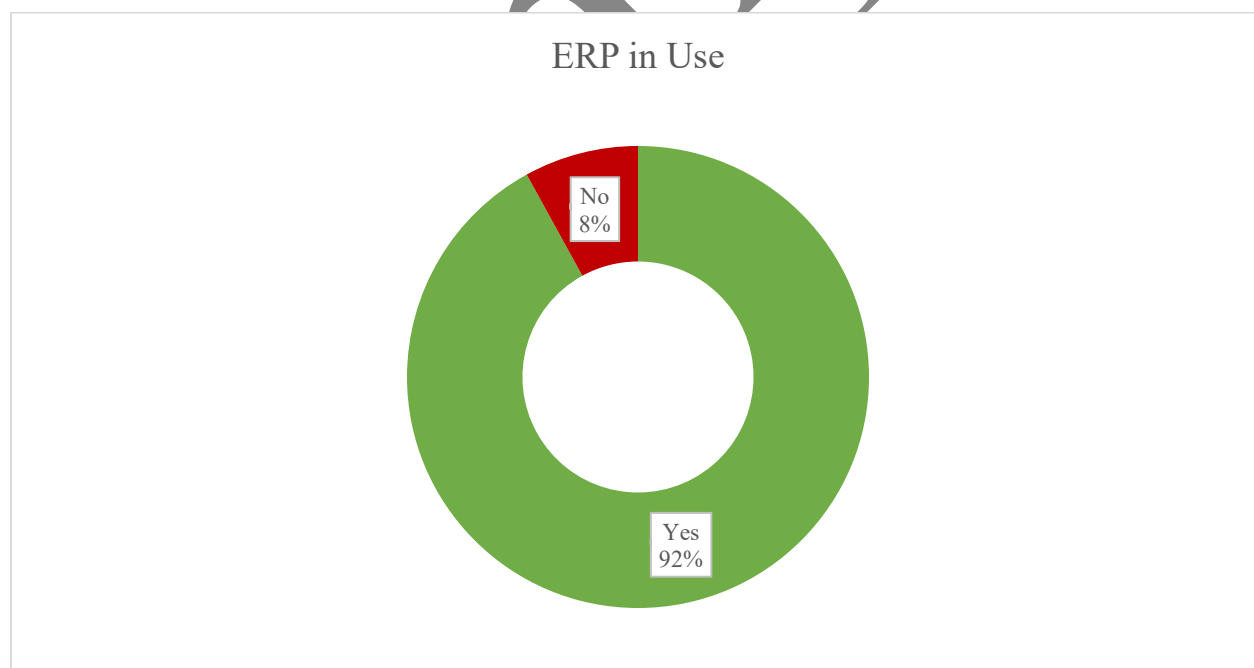
The participants were asked whether or not they are currently using an ERP system. The answers obtained were in the form of a yes or a no. The table no. 4 above and its corresponding donut chart in figure no. 3 below illustrate the current usage of Enterprise Resource Planning (ERP) systems among the 200 survey participants. The results unfolded that a substantial majority of respondents, specifically 184 individuals, reported that their organization is currently using an ERP system.

This accounts for 92% of the total participant pool. In contrast, only 16 participants, representing 8%, indicated that their organization does not utilize an ERP system at present.

The visual representation through the donut chart reinforces this significant disparity. The green portion, which dominates the chart, corresponds to the “Yes” responses, clearly depicting the overwhelming prevalence of ERP adoption among the surveyed organizations. The smaller red segment denotes the “No” responses, emphasizing the relatively minor portion of participants whose organizations have not yet implemented an ERP system.

This distribution suggests that ERP systems are widely established across the conglomerates represented in this study, reflecting their foundational role in managing business processes. The chart’s design—with percentage labels placed within each segment—enhances readability and provides immediate visual insight into the overall trend. This high rate of ERP usage sets a relevant context for exploring perceptions of AI adoption, as most participants are likely drawing comparisons between existing ERP systems and the potential benefits of AI-driven solutions.

Figure 3: Currently using an ERP system (Yes/No)



1.1.1.5. AI Integration

Table 5: AI Integration

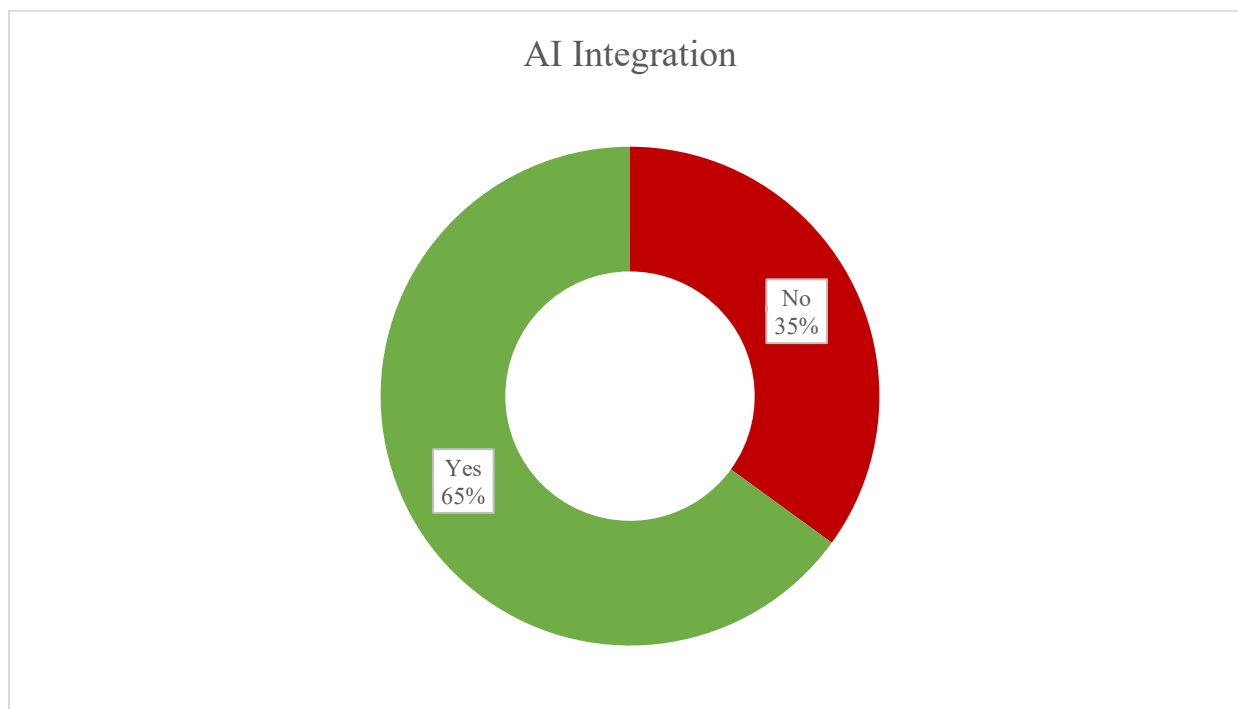
AI Integration	No. of Participants
Yes	130
No	70
Grand Total	200

The table no.5 presented above the visual of results in figure no. 4 below in the form of donut chart depict the participants' responses to the question: *"Has your organization started integrating AI technologies into business operations?"* Out of the 200 total participants, 130 individuals responded "Yes," indicating that their organizations have already initiated AI integration within their operational frameworks. This group constitutes 65% of the total sample, reflecting a growing trend toward embracing artificial intelligence across various industries and departments.

On the other hand, 70 participants responded "No," meaning their organizations have not yet begun integrating AI technologies. This segment makes up 35% of the total population surveyed. While this indicates that a significant number of organizations are still in the preliminary or planning phases of AI adoption, it also highlights a noticeable divide in technological readiness and strategic priorities among the surveyed companies.

The donut chart provides a clear visual representation of these proportions. The green segment, representing the "Yes" responses, dominates two-thirds of the chart, while the red segment, denoting "No" responses, fills the remaining one-third. The percentage labels within the chart segments enhance readability, offering an immediate grasp of the AI adoption landscape among respondents. This data serves as a crucial contextual indicator for understanding organizational maturity in AI adoption and helps frame the broader discussion around readiness, implementation challenges, and perceived benefits of transitioning from ERP systems to AI-driven management.

Figure 4: AI Integration



4.1.2. Pre-Implementation Survey

1.1.2.1. *ERP meets business needs*

Table 6: ERP meets business needs

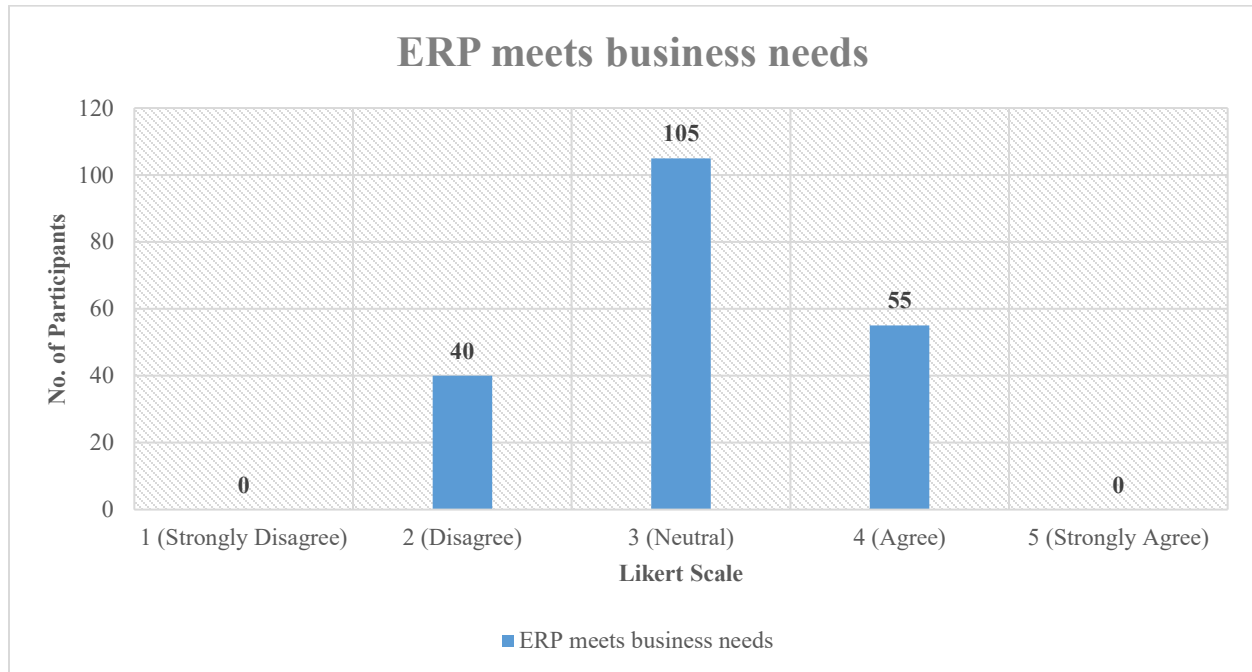
ERP meets business needs	No. of Participants
1 (Strongly Disagree)	0
2 (Disagree)	40
3 (Neutral)	105
4 (Agree)	55
5 (Strongly Agree)	0
Grand Total	200

Before the implementation of AI, the survey first asked participants to assess their existing ERP systems with the statement: “ERP systems currently meet the strategic and operational needs of our business.” This question was intended to gauge baseline satisfaction with traditional enterprise resource planning platforms before introducing AI-driven enhancements. The results are shown in Table 6 and Figure 5 that represent a predominantly ambivalent scenario.

Out of 200 respondents, none chose the extremes of “Strongly Disagree” or “Strongly Agree,” signaling that very few hold staunchly positive or negative views. Instead, 40 participants (20%) expressed clear dissatisfaction by selecting “Disagree,” suggesting they see important gaps in functionality or strategic alignment. The majority—105 individuals, equating to 52.5%—opted for the neutral midpoint. Such a heavy lean toward neutrality implies that many managers recognize both strengths and weaknesses in their ERP systems, perhaps finding them adequate for routine tasks but lacking in agility or advanced analytics. Meanwhile, 55 respondents (27.5%) agreed that their ERPs do meet business requirements, reflecting a modest level of confidence.

Taken together, these responses underscore a landscape in which ERPs are viewed as serviceable yet insufficient for the full range of strategic demands. This baseline ambivalence sets the stage for exploring how AI integration might address perceived shortfalls in decision-support, data sharing, and process optimization.

Figure 5: ERP Meets Business Needs



1.1.2.2. Prepared for ERP to AI transition

Table 7: Prepared for ERP to AI transition

Prepared for ERP to AI transition	No. of Participants
1 (Strongly Disagree)	0
2 (Disagree)	56
3 (Neutral)	79
4 (Agree)	65
5 (Strongly Agree)	0
Grand Total	200

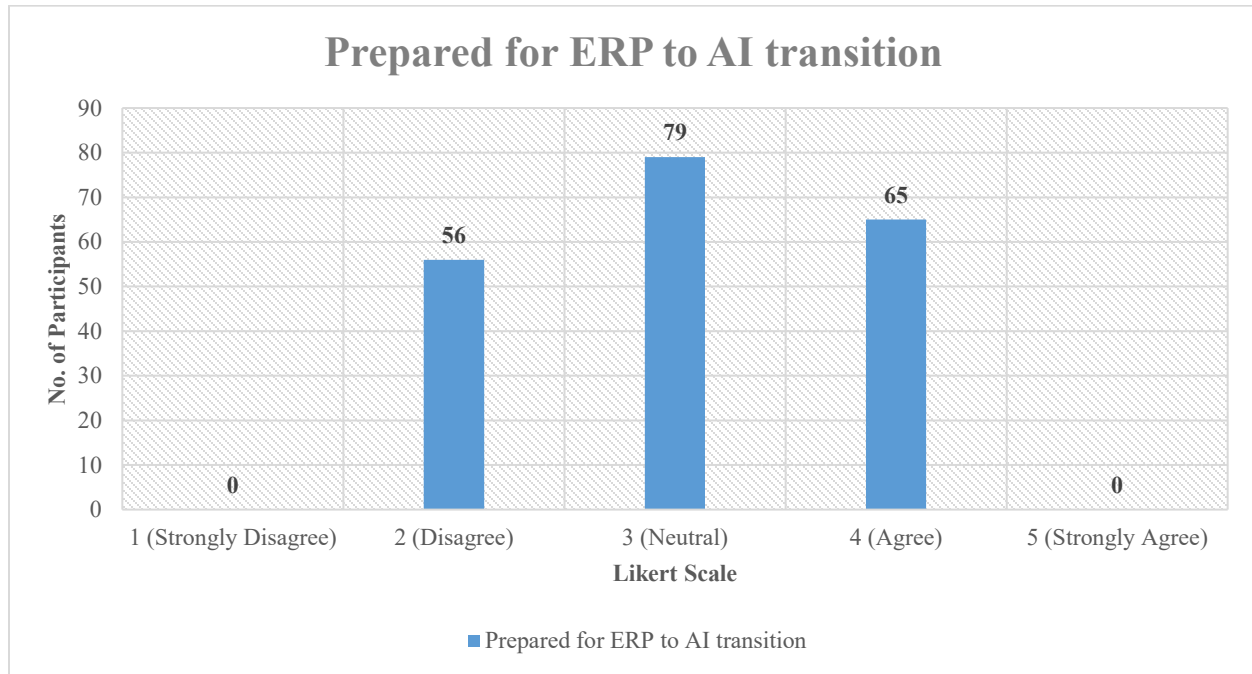
The second survey question during pre-implementation phase asked participants to evaluate their organization's readiness for moving from traditional ERP platforms to AI-based systems, phrased as: "Our organization is prepared for transitioning from ERP to AI-based systems." This probe

was designed to capture managers' confidence in their company's infrastructure, skills, and change-management capabilities ahead of any AI rollout.

As displayed in Table 7 and Figure 6, none of the 200 respondents selected "Strongly Disagree" or "Strongly Agree," suggesting that opinions cluster around the middle of the scale rather than at its extremes. A total of 56 participants (28%) chose "Disagree," signaling that over a quarter of respondents feel their organizations lack sufficient readiness—perhaps due to gaps in technology, expertise, or strategic alignment. The largest group, 79 individuals (39.5%), sat squarely in the "Neutral" category, implying uncertainty or ambivalence about the transition's feasibility. This could reflect mixed experiences with past technology initiatives or unclear roadmaps for AI adoption. Meanwhile, 65 participants (32.5%) "Agree" that their organization is prepared, indicating that nearly one-third of respondents believe the necessary groundwork—such as data governance, infrastructure upgrades, and change-management processes—is in place.

Hence, these responses (at the collective and wider level) highlight a tempered optimism tempered by caution: while a significant portion of managers feel some level of readiness, nearly two-thirds express reservations or uncertainty. This middle-heavy distribution underscores the need for clear planning, communication, and capability-building before embarking on large-scale AI integration.

Figure 6: Prepared for ERP to AI transition



1.1.2.3. AI can improve decisions

Table 8: AI can improve decisions

AI can improve decisions	No. of Participants
1 (Strongly Disagree)	0
2 (Disagree)	0
3 (Neutral)	40
4 (Agree)	100
5 (Strongly Agree)	60
Grand Total	200

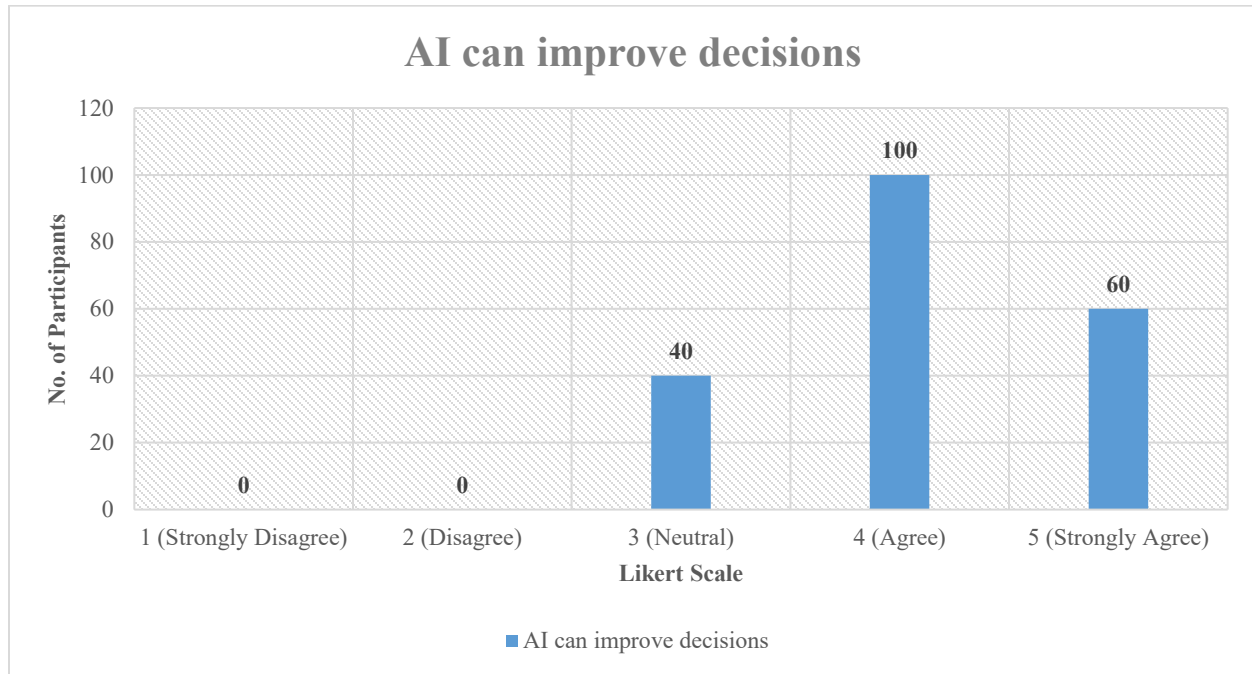
The third pre-implementation survey question—“I believe AI can improve management decision-making in complex organizations”—elicited a strongly positive response profile. According to Table 8 and Figure 7, none of the 200 participants selected “Strongly Disagree” or “Disagree,”

indicating unanimous basic agreement on AI's potential. Forty respondents (20%) chose the neutral midpoint, suggesting a small contingent that remains cautious or awaiting evidence. However, the vast majority expressed confidence: 100 participants (50%) "Agree" that AI can enhance decision-making, while an additional 60 respondents (30%) "Strongly Agree."

This distribution reveals that eight in ten surveyed managers hold an affirmative view of AI's value in guiding strategic and operational choices. The high concentration of "Agree" and "Strongly Agree" responses underscores widespread optimism about AI's analytical capabilities—its ability to process complex datasets, identify patterns, and generate predictive insights. The neutral segment, representing one-fifth of participants, may reflect those who reserve final judgment until they observe tangible AI outcomes within their own organizations.

Largely, the consensus conveyed—that AI holds promise for improving decision-making—establishes fertile ground for exploring how AI integration might address the ERP limitations identified earlier. It also highlights a prevailing managerial attitude: while traditional enterprise systems may be perceived as only partially adequate, AI is regarded as a promising enabler of more informed, agile, and data-driven decisions in complex conglomerate environments.

Figure 7: AI can improve decisions



1.1.2.4. AI enhances cross-subsidiary collaboration and data sharing

Table 9: AI enhances cross-subsidiary collaboration and data sharing

AI enhances cross-subsidiary collaboration and data sharing	No. of Participants
1 (Strongly Disagree)	0
2 (Disagree)	0
3 (Neutral)	52
4 (Agree)	93
5 (Strongly Agree)	55
Grand Total	200

Before any AI tools were deployed, the fourth survey question asked respondents to rate their confidence in AI's ability to "enhance cross-subsidiary collaboration and data sharing." This item

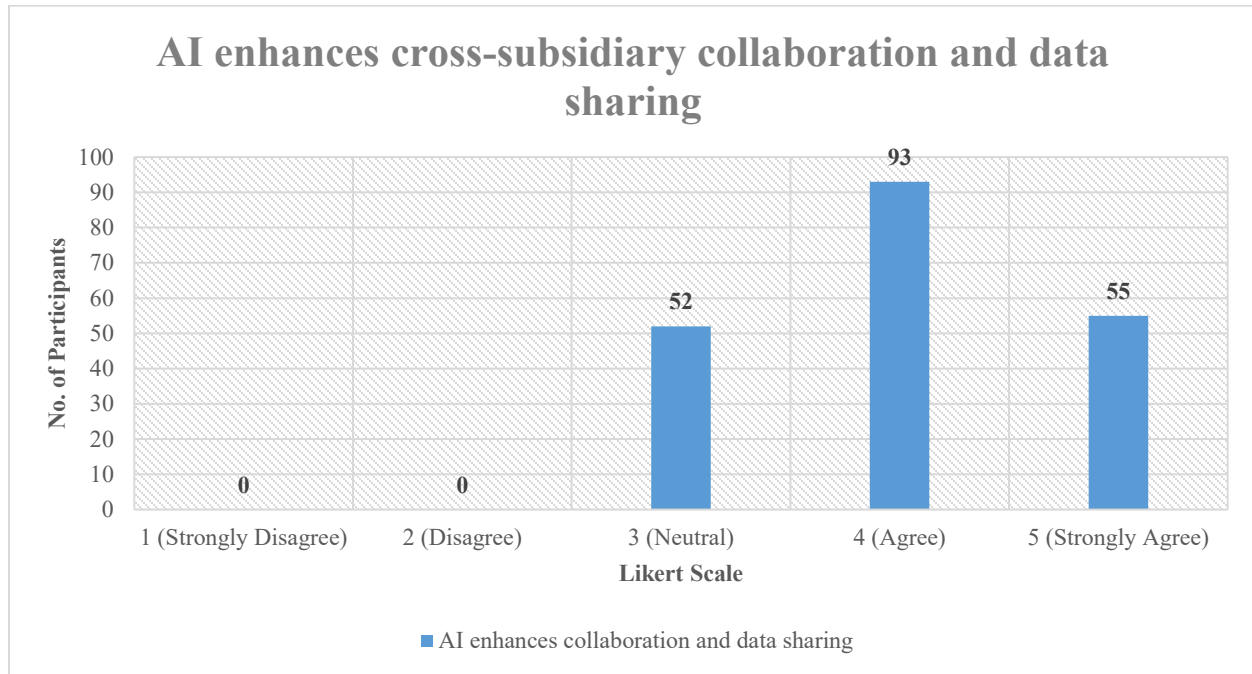
was designed to capture managers' expectations about AI's potential to break down silos and unify information flows across diverse business units.

Table 9 and Figure 8 show that all 200 participants hold a positive or neutral view—no one selected “Strongly Disagree” or “Disagree.” A modest group of 52 respondents (26%) remained neutral, perhaps reflecting hesitation until they see real-world results. By contrast, a strong majority expressed active confidence: 93 individuals (46.5%) “Agree” that AI will improve collaboration and data sharing, while 55 respondents (27.5%) “Strongly Agree.”

Together, these figures indicate that nearly three-quarters of managers (74%) are optimistic about AI's integrative capabilities. Their belief likely stems from awareness of AI's data-mining and machine-learning functions, which can harmonize disparate datasets, surface interdependencies, and streamline communication channels across subsidiaries. The substantial “Agree” and “Strongly Agree” responses underscore a prevailing expectation that AI will serve as a connective platform—bridging departmental boundaries, enabling real-time insights, and fostering more cohesive decision-making.

This widespread confidence sets a favorable baseline for subsequent pilot projects, suggesting that organizational leaders are primed to support AI-driven initiatives aimed at improving enterprise-wide collaboration.

Figure 8: AI enhances cross-subsidiary collaboration and data sharing



1.1.2.5. Adequately trained for AI

Table 10: Adequately trained for AI

Adequately trained for AI	No. of Participants
1 (Strongly Disagree)	0
2 (Disagree)	82
3 (Neutral)	84
4 (Agree)	34
5 (Strongly Agree)	0
Grand Total	200

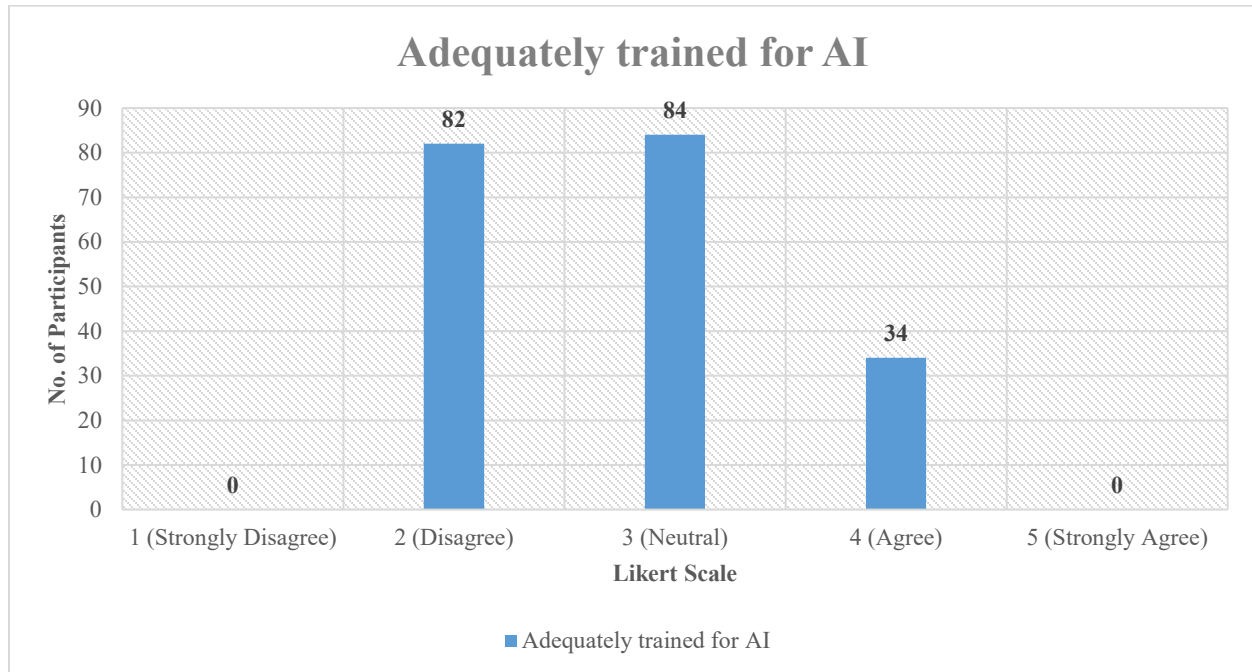
Prior to any AI rollout, the fifth question in the pre-implementation survey asked participants to rate their own preparedness: “I feel adequately trained or informed about AI applications in our business processes.” This item probed whether managers felt they already possessed the

knowledge and skills needed to work effectively with AI technologies. Table 10 and Figure 9 reveal a noteworthy gap in self-assessed readiness. A substantial 82 respondents (41%) disagreed that they felt adequately trained, while an even slightly larger group—84 participants (42%)—chose the neutral midpoint, indicating ambivalence or uncertainty about their level of AI competence. Only 34 individuals (17%) agreed that they had sufficient training or information.

The complete absence of “Strongly Disagree” or “Strongly Agree” responses underscores that most managers occupy a middle ground: they neither feel fully confident nor completely unprepared. The predominance of “Disagree” and “Neutral” responses suggests that, on the eve of AI implementation, many participants recognized gaps in their own AI-related expertise. This likely reflects limited exposure to AI tools, scarce training opportunities, or the novelty of applying AI in complex organizational settings.

Overall, these findings highlight a clear need for comprehensive education and upskilling initiatives. Before AI systems can be widely adopted and yield their promised benefits, decision makers and end users must first develop a foundational understanding of AI capabilities and limitations. Addressing this training shortfall will be critical for ensuring that the subsequent AI transition is embraced, effectively managed, and ultimately successful.

Figure 9: Adequately trained for AI



1.1.2.6. AI threatens job security

Table 11: AI threatens job security

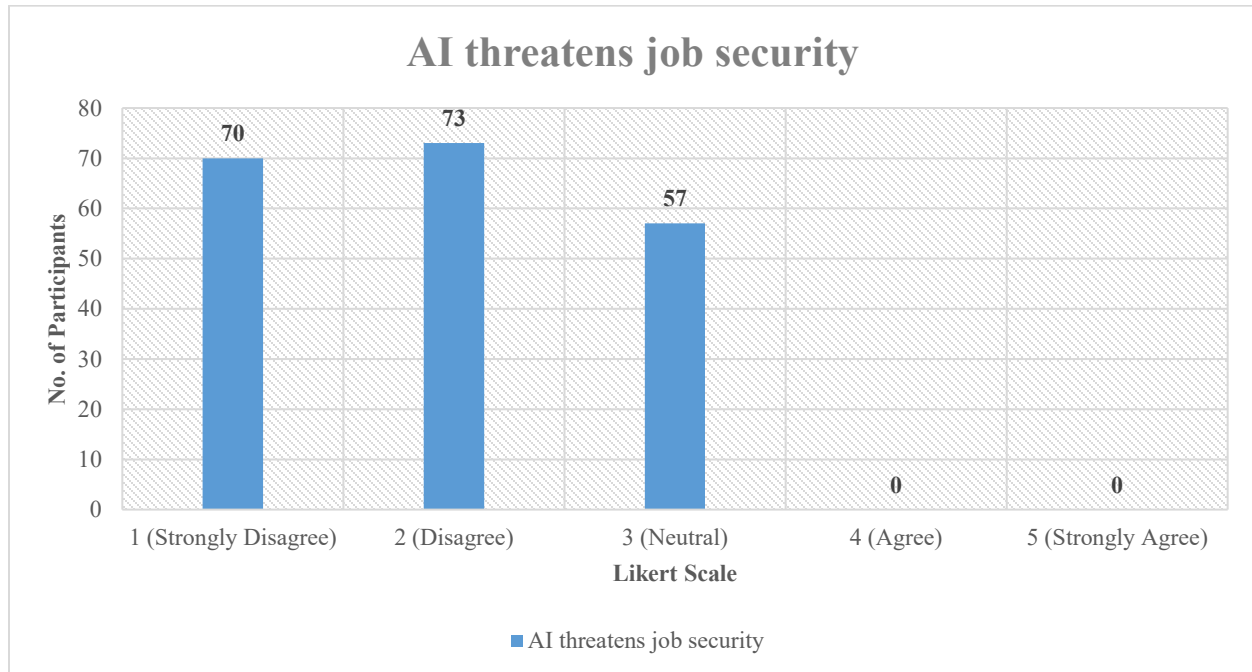
AI threatens job security	No. of Participants
1 (Strongly Disagree)	70
2 (Disagree)	73
3 (Neutral)	57
4 (Agree)	0
5 (Strongly Agree)	0
Grand Total	200

The sixth pre-implementation survey item asked managers to evaluate whether they felt that “AI poses a threat to job security in my department.” This question was designed to surface any anxiety or resistance rooted in fears of automation. According to Table 11 and its accompanying chart,

none of the 200 respondents selected “Agree” or “Strongly Agree,” indicating that outright alarm about AI eliminating roles was absent. Instead, a combined 143 participants—70 (35%) who “Strongly Disagree” and 73 (36.5%) who “Disagree”—expressed confidence that AI would not jeopardize their job security. Meanwhile, 57 individuals (28.5%) remained neutral on the matter. This distribution suggests that nearly three-quarters of participants feel secure in their positions, even in the face of impending AI implementation. Their strong disagreement likely reflects confidence that AI will augment rather than replace human expertise and that they possess skills and institutional knowledge not easily replicated by machines. The neutral group may represent those who are unsure or awaiting concrete evidence of AI’s impact before forming a definitive stance. Importantly, the absence of affirmative “Agree” or “Strongly Agree” responses signals that overt job-loss fears are not a dominant concern among this sample of mid- to senior-level managers.

Taken together, these findings indicate that while managers recognize both the potential and the uncertainties of AI adoption, they largely do not view it as an existential threat to their own roles. This baseline of job-security confidence is a positive indicator for organizations planning AI transitions, as it suggests fewer barriers from employee resistance based on fear. At the same time, the sizable neutral contingent underscores that clear communication and role-redefinition strategies will remain essential to maintain this confidence as AI initiatives move from planning into practice.

Figure 10: AI threatens job security



1.1.2.7. AI faces resistance

Table 12: AI faces resistance

AI faces resistance	No. of Participants
1 (Strongly Disagree)	0
2 (Disagree)	0
3 (Neutral)	62
4 (Agree)	88
5 (Strongly Agree)	50
Grand Total	200

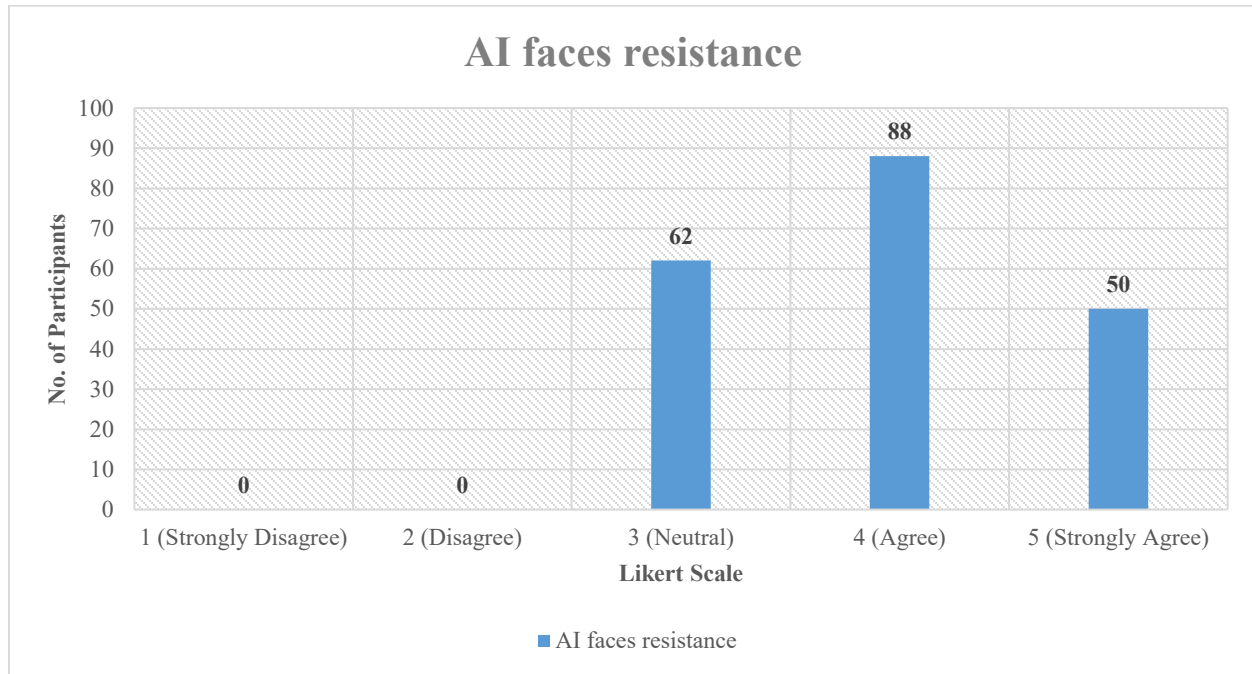
Finally, respondents were asked to anticipate employee pushback with the statement: “AI implementation will likely face resistance from employees in our organization.” As shown in Table

12 and Figure 11, not a single participant “Strongly Disagreed” or “Disagreed” with this assertion, indicating unanimous expectation of at least some reluctance. Sixty-two managers (31%) remained neutral, perhaps signaling uncertainty about the magnitude of resistance or a wait-and-see stance. However, a substantial majority—138 participants, or 69%—took an affirmative position: 88 (44%) “Agreed” and 50 (25%) “Strongly Agreed.”

This pronounced skew toward agreement reveals that most mid- and senior-level managers foresee genuine hurdles in securing employee buy-in for AI initiatives. The complete absence of dissent underscores a shared recognition that AI, despite its potential benefits, will disrupt established workflows, provoke cultural anxieties, or challenge entrenched roles. At the same time, the neutral cohort suggests some ambivalence or belief that resistance could vary by department or depend on the change-management approach.

Overall, these responses establish clear managerial expectations that resistance will be a significant factor in any AI rollout. They highlight the importance of proactive strategies—such as transparent communication, early involvement of end users, and targeted training—to address concerns and foster a more receptive environment before, during, and after the transition from ERP to AI-driven systems.

Figure 11: AI faces resistance



4.1.3. Post-Implementation Survey

1.1.3.1. *AI Improved efficiency*

Table 13: AI Improved efficiency

AI Improved efficiency	No. of Participants
1 (Strongly Disagree)	0
2 (Disagree)	0
3 (Neutral)	0
4 (Agree)	114
5 (Strongly Agree)	86
Grand Total	200

Following the AI rollout, the first post-implementation question asked participants to evaluate the tangible impact on day-to-day work: “AI tools have improved the efficiency of my department’s

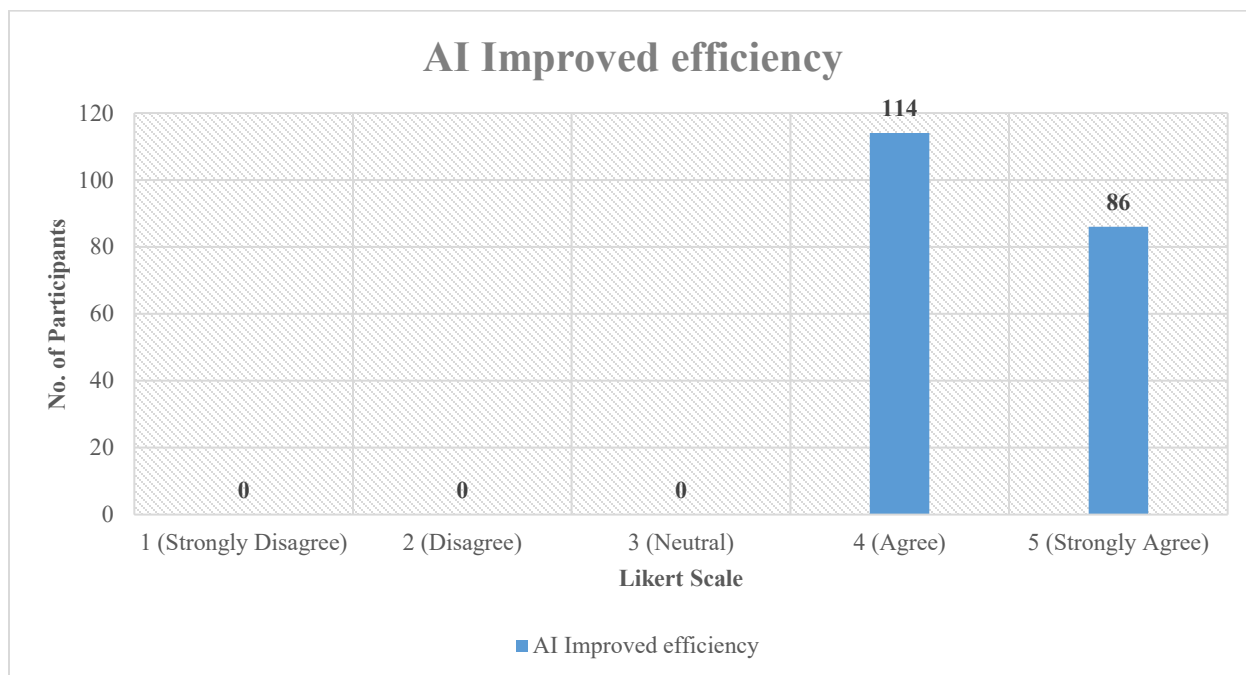
operations.” Table 13 and Figure 12 leave little room for doubt—every single respondent registered a positive outcome. Of the 200 surveyed managers, 114 (57%) selected “Agree” and a further 86 (43%) “Strongly Agree,” while no one remained neutral or registered any level of disagreement.

This unanimity suggests that AI integration translated swiftly into measurable gains in workflow speed, task automation, and reduced manual errors. The fact that nearly half of all respondents “Strongly Agree” indicates that for many teams, the efficiency benefits were not merely incremental but substantial—enough to move them from cautious optimism in the pre-implementation phase to enthusiastic endorsement in practice.

The absence of any “Neutral” or negative responses also speaks volumes about alignment between promised and delivered value. In a real-world context, AI systems can throttle data processing, trigger alerts, and automate routine approvals—functions that directly free up managers’ time for higher-value strategic work. The overwhelming consensus captured here implies that such capabilities were successfully deployed and quickly adopted across multiple departments.

In sum, the post-implementation data confirms that AI’s theoretical promise of streamlining operations was realized in this multi-functional conglomerate setting. The shift from pre-implementation ambivalence about ERP limitations to unanimous satisfaction with AI-driven efficiency underscores a clear narrative: where traditional systems had plateaued, AI has driven a new wave of operational productivity. This sets an encouraging precedent for the remaining post-implementation measures, reinforcing that the organization’s investment in AI yielded the expected—and broadly felt—efficiency improvements.

Figure 12: AI Improved efficiency



1.1.3.2. AI improved decision speed

Table 14: AI improved decision speed

AI improved decision speed	No. of Participants
1 (Strongly Disagree)	0
2 (Disagree)	0
3 (Neutral)	0
4 (Agree)	106
5 (Strongly Agree)	94
Grand Total	200

In the second post-implementation question—“AI has led to faster and more informed decision-making in our organization”—all 200 respondents registered unequivocal agreement. As shown in Table 14 and illustrated in Figure 13, 106 participants (53%) selected “Agree” and a further 94

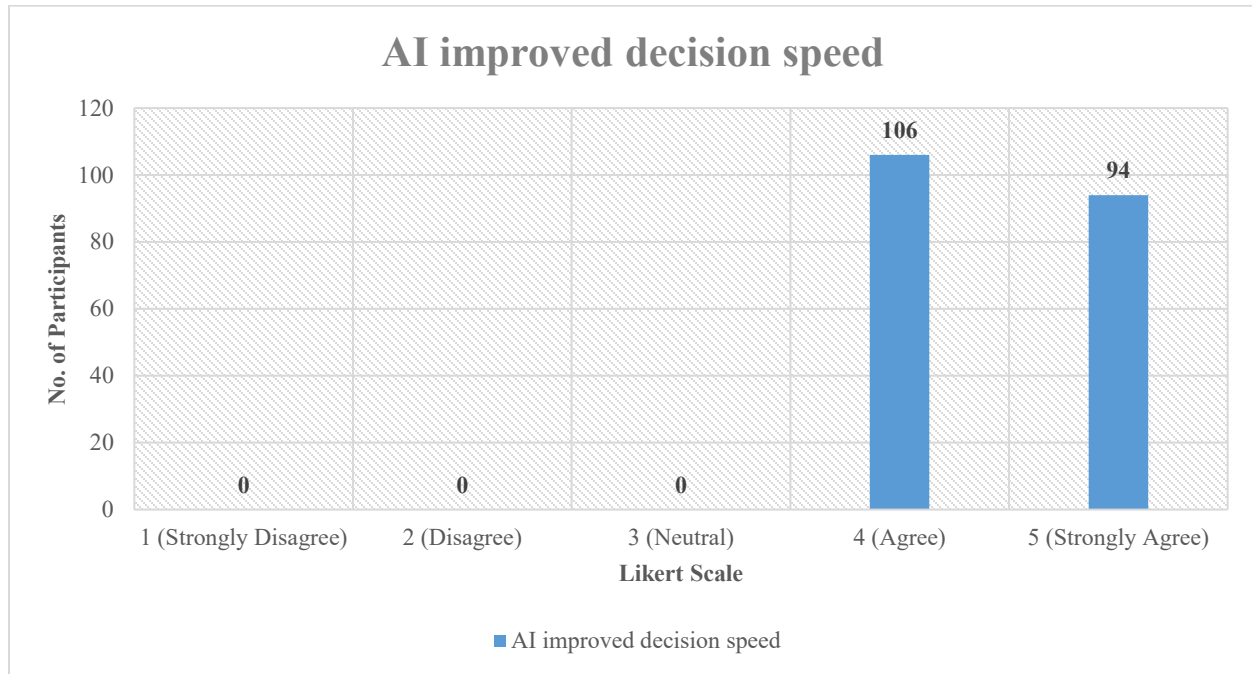
(47%) chose “Strongly Agree,” with no one remaining neutral or dissenting. This perfect consensus underscores that the AI deployment not only accelerated the pace of decisions but also enriched their quality through data-driven insights.

Managers clearly experienced a tangible shift: automated analytics, real-time forecasting, and AI-powered dashboards appear to have replaced slower, manual analysis cycles. The fact that nearly half of respondents “Strongly Agree” suggests that the impact went beyond modest speed gains—decision makers felt a pronounced uplift in their ability to act quickly and confidently.

This uniformly positive response highlights that AI’s predictive models and scenario-planning tools were successfully integrated into existing workflows, enabling teams to move from reactive to proactive management. In effect, the organization achieved one of AI’s core promises: turning raw data into clear recommendations at the moment they are needed. The absence of any neutral or negative feedback further confirms that the system’s decision-support capabilities were both robust and user-friendly, fostering broad adoption across departments.

Overall, these findings demonstrate that the transition from ERP-centric processes to AI-augmented decision frameworks delivered on its key objectives—speed and insight—thereby reinforcing the strategic value of the investment.

Figure 13: AI improved decision speed



1.1.3.3. AI improved coordination

Table 15: AI improved coordination

AI improved coordination	No. of Participants
1 (Strongly Disagree)	0
2 (Disagree)	0
3 (Neutral)	0
4 (Agree)	110
5 (Strongly Agree)	90
Grand Total	200

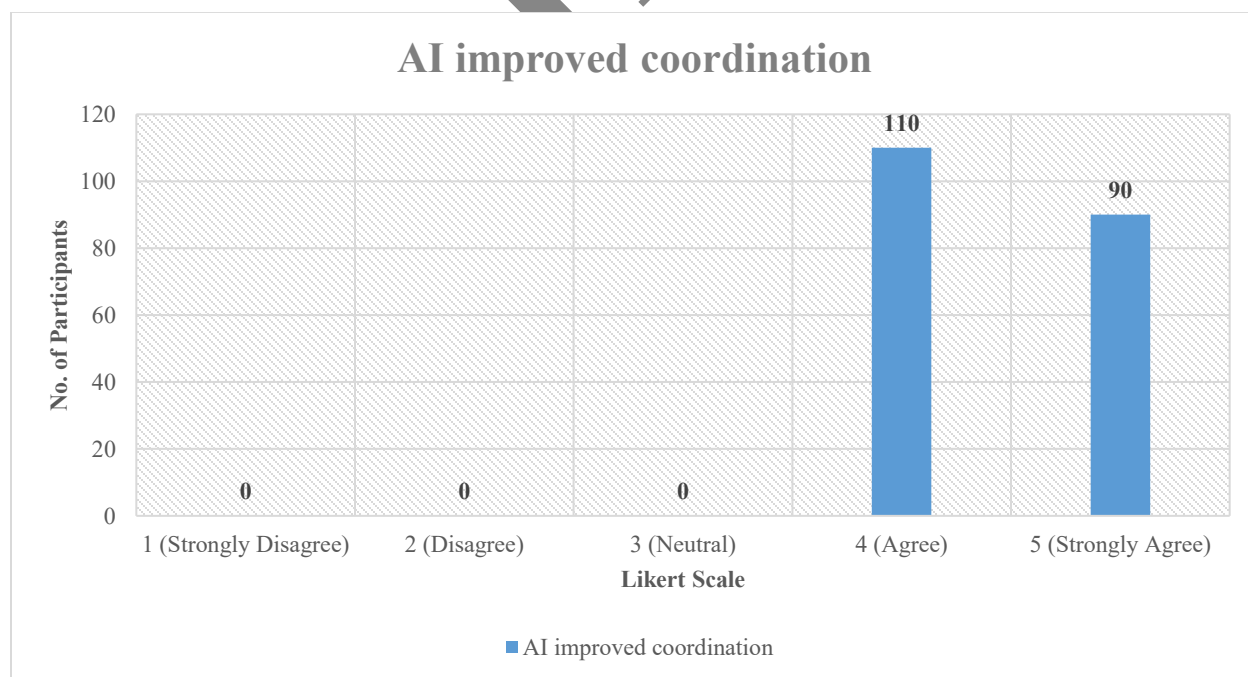
In the third post-implementation question—“Integration with AI has improved coordination across business units”—all 200 respondents again registered unqualified agreement. According to Table

15 and Figure 14, 110 participants (55%) selected “Agree” and 90 (45%) “Strongly Agree,” with no neutral or dissenting responses. This unanimity underscores that, in practice, AI did more than streamline individual department workflows—it served as a connective tissue unifying previously siloed functions.

Managers reported that AI-driven platforms, by centralizing data and automating information sharing, eliminated the delays and miscommunications that often arise when finance, operations, HR, and IT work in isolation. The fact that nearly half of the respondents “Strongly Agree” suggests these improvements were both substantial and immediately apparent. AI’s predictive analytics and real-time dashboards appear to have fostered a shared operational picture, enabling departments to synchronize plans, anticipate dependencies, and respond collectively to emerging challenges.

This broad consensus confirms that AI integration did not merely enhance standalone efficiency but fundamentally strengthened enterprise-wide collaboration—turning fragmented processes into a cohesive, agile network of interlinked business units.

Figure 14: AI improved coordination



1.1.3.4. Trust in AI insights

Table 16: Trust in AI insights

Trust in AI insights	No. of Participants
1 (Strongly Disagree)	0
2 (Disagree)	20
3 (Neutral)	94
4 (Agree)	86
5 (Strongly Agree)	0
Grand Total	200

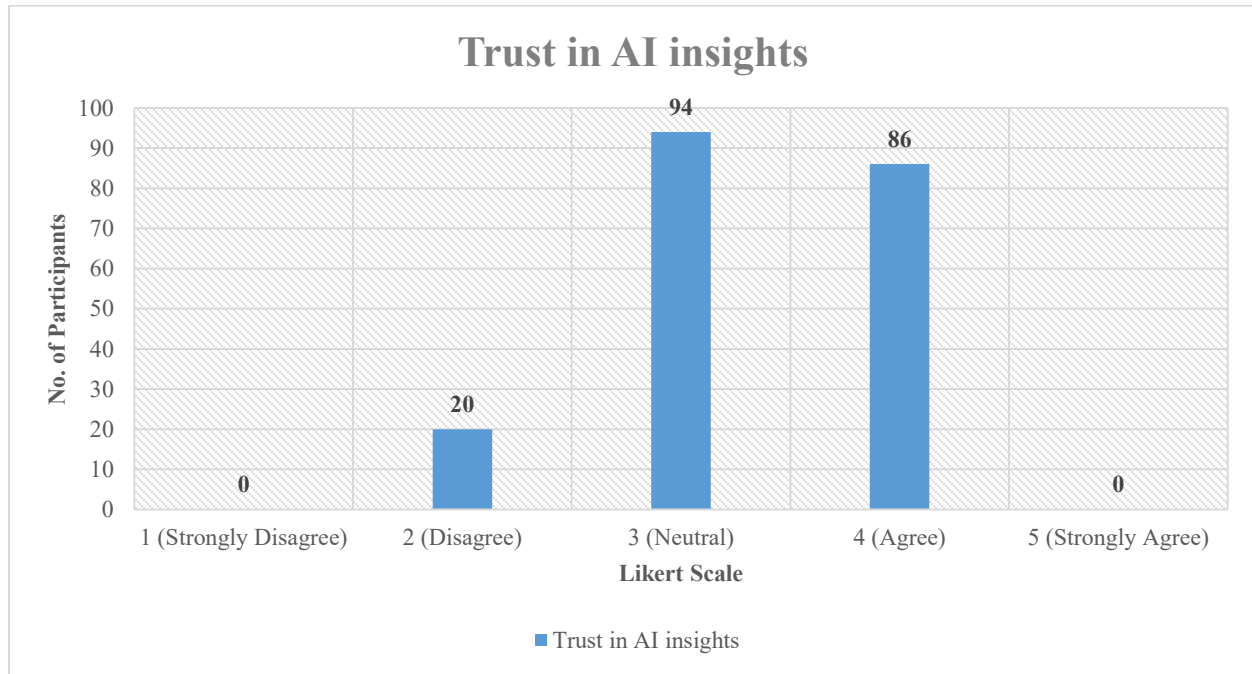
After working with the new AI-driven tools, participants were asked to rate their confidence in the quality and transparency of AI-generated recommendations with the statement: “I trust AI systems to deliver reliable and explainable insights.” The responses, detailed in Table 16 and Figure 15, reveal a more cautious outlook compared to earlier post-implementation items. Twenty respondents (10%) disagreed, indicating lingering doubts about the dependability or clarity of AI outputs. The largest segment—94 managers (47%)—chose “Neutral,” suggesting they neither fully trust nor outright reject AI insights without further evidence or experience. Meanwhile, 86 participants (43%) agreed that AI provides dependable, understandable recommendations, reflecting a solid but not overwhelming level of trust.

This distribution points to a nuanced reality: while AI has demonstrably boosted efficiency, decision speed, and coordination, nearly half of the participants remain on the fence when it comes to trusting the underlying algorithms. Their neutrality likely stems from concerns about “black-box” decision-making, data biases, or insufficient explainability in certain AI modules. At the same time, the 43% who affirm trust suggest that when AI outputs align with their expectations—such as accurate forecasts or actionable scenarios—confidence grows.

Overall, these findings highlight trust in AI as an area requiring ongoing attention. To convert neutrals into advocates, organizations may need to invest in explainable AI frameworks, transparent communication about model limitations, and further training on interpreting AI-driven

insights. Such measures will be critical to ensuring that the AI systems not only perform well but also earn the enduring confidence of the decision makers who rely on them.

Figure 15: Trust in AI insights



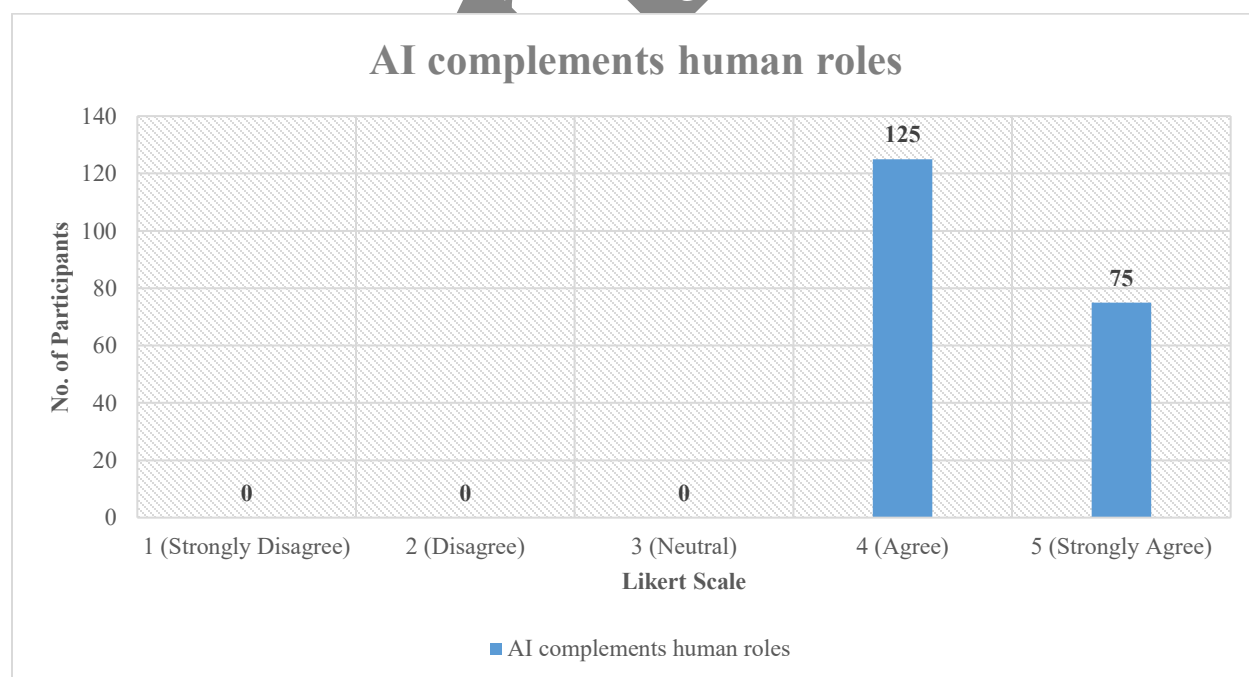
1.1.3.5. AI complements human roles

Table 17: AI complements human roles

AI complements human roles	No. of Participants
1 (Strongly Disagree)	0
2 (Disagree)	0
3 (Neutral)	0
4 (Agree)	125
5 (Strongly Agree)	75
Grand Total	200

In the fifth post-implementation question—“AI has complemented — not replaced — human roles in strategic tasks”—every participant registered a positive response. As shown in Table 17 and Figure 16, 125 respondents (62.5%) chose “Agree,” while the remaining 75 (37.5%) “Strongly Agree.” No one remained neutral or expressed disagreement. This unanimous endorsement indicates that managers across all levels perceive AI as an empowering partner rather than a job-substituting threat. In practice, AI’s advanced analytics and automation capabilities appear to have taken over low-value, repetitive activities—freeing human experts to focus on higher-order strategic thinking, relationship building, and nuanced judgment calls. The strong leaning toward “Agree” and “Strongly Agree” underscores a clear narrative: AI tools have successfully augmented human decision-making processes without displacing the critical creative and contextual skills that only people provide. This consensus bodes well for sustained AI adoption, as it suggests employees see the technology as enhancing their roles and career trajectories rather than rendering them obsolete.

Figure 16: AI complements human roles



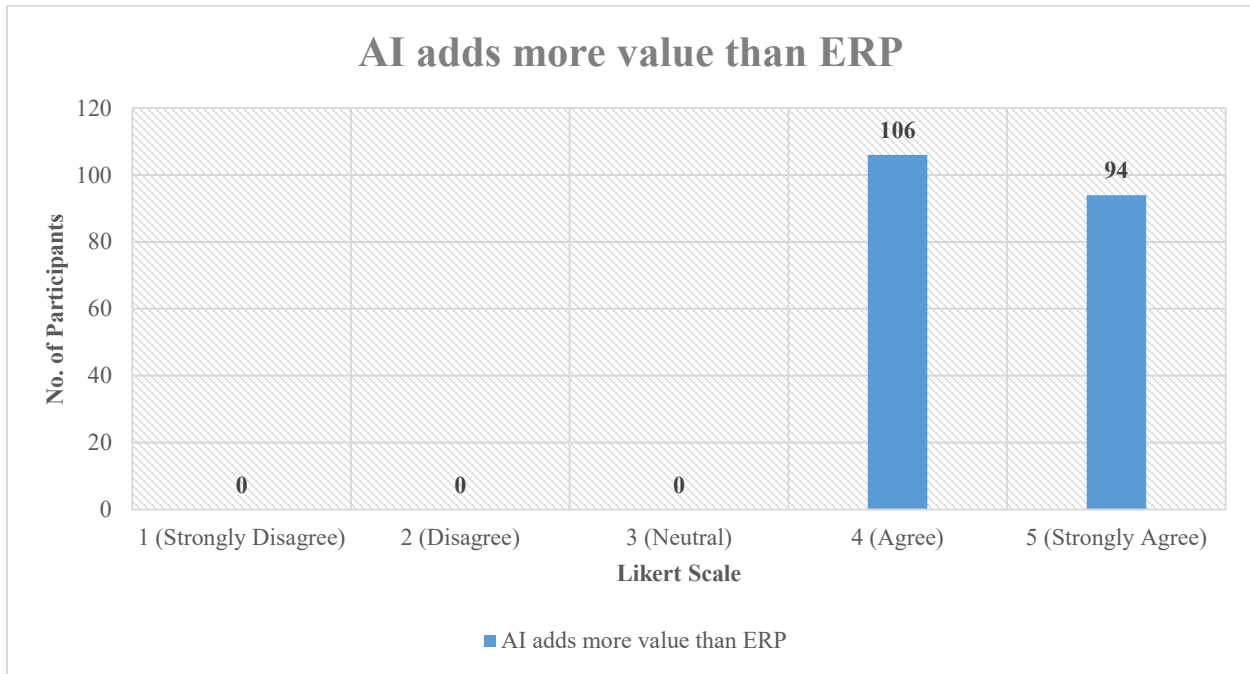
1.1.3.6. *AI adds more value than ERP*

Table 18: *AI adds more value than ERP*

AI adds more value than ERP	No. of Participants
1 (Strongly Disagree)	0
2 (Disagree)	0
3 (Neutral)	0
4 (Agree)	106
5 (Strongly Agree)	94
Grand Total	200

The final post-implementation question invited participants to reflect on AI's overall contribution compared to their legacy ERP platforms: "Altogether, AI has added value beyond the capabilities of our previous ERP systems." As shown in Table 18 and Figure 17, every single one of the 200 respondents registered agreement—106 (53%) selected "Agree" and 94 (47%) "Strongly Agree." There were no neutral or negative responses. This unanimity indicates that across the board, managers perceive AI not simply as an incremental upgrade to their ERP but as a fundamentally more powerful toolset. Where traditional ERP systems centralized transactions and standardized reporting, the newly deployed AI solutions have delivered predictive analytics, real-time scenario modeling, automated decision support, and seamless cross-unit integration—all capabilities that fell outside the scope of the prior ERP. The strong leaning toward "Strongly Agree" underscores just how transformative respondents found these new features. In essence, the organization has moved beyond static data consolidation to dynamic, intelligence-driven management—validating the strategic pivot from ERP to AI as a clear step-change in operational and strategic value.

Figure 17: AI adds more value than ERP



4.2. Inferential Statistics from Quantitative Data

4.2.1. AI vs. ERP Integration

Table 19: AI vs. ERP Integration

Industries	Observed AI Integration		Expected AI Integration	
	Yes	No	Exp_No	Exp_Yes
Finance	13	28	14.35	26.65
Healthcare	10	19	10.15	18.85
Manufacturing	18	36	18.9	35.1
Retail	12	27	13.65	25.35
Tech	17	20	12.95	24.05

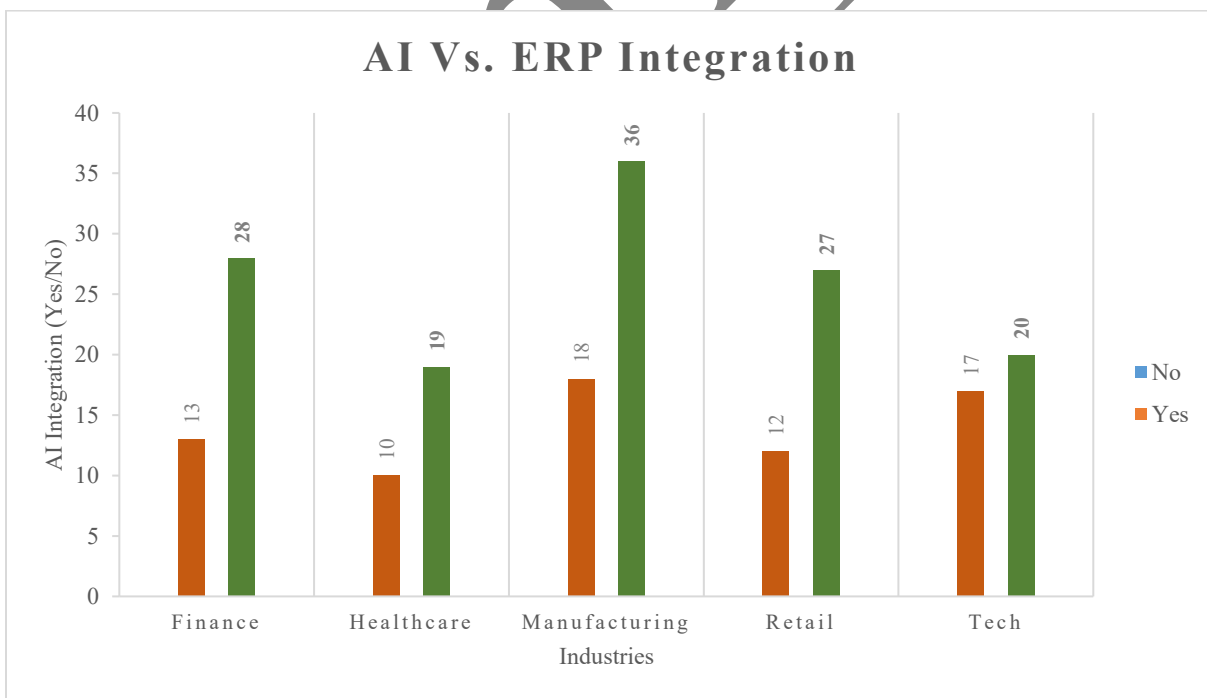
To determine whether AI adoption differs by industry (*Objective 1*), we examined the association between participants' sectors (Finance, Healthcare, Manufacturing, Retail, Tech) and their

responses to “Has your organization started integrating AI technologies into business operations?” (Table 19; Figure 18).

Using a Chi-Square test of independence, we compared the observed counts in each industry–integration cell against the expected counts under the assumption of uniform adoption. The resulting p-value of 0.641 greatly exceeds our 0.05 significance threshold.

These results indicate that we cannot reject the null hypothesis of independence. In other words, AI integration rates—70 “No” and 130 “Yes” overall—do not vary in a statistically significant way across the five industries. Manufacturing, which accounts for the largest share of adopters in absolute numbers, shows an integration rate proportional to its sample size, as do Finance, Retail, Healthcare, and Tech. hence, this particular finding suggests that, within our conglomerate sample, AI uptake is broadly consistent across diverse functional domains. No single sector emerges as an early adopter or laggard at a level that would exceed random variation. This uniformity lays a balanced foundation for subsequent analyses of AI’s operational impact.

Figure 18: AI vs. ERP Integration



4.2.2. Impact on Operational Efficiency

Table 20: t-Test: Paired Two Sample for Means

t-Test: Paired Two Sample for Means		
	<i>AI improved efficiency</i>	<i>NullMean_3</i>
Mean	4.43	3
Variance	0.246331658	0
Observations	200	200
Hypothesized Mean Difference	0	
df	199	
t Stat	40.74655723	
P(T<=t) one-tail	8.1525E-99	
t Critical one-tail	1.652546746	
P(T<=t) two-tail	1.6305E-98	
t Critical two-tail	1.971956544	

To determine whether post-implementation efficiency (*Objective 2*) ratings are significantly higher than the neutral midpoint of 3, we conducted a paired t-test comparing each manager’s “AI improved efficiency” score against a constant value of 3 (Table 20).

In Excel’s “t-Test: Paired Two Sample for Means,” we used our 200 actual efficiency scores (Mean = 4.43, Variance ≈ 0.25) against a column of 200 threes. The resulting t-statistic of **40.75** far exceeds the one-tailed critical value of 1.65 at 199 degrees of freedom. More strikingly, the one-tailed p-value is 8.15×10^{-99} , effectively zero for all practical purposes.

Because $p \ll 0.05$, we reject the null hypothesis that average efficiency equals 3. In other words, the chance of observing a mean as high as 4.43 if true efficiency were only neutral is virtually nil. These findings provide strong statistical evidence that AI implementation has driven a real and substantial improvement in departmental efficiency—well beyond what could be attributed to random variation or mere neutrality.

4.2.3. Decision-Making Enhancements

Table 21: Paired t-Test on Pre- vs. Post-Implementation Perceptions

Test A: Paired t-Test on Pre- vs. Post-Implementation Perceptions		
t-Test: Paired Two Sample for Means		
	<i>AI can improve decisions</i>	<i>AI improved decision speed</i>
Mean	4.1	4.47
Variance	0.492462312	0.250351759
Observations	200	200
Pearson Correlation	0.037209895	
Hypothesized Mean Difference	0	
df	199	
t Stat	-6.180918883	
P(T<=t) one-tail	1.7706E-09	
t Critical one-tail	1.652546746	
P(T<=t) two-tail	3.5412E-09	
t Critical two-tail	1.971956544	

The above table no. 21 represents paired t-Test on Pre- vs. Post-Implementation Perceptions that seeks to quantify AI's impact on decision-making enhancements (*Objective 3*). To that end, we compared each manager's pre-implementation belief ("AI can improve decisions," Mean = 4.10) against their post-implementation experience ("AI improved decision speed," Mean = 4.47).

The researcher ran a paired two-sample t-test on those two columns for all 200 respondents to test whether the average post-implementation score significantly exceeds the pre-implementation expectation (hypothesized mean difference = 0). The observed mean difference ($4.47 - 4.10 = 0.37$) reflects a clear lift in managers' perceptions once they'd actually used the AI tools. Along these lines, the t-statistic of -6.18 (in absolute value, $|t| = 6.18$) far surpasses the one-tailed critical

value of 1.65 at $df = 199$. Moreover, the one-tailed p-value of 1.77×10^{-9} (and two-tailed $p = 3.54 \times 10^{-9}$) is effectively zero. Because $p \ll 0.05$, we reject the null hypothesis and conclude that the actual decision-speed improvements delivered by AI are statistically greater than managers' original expectations. In practical terms, AI not only met but exceeded its promised decision-making benefits.

Table 22: Pearson Correlation between Decision Speed and Trust

Test B: Pearson Correlation between Decision Speed and Trust		
	<i>AI improved decision speed</i>	<i>Trust in AI insights</i>
AI improved decision speed	1	
Trust in AI insights	-0.015746741	1

Table no. 22 (above) depicts the Pearson correlation between Decision Speed and Trust as beyond measuring speed gains, objective 3 also explores whether faster AI-driven decisions translate into greater trust in AI insights. The researcher has calculated the Pearson correlation coefficient (r) between each manager's "AI improved decision speed" score and their "Trust in AI insights" score across the same 200 respondents. The resulting $r = -0.016$ is essentially zero, indicating no linear relationship between decision-making speed improvements and managers' trust in AI's recommendations. This near-zero coefficient shows that—even though AI systems made decisions faster—those speed gains did not automatically boost confidence in the AI outputs.

The paired t-test confirms that real-world experience with AI surpassed managers' prior expectations for decision-making speed by a highly significant margin. Yet the lack of correlation between speed and trust underlines that performance alone does not engender belief in AI's reliability or transparency. In other words, while AI demonstrably accelerates decision cycles, building confidence in its insights requires separate focus—such as explainability, user training, and transparent model governance—beyond simply delivering faster results.

4.2.4. *Challenges—Training & Trust*

To test whether better AI training leads to greater trust in AI insights, the researcher regressed managers' post-implementation "Trust in AI insights" scores on their self-rated "Adequately trained for AI" scores.

Table 23: Regression Statistics

<i>Regression Statistics</i>	
Multiple R	0.023026586
R Square	0.000530224
Adjusted R Square	-0.004517603
Standard Error	0.652018407
Observations	200

The regression output (Table no. 23) shows an R^2 of 0.00053, indicating that training explains virtually none of the variance in trust. The Training coefficient is -0.0207 with a p-value of 0.746, far above 0.05.

Table 24: ANOVA

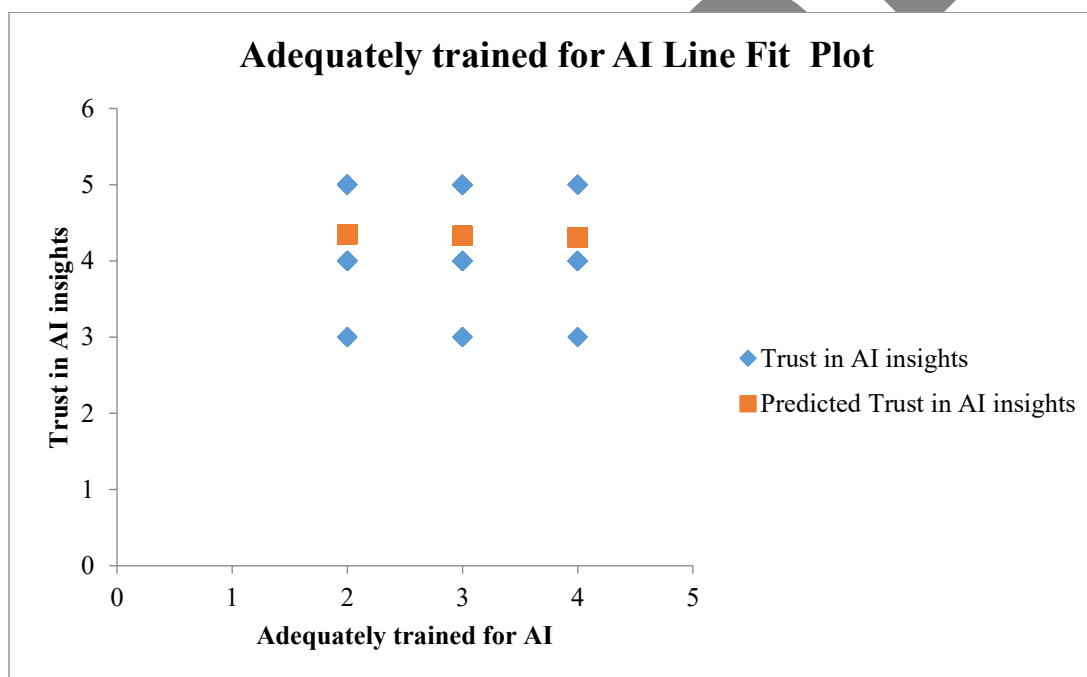
ANOVA					
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	1	0.044655436	0.044655436	0.105039979	0.746205404
Residual	198	84.17534456	0.425128003		
Total	199	84.22			

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	4.387059724	0.181993332	24.1056069	8.30252E-61	4.028165692	4.745953756	4.028165692	4.745953756

Adequately trained for AI	-	0.06378	-	0.74620	-	0.10511	-	0.10511
	0.02067	863	0.32409	5404	0.14646	848	0.14646	848
	3813		8718		6106		6106	

The ANOVA's Significance F is 0.746 (as shown in table no. 214, confirming the model is not statistically significant. In effect, there is no evidence that managers who feel more trained in AI report higher trust in its insights.

Figure 19: Line Fit Plot



The line-fit plot, in figure no. 19 above, overlays predicted trust values (red squares) on actual trust observations (blue diamonds) across training levels. The near-horizontal regression line demonstrates almost zero slope. Data points scatter vertically with no upward trend, visually reinforcing that increasing training scores do not correspond to systematically higher trust ratings.

Figure 20: Residual Plot

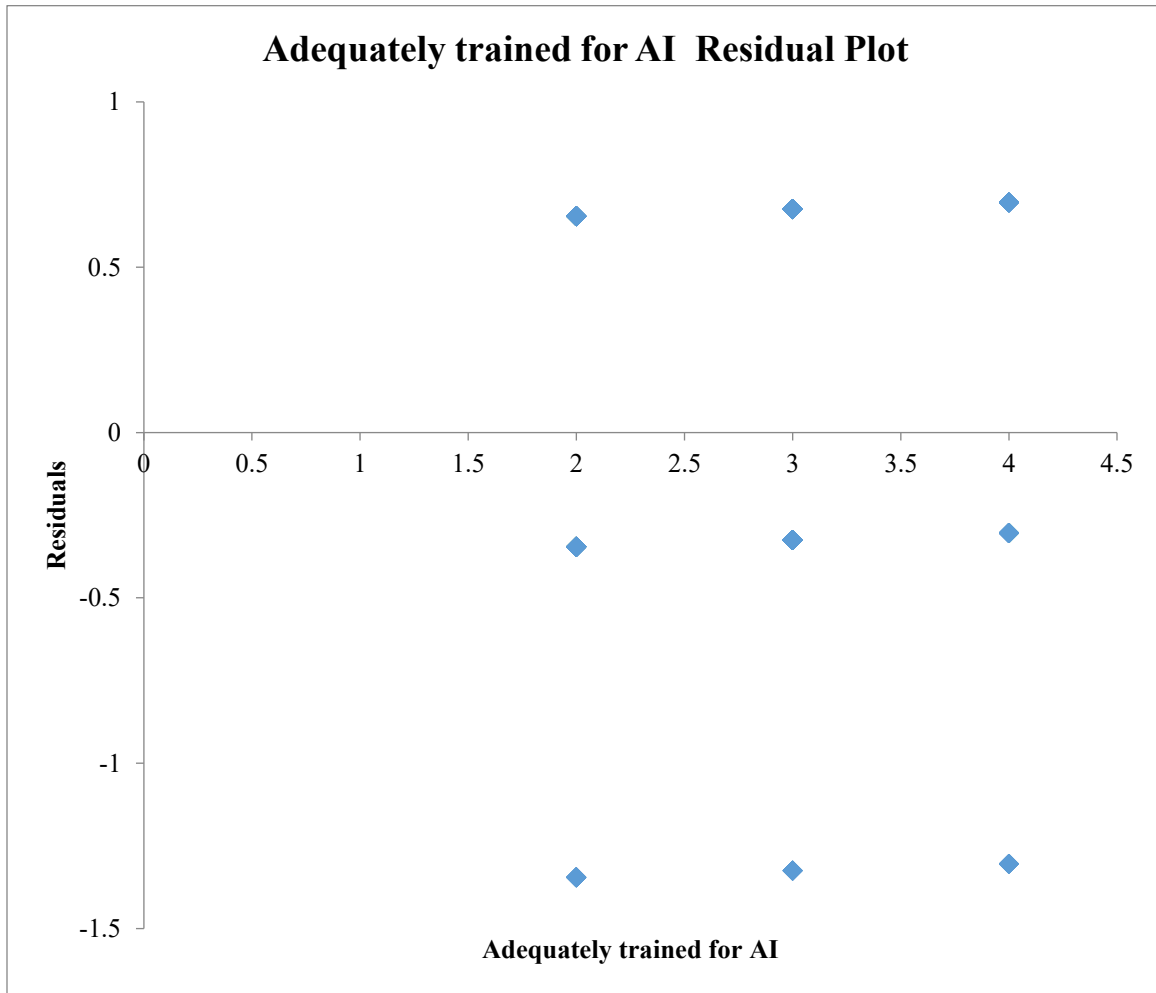


Figure no. 20 represents residual plot that exhibits prediction errors against training scores. Points cluster randomly above and below zero with a consistent vertical spread. There are no discernible patterns or funnels, indicating no clear relationship, no heteroscedasticity, and confirming that training does not systematically over- or under-predict trust.

Based on these results and tests, it can be said that being adequately trained for AI is not a significant predictor of having/gaining trust in AI insights. The regression model fails significance tests, the slope is effectively zero, and residuals show no structure. These results suggest that simply providing AI training—at least at its current scale and format—does not automatically build manager confidence in AI outputs. To boost trust, organizations must consider additional factors

beyond basic training, such as enhancing model explainability, demonstrating reliability through pilot successes, and fostering transparent governance around AI decision logic.

4.2.5. Opportunities for Different Departments

To examine whether perceptions of “AI adds more value than ERP” differ by managerial role (*Objective 5*), the researcher performed a single-factor ANOVA across six groups: Department Head, Finance Manager, HR Manager, IT Manager, Operations Manager, and Senior Manager.

Table 25: Anova: Single Factor Summary

Anova: Single Factor				
SUMMARY				
Groups	Count	Sum	Average	Variance
Department Head	24	109	4.541666667	0.259057971
Finance Manager	34	153	4.5	0.257575758
HR Manager	42	188	4.476190476	0.255516841
IT Manager	32	141	4.40625	0.248991935
Operations Manager	27	119	4.407407407	0.250712251
Senior Manager	41	184	4.487804878	0.256097561

Table no. 25 is a summary that shows that all six roles rated AI’s added value very highly—group averages range narrowly from 4.40 (IT Manager) to 4.54 (Department Head) on the 1–5 Likert scale. Variances are also tight (≈ 0.25 for each role), indicating consistent agreement within each group.

Table 26: Anova: Single Factor Statistics

ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit

Between Groups	0.404305233	5	0.080861047	0.317450622	0.902097814	2.260647462
Within Groups	49.41569477	194	0.254720076			
Total	49.82	199				

The ANOVA table no. 26 reports a between-groups MS of 0.0801 and a within-groups MS of 0.2547, yielding an F statistic of 0.3175 ($df_1=5$, $df_2=194$). The associated p-value is 0.9021, far above the 0.05 alpha threshold, and the critical F is 2.2606. Because $p > 0.05$, we fail to reject the null hypothesis of equal means. In other words, differences in mean ratings across roles are so small they could easily be due to chance.

The tables from the results depict that all roles—whether Department Heads or Operations Managers—viewed AI as adding significantly more value than legacy ERP systems, with no single group rating it higher or lower in any statistically meaningful way. This uniformity across functions suggests that the transition to AI delivers a consistently perceived lift in strategic value, regardless of managerial domain. This cross-role consensus highlights the organization-wide relevance and acceptance of AI’s benefits over traditional ERP alone.

4.2.6. Cross-Cutting Examination

To quantify the overall shift in perceptions from legacy ERP to AI-driven management, we conducted a paired t-test comparing each manager’s “ERP meets business needs” score (pre-implementation) against their “AI adds more value than ERP” score (post-implementation) across the same 200 respondents (Tabl no. 27).

Table 27: : Paired Two Sample for Means (Business needs vs. Adds Value)

t-Test: Paired Two Sample for Means		
	<i>AI adds more value than ERP</i>	<i>ERP meets business needs</i>
Mean	4.47	3.075
Variance	0.250351759	0.471733668

Observations	200	200
Pearson Correlation	0.043136527	
Hypothesized Mean Difference	0	
df	199	
t Stat	23.70822357	
P(T<=t) one-tail	3.54458E-60	
t Critical one-tail	1.652546746	
P(T<=t) two-tail	7.08917E-60	
t Critical two-tail	1.971956544	

The pre-implementation mean was 3.075 (variance ≈ 0.47), indicating indifferent agreement that ERP met needs. However, the post-implementation mean jumped to 4.47 (variance ≈ 0.25), which reflects a strong agreement that AI adds greater value. The calculated t-statistic of 23.71 ($|t| \gg t_{(0.05,199)} = 1.65$) and a two-tailed p-value of 7.09×10^{-60} represent an overpowering evidence to reject the null hypothesis of no mean difference. Thus, it can be said that managers' perceptions shifted dramatically in favor of AI, with actual experience of AI's capabilities far outstripping the modest satisfaction they held for ERP. This highly significant change underscores that AI implementation did more than tweak existing processes—it fundamentally elevated the perceived strategic and operational value beyond what ERP systems had delivered.

Next, to evaluate how AI's promise of enhanced collaboration translated into real operational gains, the researcher conducted a paired t-test comparing each manager's pre-implementation belief—"AI enhances cross-subsidary collaboration and data sharing" (Mean = 4.015, Variance ≈ 0.54)—against their post-implementation experience—"AI improved coordination across business units" (Mean = 4.45, Variance ≈ 0.25) (as shown in Table no. 28).

Table 28: Paired Two Sample for Means (Collaboration vs. Coordination)

t-Test: Paired Two Sample for Means		
	<i>AI improved coordination</i>	<i>AI enhances collaboration</i>

Mean	4.45	4.015
Variance	0.248743719	0.537462312
Observations	200	200
Pearson Correlation	-0.087271126	
Hypothesized Mean Difference	0	
df	199	
t Stat	6.672496786	
P(T<=t) one-tail	1.21909E-10	
t Critical one-tail	1.652546746	
P(T<=t) two-tail	2.43817E-10	
t Critical two-tail	1.971956544	

The paired analysis yielded a t-statistic of 6.67 (df = 199), which is well above the one-tailed critical value of 1.65, and a one-tailed p-value of 1.22×10^{-10} (two-tailed $p = 2.44 \times 10^{-10}$). Because $p \ll 0.05$, we reject the null hypothesis that mean coordination gains merely equaled the collaboration expectations. Therefore, it can be said that while managers already expected AI to break down silos (pre-mean ~ 4.02), their actual coordination experience with AI was rated significantly higher (~ 4.45). It confirms that AI met the needs while it also substantially exceeded the collaborative promise by delivering even stronger cross-unit coordination than anticipated.

Now, next in line is to assess whether managers' initial fears about AI displacing jobs were allayed by their actual experience of AI working alongside human roles. Thus, the researcher ran a paired t-test again for comparing the pre-implementation score for "AI threatens job security" (Mean = 1.935, Variance ≈ 0.63) against the post-implementation score for "AI complements human roles" (Mean = 4.375, Variance ≈ 0.24) across the same 200 respondents (as illustrated in the Table no. 29).

Table 29: Paired Two Sample for Means (Threat vs. Complement)

t-Test: Paired Two Sample for Means
--

	<i>AI complements human roles</i>	<i>AI threatens job security</i>
Mean	4.375	1.935
Variance	0.235552764	0.633944724
Observations	200	200
Pearson Correlation	0.037386514	
Hypothesized Mean Difference	0	
df	199	
t Stat	37.63651066	
P(T<=t) one-tail	9.73493E-93	
t Critical one-tail	1.652546746	
P(T<=t) two-tail	1.94699E-92	
t Critical two-tail	1.971956544	

The test produced a t-statistic of 37.64 with 199 degrees of freedom—far exceeding the critical one-tailed t of 1.65—and a one-tailed p-value of 9.73×10^{-93} (two-tailed $p = 1.95 \times 10^{-92}$). Because $p \ll 0.05$, we strongly reject the null hypothesis that managers' post-implementation perceptions simply equaled their pre-implementation fears.

In practical terms, while managers initially sat near the “disagree” end of the scale on job threats (just under 2 on a 1–5 scale), their subsequent ratings of AI as a complement to human work soared above 4. This dramatic reversal demonstrates that real-world AI deployment not only neutralized security concerns but delivered clear evidence that AI augments, rather than replaces, human roles—exceeding early anxieties by a wide margin.

To determine whether AI's perceived strategic value outweighed initial concerns about resistance, we performed a paired t-test comparing managers' pre-implementation score for “AI faces resistance” (Mean = 3.94, Variance ≈ 0.56) with their post-implementation score for “AI adds more value than ERP” (Mean = 4.47, Variance ≈ 0.25) across the same 200 respondents (Table no. 30).

Table 30: Paired Two Sample for Means (Resistance vs. Value Reversal)

t-Test: Paired Two Sample for Means		
	<i>AI adds more value than ERP</i>	<i>AI faces resistance</i>
Mean	4.47	3.94
Variance	0.250351759	0.55919598
Observations	200	200
Pearson Correlation	-0.018265371	
Hypothesized Mean Difference	0	
df	199	
t Stat	8.26102516	
P(T<=t) one-tail	9.99358E-15	
t Critical one-tail	1.652546746	
P(T<=t) two-tail	1.99872E-14	
t Critical two-tail	1.971956544	

The analysis yielded a t-statistic of 8.26 (df = 199), well above the one-tailed critical value of 1.65, with a one-tailed p-value of 9.99×10^{-15} (two-tailed $p = 1.9987 \times 10^{-14}$). Because $p \ll 0.05$, we reject the null hypothesis of no mean difference.

In concrete terms, managers initially anticipated significant pushback (averaging nearly “Agree” on resistance), yet after deployment they rated AI’s value over ERP decisively higher—averaging 4.47 on a 1–5 scale. This statistically significant shift reveals that, despite early resistance concerns, actual results proved AI’s benefits clear and convincing, overwhelmingly outweighing any adoption hurdles.

4.2.7. Multi-Variable Regression

The researcher now sought to identify which pre-implementation factors—namely, Preparedness for ERP→AI transition, Adequacy of AI training, and Fear of job loss due to AI—actually drive post-implementation efficiency gains (“AI improved efficiency”).

Table 31: Multiple Regression Predicting AI-Driven Efficiency Gains from Pre-Implementation Factors

Regression Statistics	
Multiple R	0.069383777
R Square	0.004814109
Adjusted R Square	-0.010418329
Standard Error	0.498896805
Observations	200

The model's $R^2 = 0.0048$ (in Table no. 31) shows that these three predictors together explain less than 0.5% of the variation in efficiency gains. The Adjusted R^2 is slightly negative, which indicates that the model performs worse than a horizontal line at the mean.

Table 32: ANOVA and Coefficient Estimates for the Efficiency Regression Model

ANOVA								
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>			
Regression	3	0.235987602	0.078662534	0.316043226	0.813770931			
Residual	196	48.7840124	0.248898022					
Total	199	49.02						
	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	4.272427631	0.225704451	18.92930166	3.99476E-46	3.82730658	4.717548682	3.82730658	4.717548682

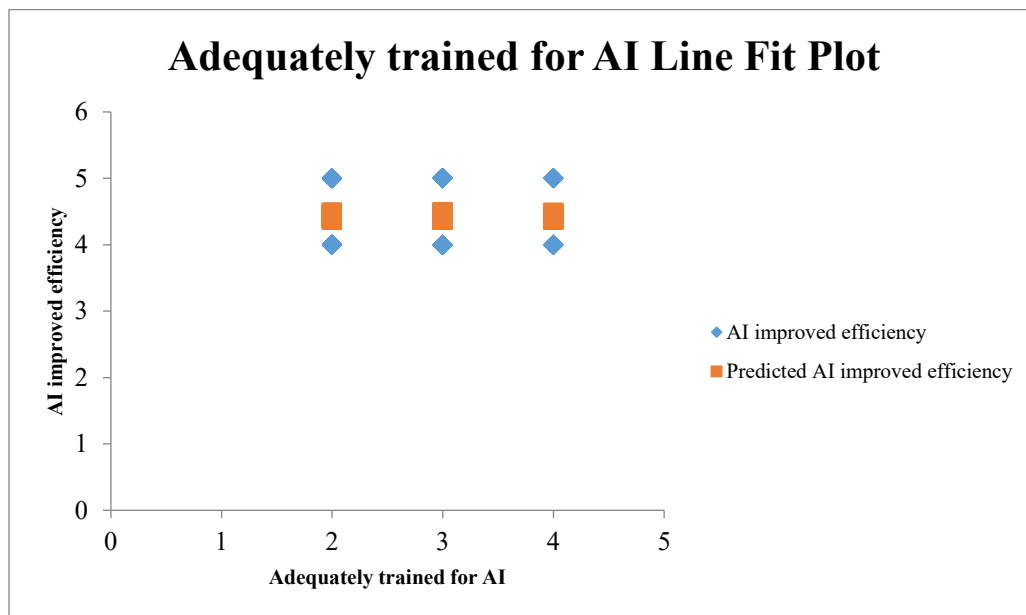
Prepared for ERP to AI transition	0.04247 7019	0.04569 1324	0.92965 1762	0.35369 4961	- 0.04763 2723	0.13258 6762	- 0.04763 2723	0.13258 6762
Adequately trained for AI	0.00194 6844	0.04912 6827	0.03962 8934	0.96842 9296	- 0.09493 8197	0.09883 1884	- 0.09493 8197	0.09883 1884
AI threatens job security	0.01181 2173	0.04446 8136	0.26563 2304	0.79080 1595	- 0.07588 5271	0.09950 9618	- 0.07588 5271	0.09950 9618

The F-statistic of 0.316 ($df_1 = 3$, $df_2 = 196$) comes with a Significance F = 0.814, well above 0.05. This means the model as a whole is not statistically significant—there is no evidence that, taken together, these three factors reliably predict efficiency improvements. Intercept is highly significant and it represents the average efficiency score (≈ 4.27) when all predictors are zero (i.e., minimal preparedness, training, and fear). Hence, none of the three predictors reach significance (all p-values $\gg 0.05$), and their confidence intervals all straddle zero. This indicates that, holding the other factors constant, neither feeling prepared, feeling trained, nor fearing job loss has any measurable impact on efficiency improvements.

These results reveal that none of the anticipated “success drivers” individually or collectively explain why some managers reported greater efficiency gains than others. Despite intuitive expectations that stronger change readiness, more thorough training, or lower resistance might boost performance, our regression shows no statistically significant relationships. Practically, this suggests that other factors—perhaps organizational culture, the quality of the AI tools themselves,

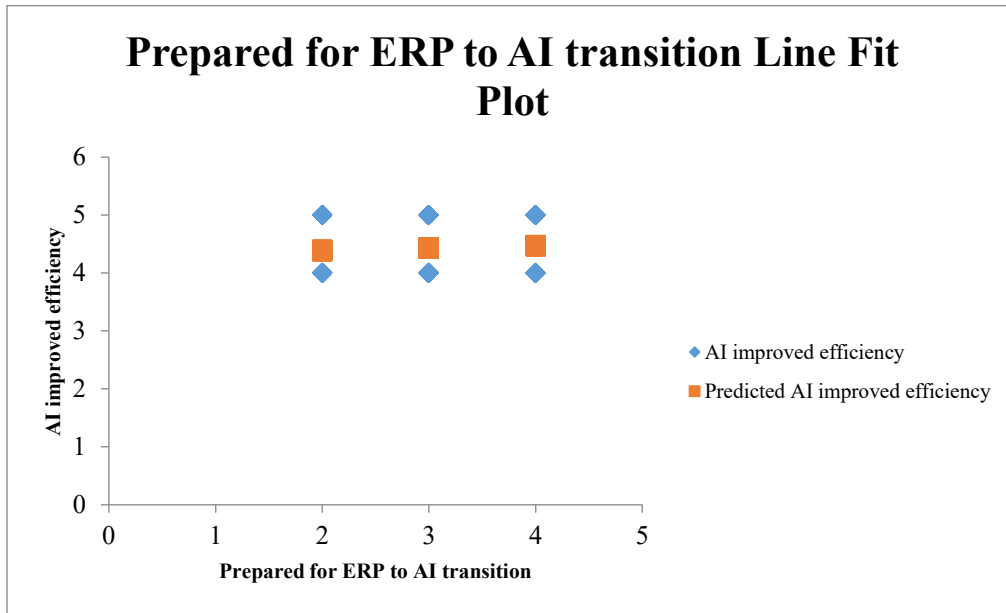
leadership support, or specifics of the pilot implementation—are far more critical in determining efficiency outcomes. For future research and practice, it will be essential to explore these alternate drivers rather than relying solely on standard readiness and training metrics.

Figure 21: Relationship between AI Training and Efficiency Gains



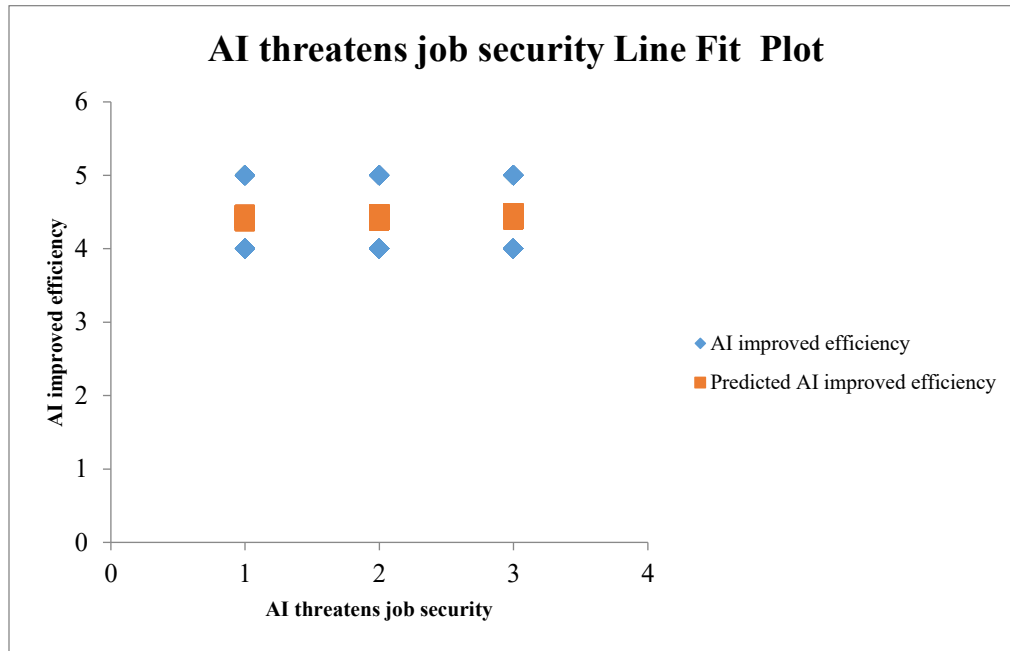
The blue diamonds plot each manager’s actual “AI improved efficiency” score against their self-rated training level, while the orange squares show the model’s predicted efficiency. The nearly horizontal line of predicted values—clustered around 4.3 regardless of training score—reveals almost no slope. In other words, across the full range from 1 (“strongly disagree” on being trained) to 5 (“strongly agree”), the regression model forecasts nearly identical efficiency gains. The scatter of actual scores around that flat trend line confirms that training level has almost no predictive power for post-implementation efficiency.

Figure 22: Relationship between Preparedness and Efficiency Gains



Here, actual efficiency gains (blue diamonds) are plotted against managers' pre-implementation readiness for the ERP→AI transition, with predicted values in orange. As with training, the predicted efficiency values form a horizontal band centered around the overall mean (~ 4.27), showing no upward or downward trend as preparedness increases from 1 to 4. The consistent spread of actual scores around that band again demonstrates that feeling well-prepared for AI does not translate into systematically higher efficiency ratings.

Figure 23: Relationship between Job-Security Fears and Efficiency Gains



This panel juxtaposes managers' initial "AI threatens job security" scores (1–3 on the x-axis) against their experienced efficiency gains (blue) and the regression's flat predictions (orange). Despite wide variation in early fears, the predicted efficiency once more stays at roughly the same level (~4.27). Actual scores fluctuated but show no pattern tied to fear levels. This confirms that anxiety about job displacement bore no systematic influence on later efficiency improvements—managers who feared job loss gained just as much efficiency from AI as those who did not.

4.3. *Thematic Analysis from Qualitative Data (Case Study: Alpha Group)*

4.3.1. *Theme 1 – Stakeholder Engagement & Communication*

Effective stakeholder engagement and clear communication emerged as a foundational theme across the interviews. Key leaders emphasized the importance of building a shared understanding and securing buy-in at every level of the organization. The Group CEO described his role as "champion[ing] the change," establishing "a clear narrative" that framed AI adoption not as an

abstract exercise but as a tool to create real business impact and improve employees' work. He explains that he

“communicated frequently with all levels of staff about why we were doing this and how it would benefit not just the company but also their daily work”.

This transparent messaging – highlighting, for example, that AI would handle tedious tasks so that staff could focus on higher-value work – helped align understanding throughout the diverse conglomerate's units.

Equally crucial was engaging stakeholders across functions. The AI Program Manager stressed that

“stakeholder engagement is everything – you need buy-in at all levels, from executives to the frontline”.

To enact this, change leaders created localized advocates (“AI Champions”) in each department – early adopters “who were excited about the technology” – and trained them deeply so they could support peers on the ground. Regular town-hall meetings, demos, newsletters and intranet updates kept employees informed:

“Communication was constant – newsletters, intranet updates, progress reports – all aimed at keeping everyone informed about why we were doing this and the wins we were getting”.

These efforts built momentum and trust. As the Program Manager noted, having

“visible support from the CEO and other top leaders made my job easier; when employees see leaders backing a change, they take it more seriously”.

From the HR perspective, ongoing dialogue was managed carefully. The HR Director explained that her team “communicat[ed] with employees throughout the process,” addressing concerns

directly. Early on, they noted mixed reactions – anxiety about jobs versus excitement about new tools – and countered fear by reassuring staff that the goal was growth, not cuts. In her words, HR

“was very clear in our communications that the goal was to use AI to augment our employees, not replace them... our AI strategy was about growth and upskilling rather than cutting headcount”.

This consistent messaging – that AI was a tool for empowerment – helped quell fears and made employees feel heard. Feedback channels such as Q&A sessions and surveys were set up so that workers “felt heard throughout the transition,” and concerns were addressed promptly. The CEO echoed that communication was

“another critical piece – being transparent about the ‘why’ and ‘how’ of the change helps bring people on board”.

Finally, engagement extended beyond internal stakeholders. The CFO noted that communicating results to external stakeholders was also important for sustaining support:

“showing our stakeholders – including investors – that we are leveraging AI and improving our operations has increased their confidence in our management”.

Hence, across interviews, leaders underscored that proactive communication and involving stakeholders from the outset – via narratives, training, champions and regular updates – were essential to align the conglomerate’s diverse units around the AI initiative. These engagement practices helped minimize resistance and created a shared commitment to the transformation.

4.3.2. Theme 2 – Training & Upskilling

Investing in people’s skills was a clear priority in the AI rollout. Across all levels of the organization, leaders reported that substantial training and upskilling were needed to enable

employees to work effectively with new AI tools. The CEO acknowledged one of his core strategies was to

“invest[] heavily in training”

and to assure staff that

“AI tools were there to augment their work, not replace them”.

The Chief Technology Officer similarly noted that the group

“realized early that we didn’t have all the necessary AI expertise in-house,”

so the technical team both hired key experts (e.g., a lead data scientist) and

“simultaneously upskilled our existing staff.”

As he described, they

“ran training programs and workshops so that our software engineers could learn about machine learning and our analysts could work with new AI-driven analytics tools”.

External consultants from the AI vendor also worked alongside internal teams, ensuring knowledge transfer.

Human Resources led a broad curriculum of learning initiatives. The HR Director outlined a “comprehensive training program”: first, company-wide “AI 101” seminars to raise awareness and demystify AI; then targeted workshops for specific tools as they were deployed. For example, when a new AI analytics dashboard was introduced to marketing, HR held hands-on workshops so team members could

“learn how to use it effectively in their day-to-day work”.

They even launched an online learning portal with courses on data analysis and machine learning, enabling employees to self-serve and learn “at their own pace”. In some cases, HR orchestrated formal role changes: for instance, staff from IT support were trained and reassigned to become junior data analysts working with the AI systems. A key philosophy was “continuous learning” – making training an ongoing process rather than a one-time event. After initial sessions, the company offered refresher courses and even a dedicated helpdesk for AI questions in the first months. These training investments not only built competence but also signaled to employees that they would be supported in the transition.

The program management team also emphasized people development. The AI Program Manager asserted that to make AI implementation “a sustained success,” the company needed to “invest in people.” The hard technology could only go so far; it was

“the training, the hand-holding early on, and the cultural support”

that would drive adoption. He further reflected that, if starting over, he would “involve end-users even more in the design of solutions from day one,” since early involvement naturally extends the benefits of training and boosts buy-in.

Practitioner interviews corroborate these accounts. For example, the Customer Service Manager explained that easing agent concerns required substantial upskilling: the team organized training so that support representatives understood how to “work alongside the chatbot” – learning to smoothly take over chats and to leverage AI-generated suggestions during calls. In Sales, the new AI-enhanced CRM was unfamiliar to many, prompting numerous questions during training: the Regional Sales Manager remembered asking about how the system computed lead scores and slowly building understanding through hands-on sessions. Over time, these learning efforts paid off: the financial analysts reported that management even sponsored them to learn data analytics, which led one analyst to observe,

“I feel like I’ve grown professionally... I’m not really worried about AI taking my job; I see it as a tool that helps me do my job better”.

In this way, training and upskilling permeated the AI program's strategy. By providing seminars, workshops, mentoring, and resources, Alpha Group equipped employees to engage with AI tools confidently. The emphasis on workforce development helped transform anxiety into ownership, aligning staff with the project's goals and enabling the broader research aim of understanding how human capital factors into AI adoption in large firms.

4.3.3. Theme 3 – Flexibility & Iteration

Respondents consistently highlighted that a rigid, one-size-fits-all plan would not suffice in a complex conglomerate. Instead, the AI implementation proceeded iteratively, with frequent adjustments in response to real-world feedback. The Program Manager stressed that “flexibility is key”: although a roadmap existed, the team

“adjusted it whenever reality turned out differently than our plans – like extending a pilot or tweaking training approaches”.

For example, when an early demand-forecasting AI model performed poorly initially, skeptical stakeholders voiced concerns. Rather than abandoning the effort, the team took it as a learning opportunity: they collaborated with data scientists to refine the model, and after improvements it “started performing well,” which “helped win some people over”. This willingness to adapt on the fly was crucial in maintaining momentum.

Flexibility also meant running parallel processes and making incremental changes. The Operations Manager described a collaborative approach on the factory floor: his team initially treated AI's maintenance predictions “as an additional input” and ran them alongside traditional methods. Over a few months, as technicians double-checked alerts and provided feedback,

“the team saw that the AI was right more often than not”

and gradually built trust. One instance – where the AI correctly flagged an impending compressor failure that humans then fixed preemptively – gave the team confidence to lean on the system. At the same time, the system itself was tuned based on user feedback to reduce false alarms. In this

way, technical and cultural flexibility went hand in hand: the plant's people slowly integrated the AI through iterative testing and open communication.

A phased approach was common in other domains as well. The Customer Service Manager recalled starting the chatbot rollout with a

“limited set of topics”

and closely monitoring outcomes, so that any errors could be fixed before scaling up. Users were always given an easy way to reach a human, which minimized frustration during early trials. In marketing, teams experimented with AI-driven content generation in low-risk ways (such as internal contests comparing human vs. AI campaign plans) before fully trusting it. Throughout, leaders noted that patience was essential: as the CEO put it,

“transformation doesn't happen overnight; it's a continuous process of learning and refining our approach”.

Financial governance also required flexibility. The CFO admitted that unexpected costs arose – for instance, mid-project upgrades to network security were needed to protect new data flows, which were not in the original budget. Rather than scrapping the upgrades, leaders treated them as necessary investments. They implemented real-time budget tracking and key performance indicators to measure outcomes as they unfolded. This iterative financial oversight allowed them to steer the initiative dynamically.

In sum, a theme of iterative learning and agile management cut across the interviews. By piloting ideas, soliciting feedback, and being willing to revise plans (sometimes extending pilot phases or reallocating funds), Alpha Group's leaders fostered an adaptive implementation process. This flexibility was seen as a lesson in itself: the Program Manager explicitly concluded that building in room to adjust – and celebrating early successes along the way – was vital for sustained progress. As a result, the company avoided doggedly sticking to failing plans and instead refined its strategy continuously, thus aligning with the research goal of uncovering best practices for managing AI projects in large organizations.

4.3.4. Theme 4 – Celebrating Wins & Momentum

Maintaining enthusiasm during a large-scale transformation required highlighting successes along the journey. Interviewees emphasized that celebrating early and small victories created positive momentum and reinforced the value of the AI initiative. The AI Program Manager pointed out that the team

“made a point of highlighting early successes, even minor ones, to build momentum and show everyone that the effort was worth it”.

This narrative of wins helped counter skepticism and kept teams engaged. Likewise, the HR Director noted that celebrating successes was key to building employee engagement: by

“addressing concerns promptly and celebrating successes, employees became more engaged. Morale, after a dip at the start, actually improved as people started seeing some of the mundane parts of their jobs being eased by AI”.

In other words, as workers witnessed tangible benefits – like tasks becoming simpler or error rates dropping – their attitude shifted from fear to curiosity and excitement.

Concrete examples of celebrated wins abounded. The group documented clear efficiency improvements, such as in reporting processes that

“used to take days” but were now completed “in minutes with AI”.

In manufacturing, saving even a few hours of downtime per month (an estimated 15–20% reduction) translated to significant cost avoidance, a fact that was highlighted as a “huge win” for the plant. Marketing saw a roughly 20% increase in email open and click-through rates after AI-driven personalization was implemented, while average order values rose thanks to recommendation engines. These data points were shared widely – in town halls, newsletters and scorecards – to show ROI in real terms.

Beyond metrics, qualitative “wins” were also celebrated. Employees who overcame initial hurdles were often recognized for their contributions. Leaders shared stories where the AI correctly

predicted an issue or uncovered a new opportunity, lending credibility to the technology. For example, one operations technician's discovery of a failing compressor part – guided by an AI alert – was cited as a memorable success that

“really converted a lot of the team to trusting the AI”.

Similarly, marketing held a fun contest pitting human-curated campaign plans against AI-generated ones; when the AI flagged an unexpected but high-performing customer segment, it became an inspiring anecdote of how the system added value. These narratives were woven into the project's communication, reinforcing the message that AI could deliver real impact.

Celebration of progress also took the form of executive recognition. The CEO publicly acknowledged that the group was

“making more data-informed decisions” and “identifying new opportunities that we hadn't seen before”

as a result of AI. Such endorsements from the top helped signal success to the entire organization. The CFO, too, highlighted financial wins – for instance, noting a first-year 5% savings on a plant's maintenance budget and faster invoicing cycles – to show stakeholders that the investment was paying off. By comparing projected versus actual outcomes and reporting favorable results (or learnings), leaders kept momentum going. In essence, celebrating wins gave concrete proof that the AI initiative was delivering on its promises, which in turn motivated teams to continue driving innovation. This systematic focus on positive feedback loops is a critical element in understanding how AI projects can gain sustained traction in large companies.

4.3.5. Theme 5 – Human Augmentation vs Job Threat

A pervasive theme was the anxiety about AI displacing jobs versus the parallel emphasis on using AI to empower employees. Across roles, interviewees noted initial fears but consistently reframed AI as a tool for augmentation. The CEO, anticipating cultural resistance, deliberately told employees that

“AI tools were there to augment their work, not replace them”.

This sentiment was echoed at every level. HR ensured early and frequent messaging clarifying that AI was meant to relieve workers of mundane tasks and enable them to focus on meaningful work. The HR Director recalled addressing nervous questions like

“Will AI automate my job?”

by reassuring staff that the strategy was one of growth and upskilling rather than layoffs. Importantly, she pointed out that the company did not actually cut any headcount due to AI; instead, employees were reskilled or reassigned to higher-value roles. In many interviews, the refrain was that AI would handle repetitive data entry or basic inquiries, freeing people to tackle complex, creative, or strategic tasks. This messaging helped shift perspectives from threat to opportunity.

Operational examples grounded this narrative. The Customer Service Manager explicitly told her team that the new chatbot was introduced to handle repetitive inquiries and reduce workloads during peak periods – not to eliminate positions. In fact, management made it clear no one would lose their job because of the chatbot. Similarly, the Financial Analyst described his personal experience: initially anxious that an AI forecasting tool might devalue his expertise, he soon found the opposite to be true. The AI freed him from laborious data gathering, allowing him to spend more time on analysis. He now reports feeling more fulfilled, having acquired new skills (even an online analytics certification) and trusting that AI

“helps me do my job better”.

This transformation – from initial concern to a sense of professional growth – exemplifies the augmentation narrative.

Veteran employees voiced similar themes. A long-serving Regional Sales Manager admitted he was

“skeptical and even uncomfortable” at first, worrying “If the AI can sell, what will they need us for?”

However, as the AI tool proved itself and sales staff saw it highlighting missed opportunities (e.g. quietly interested leads), attitudes softened. The Sales Manager now cautions that AI

“shouldn’t replace the human side,”

but acknowledges that when integrated wisely, it can remove guesswork and drudgery from the job. He praised the leadership’s balanced approach – requiring the team to use the AI but always

“leav[ing] room for our judgment”

– which framed the system as an aid rather than a mandate.

Hence, the tension between augmentation and job threat was a prominent concern, but one that the company actively managed through transparent communication, training, and role redesign. By repeatedly asserting that AI would augment human capabilities (and demonstrating it through tangible examples), leaders eased fears and gradually won acceptance. This theme is central to the broader research objective, as it shows how conglomerates can navigate workforce anxieties during AI transformations by emphasizing upskilling and new opportunities for employees. Ultimately, instead of layoffs, the company even created new positions (e.g. a part-time AI ethics officer and data analysts) reflecting a net enrichment of roles. These experiences suggest that positioning AI as a complementary tool fosters trust and engagement among employees, which is critical for successful implementation.

4.3.6. Theme 6 – Leadership Support & Advocacy

Strong leadership endorsement emerged as another key theme. Across interviews, participants highlighted how executive sponsorship and advocacy from the top accelerated the AI initiative. From the outset, the Group CEO took personal ownership of the program. He described making himself

“visibly involved – from kickoff meetings to periodic check-ins – to signal that this was a top priority supported at the highest level”.

By establishing a clear vision (“not AI for AI’s sake but to create real business impact,” for example) and modeling enthusiasm, he set the tone for the organization. As he reflected,

“leading by example is vital; if you want an organization to embrace AI, you have to embrace it yourself and be its advocate”.

His active role – as executive sponsor – sent a strong message that the transformation was not a side project but integral to the company’s strategy.

This top-down commitment resonated through the ranks. The CTO, for instance, noted that the CEO’s strategic direction was translated into action by the tech team: they

“translated the CEO’s vision into a concrete technology plan”

and even built an AI Center of Excellence under his mandate. The CTO’s formation of this cross-functional CoE – explicitly with leadership backing – enabled consistent piloting and scaling of solutions across business units. Similarly, the AI Program Manager pointed out that visible leadership support made his job of coordinating the rollout easier:

“when employees see leaders backing a change, they take it more seriously”.

In other words, executive advocacy helped legitimize the effort and ensured departmental leaders did not treat it as optional.

Board-level support was also crucial, particularly in legitimizing the investment. The CFO described the rigorous process of building the business case to convince the board, showing concrete ROI projections and strategic necessity. Once the board approved the substantial upfront costs (for data infrastructure and vendor contracts), the CFO made sure to report back on the gains. He observed that stakeholders – including investors – felt more confident in Alpha Group as a management team, seeing that it was actively

“leveraging AI and improving our operations”.

Presenting positive outcomes (such as productivity gains and cost savings) to the board and shareholders reinforced ongoing support and secured the budget needed for continued transformation.

In practice, leadership advocacy took many forms beyond financial approval. Several interviewees mentioned that senior managers and department heads were personally involved – for example, senior HR partnered with IT to monitor AI tool ethics, and operations and finance leaders championed projects in their areas. Moreover, the company instituted “AI Champions” not only at the staff level (as noted earlier) but also had middle managers publicly endorsing AI in their teams. Even where new procedures were introduced (like data entry disciplines for sales), leaders eased the transition by explaining the long-term benefits rather than imposing them. One salesperson praised the inclusive approach: management did not force blind adherence to AI recommendations but

“encouraged us to integrate it into our decision-making but ultimately left room for our judgment”.

This respectful stance from leadership – balancing direction with autonomy – further built trust. Overall, consistent executive engagement – from the CEO articulating the why and how of AI, to department heads actively communicating and allocating resources – was repeatedly cited as a success factor. It ensured alignment of vision, secured funding, and signaled to employees that the AI effort was legitimate and supported. In effect, leadership support and advocacy wove together the technical and human dimensions of the project, bridging strategy and execution. Understanding this theme highlights how conglomerates’ top management can influence AI adoption: when leaders visibly prioritize the initiative, they drive the cultural and structural backing needed for broad implementation.

4.3.7. Theme 7 – Data Governance & Infrastructure

Another salient theme was the central role of data and IT infrastructure in enabling AI. Leaders made clear that without the right data platforms and governance, AI projects could not succeed at scale. In the early stages, the CTO described a major effort to

“ensure our data was in order.”

This involved consolidating disparate data sets from across the conglomerate into a centralized data lake and rigorously cleaning it. Legacy systems required integration work: some older software was not AI-ready, so the IT team built custom interfaces or even replaced outdated modules to link them with modern AI tools. Meanwhile, inconsistent data across business units necessitated strong data governance measures. The CTO stated that they

“discovered early on that data coming from different units had inconsistencies” and responded by “establishing data governance standards and investing in data management tools”.

These steps improved data quality and made it possible to feed reliable inputs into machine learning models.

The infrastructure itself was significantly upgraded. The company created a new central data platform that now underpins all AI and analytics activities. The CTO remarked that the resulting setup is

“much more robust and modern” – it “supports the AI applications but has improved our overall data accessibility”.

To handle the heavy computational demands, many workloads were migrated to the cloud, and network and server capacities were increased. In fact, the CFO noted that one of the largest capital expenditures was on data infrastructure and AI platform contracts, underlining the scale of investment. Security also became a consideration: midway through the project, an unanticipated

expense arose to upgrade network security to safeguard new data flows, reflecting the emergent needs of the new infrastructure.

From a governance standpoint, the organization implemented new policies. Across interviews there was mention of setting clear rules for data management and even AI ethics. For example, the HR leader noted the company appointed an AI ethics officer (on a part-time basis) to oversee responsible use of emerging tools. This ensured that data-driven HR tools, such as automated resume screening, were monitored for bias. In marketing and sales, data quality became a shared responsibility: marketers worked with IT to clean up customer databases, and the sales force acknowledged it had to improve CRM data hygiene so that the AI's lead-scoring suggestions would be meaningful. These steps show that data governance was treated not as an afterthought, but as an integral piece of the AI deployment.

In practice, the quality of insights was closely tied to the infrastructure. The Marketing Manager observed that initially

“some of our customer data was outdated or inconsistent, and if you feed bad data into AI, you get bad recommendations out”.

Recognizing this, marketing and IT teams cleaned and standardized the data early on. Sales similarly learned that the AI's performance would mirror the state of the CRM data, prompting improvements in how calls and customer information were logged. Over time, the investments paid off: predictive models became more accurate and the AI-supported processes – from inventory management to predictive maintenance – yielded tangible benefits.

This theme highlights that a strong technical foundation was essential for AI success. The interviews demonstrate that Alpha Group's conglomerate-wide implementation depended on scalable infrastructure (data lakes, cloud computing, connectivity) and disciplined data management. By explicitly addressing data governance and system upgrades, leaders ensured that AI tools had high-quality inputs and reliable platforms. For the broader research aims, these findings underscore the criticality of “back-end” capabilities in AI initiatives – in conglomerates, fragmented data sources and legacy systems must be tackled head-on to unlock AI's potential.

4.3.8. Theme 8 – Technical Challenges & Solutions

The interviews detailed numerous technical obstacles encountered, along with creative solutions to overcome them. A recurring challenge was integrating AI with legacy systems. The CTO explained that some older software was not designed to interface with modern AI algorithms, so the team had to

“build custom interfaces and, in a few cases, replace outdated modules entirely”.

This meant additional development effort and, occasionally, procuring new software. In manufacturing, integrating IoT sensors and AI platforms with existing control systems required careful engineering.

Data quality itself was a significant technical hurdle. Teams spent extensive time on data cleaning and standardization until a governance framework was in place. The process was often painstaking: the CTO admitted that data preparation

(“things like data cleaning, integration, and infrastructure upgrades”)

took more time than even building the AI models. Recognizing this, Alpha Group invested in data management tools and standards early. For example, the AI Center of Excellence mandated that data scientists validate inputs before modeling, which prevented many downstream errors. In marketing and sales, poor data initially led to subpar AI outputs, but targeted data cleanup (e.g. removing duplicate records, updating contact data) improved results substantially.

Scalability was another technical constraint. The pilot projects ran on limited datasets, but scaling to company-wide use required significant computing resources. The CTO noted that after pilots proved successful, they

“needed to scale them up to the entire organization, which required significant computing resources and network upgrades,”

leading to substantial cloud migration. For example, the predictive maintenance system had to process continuous streams of sensor data from dozens of machines, which would not have been feasible on the old on-premise servers. Moving workloads to scalable cloud services allowed them to expand usage without debilitating hardware strain.

In some cases, initial model performance necessitated iterative fixes. The Program Manager recounted that one early sales-forecasting model

“wasn’t very accurate initially,”

prompting skepticism. Instead of scrapping it, the team treated it as a learning case:

“we worked with the data science team to improve the model, and eventually it started performing well”.

This responsiveness to technical failures was characteristic: when outputs were wrong, feedback loops were put in place (such as having end-users validate results) to refine algorithms. Similarly, the maintenance AI was fine-tuned based on technicians’ reports of false alarms. These adjustments illustrate how Alpha Group approached technical challenges with an experimental, solutions-oriented mindset.

Security and risk management also posed issues. As previously noted, unexpected funding was needed to upgrade network security for the new data flows. This served as a reminder that a robust AI infrastructure must also be protected. The CFO saw this as an investment in success rather than an overrun, indicating a flexible approach to emerging needs.

Overall, the theme of technical challenges underscores that deploying AI in a large conglomerate is not plug-and-play. It requires tackling legacy integration, cleaning and governing data, expanding compute capacity, and continuously debugging AI models. Alpha Group addressed these by establishing an AI Center of Excellence, combining in-house and vendor solutions, migrating to modern infrastructure, and involving end-users in testing. The success in automating processes and improving systems (e.g. an AI monitoring system that reduced IT downtime) demonstrates that these solutions paid off. For the research on AI implementation, the lesson is

clear: anticipating and systematically solving technical obstacles is essential, and concerted efforts in data engineering and infrastructure underpin any AI strategy in complex organizations.

4.3.9. Theme 9 – ROI & Financial Impact

Quantifying return on investment (ROI) and financial benefits was a critical theme, given the significant resources poured into the AI program. The CFO and other interviewees laid out both the upfront costs and the tangible gains observed so far. In preparing the business case, the finance team

“identified key areas where AI could either increase revenue or decrease costs,”

such as reducing downtime in operations or improving marketing targeting. They estimated benefits and compared them to expenses (software licenses, hardware upgrades, personnel, training hours, etc.), projecting that over a 3–5 year horizon, the AI initiative would

“more than pay for itself”

through efficiency gains and new growth. The board ultimately approved the investment by weighing both quantitative improvements and strategic value (staying competitive and gaining better insights).

In practice, the early financial outcomes have been encouraging. Across multiple divisions, leaders reported cost savings and revenue enhancements tied to AI tools. The CFO provided concrete figures: for one major plant, the predictive maintenance AI cut unplanned downtime enough to save

“about 5% of the annual maintenance budget in its first year”.

In corporate finance, automating invoice processing reduced a task’s time by around 30%, enabling faster monthly closes and freeing analysts for higher-level work. These efficiency gains are already measurable in reduced labor and overtime expenses. In the retail division, better demand

forecasting translated into fewer stockouts; while harder to precisely attribute, this likely led to increased sales that would otherwise have been lost. The CFO conservatively summarized that when comparing cumulative costs to savings, the company is

“on track to achieve the ROI we projected”

over the multi-year period. He noted that some returns came quickly (like the maintenance savings), while others accumulate over time, but overall confidence in the investment’s worth is high.

Other leaders provided additional ROI evidence. The Operations Manager reported that downtime fell by roughly 15–20% over the last year, which is “a huge win” for production efficiency. This not only saved repair and idle-time costs, but also stabilized scheduling (maintenance could be done at optimal times). Marketing likewise reported better financial results: AI-driven email and personalization campaigns led to about a 20% lift in open and click-through rates, and the product recommendation engine increased average order values. Improved targeting of digital ad spend, guided by AI predictions, also boosted return on ad spend. Customer support saw indirect financial impacts: because a chatbot now handles roughly 30–40% of simple inquiries, the human team was able to serve more customers without proportional headcount growth, effectively absorbing increased volume at lower marginal cost. Measures like higher customer satisfaction on complex cases and stable staffing levels indicate cost-effectiveness there.

On the expenses side, the CFO candidly described unexpected costs encountered, such as the aforementioned network security upgrade. He also mentioned investing in user incentives – unusual in IT projects – to encourage training completion and adoption. These “so-called overruns” were reframed as necessary investments in the program’s success. Rigorous tracking of metrics was established: for each AI use case, KPIs (e.g. downtime hours, process cycle-times, accuracy rates) were measured pre- and post-implementation. Though gathering this data required effort, it provided accountability. The CFO stressed that without these metrics, it would be hard to verify that promised benefits were realized.

Beyond raw numbers, strategic ROI was also noted. The CFO observed that having better predictive insights (like early warnings of demand shifts) allows the company to act proactively –

an intangible yet valuable gain. Moreover, demonstrating AI success has improved stakeholder confidence, which can translate into higher stock valuation or easier financing. Some leaders framed the long-term cost of inaction: as the CFO put it,

“if we had decided not to invest in AI, I suspect we’d gradually lose our competitive edge”.

By shifting the narrative to “What’s the risk if we don’t move forward,” management bolstered support.

Taken together, the interviews paint a picture of measured but positive financial impact from AI. Early wins in efficiency and revenue support the initial business case, while ongoing tracking keeps course corrections possible. This theme contributes to the broader research by showing that in a conglomerate setting, building and communicating a solid ROI narrative – with both quick wins and strategic gains – is crucial for sustaining AI projects. It also illustrates that to maintain support, organizations must be prepared to monitor and justify AI’s value in business terms.

4.3.10. Theme 10 – Culture & Mindset Shift

A deeper shift in company culture and mindset was found in another theme that was underlying the themes related to practical implementation. It has been reported by the interviewees that AI initiative catalyzed a more data-driven and innovation-oriented culture across Alpha Group. It is demonstrated from CEO told the researcher as his observation. He mentioned that he had:

“seen a shift in mindset – more of our teams are now data-driven and open to innovation”.

This change in culture was reflected in different ways; such as in the form of increased collaboration between departments, in the form of using data more proactively, and/or in the form of an overall willingness to experiment with new ideas.

In the IT department, the CTO noted that the culture had notably evolved and teams have become

“conversant with AI and machine learning concepts”

as they are actively proposing new AI use cases. From these narratives, it can be interpreted that rather than IT being a gatekeeper of technology, it transformed into an enabler and work closely with operations and analytics teams. The Digital Transformation Manager likewise saw a positive

“buzz around innovation”

that had not existed a few years prior. Employees began discussing new AI-driven ideas across functions – for example, marketing talking to data scientists about cross-selling opportunities – indicating that barriers between silos were breaking down.

Perhaps most explicitly, the HR Director documented the cultural evolution. She described a transition

“towards a more learning-oriented and innovative culture”.

Initially, there was uncertainty and fear, but as people became comfortable with the new tools, many “started taking initiative” – for instance, by experimenting on their own or suggesting improvements. The prevailing attitude shifted from “How can I stop this?” to “This is interesting, how can I use it?”. This attitude change was facilitated by the transparent, open communication strategy (feedback channels and Q&A sessions) which helped employees feel their voices were heard. Over time, even employees who had been resistant began to acknowledge benefits. The HR leader noted that after initial dips, morale actually rose because

“people started seeing some of the mundane parts of their jobs being eased by AI”.

Although some individuals still prefer legacy methods, the aggregate outcome was a workforce more willing to embrace technology.

The human element of sales and finance also reflected mindset shifts. The veteran Sales Manager conceded he had felt a bit “skeptical and uncomfortable” at first, but eventually moved to being “cautiously appreciative” of AI’s contributions. He came to view the AI tools as complementary – helping with lead scoring and forecasting – while maintaining pride in the human aspects of his

work. Likewise, the Financial Analyst reported that after the transition, he found his role more satisfying:

*“I do less rote spreadsheet work and more analysis and decision support,
which is the part of the job I enjoy most.”*

He emphasized that adapting to new technology had become part of his professional growth, and that embracing it had

“made me more valuable to the company”.

This personal transformation – from anxiety to enthusiasm – exemplifies the mindset change at the employee level.

Leaders and staff also highlighted that AI’s introduction emphasized the importance of continuous learning. The Program Manager noted that the project made everyone aware that

“continuously learning”

was no longer optional: teams had to stay updated on the fast-changing AI field. In marketing, for instance, the team holds regular sessions to share new tips on AI tools, ensuring the mindset stays current. HR codified this by promoting ongoing development programs, not just one-off training. The cultural message was clear: agility and curiosity are prized traits going forward.

In the end, the interviews suggest a shift in leadership culture. Executives expressed a degree of humility and willingness to listen. The CEO emphasized that co-creating solutions with employees reduced fear and built ownership, reflecting a leader who values input from all levels. The Operations Manager mentioned spending a lot of time

“just listening to concerns and reinforcing that this was a positive change”,

which shows that managers were attentive to workforce sentiment. Such empathetic leadership contributed to a more trusting environment.

It brings to summarise this theme by stating that the cultural and mindset changes observed are broad. It starts from leadership prioritizing innovation and reaches out to teams embracing data and to individual employees feeling empowered rather than threatened by technology. This theme is critical for the overall research aim, as it demonstrates that implementing AI in large, established organizations often entails deep change in attitudes and working norms. The Alpha Group case shows that by fostering transparency, continuous learning, and human-centered leadership, a culture that once feared AI can evolve into one that leverages it for collective advancement.

4.4. Summary of Chapter

Chapter 4 presents the quantitative analysis of survey data that is organized into descriptive and inferential sections. From demographic standpoint, 200 mid- to senior-level managers participated and most of them were notably HR Managers (21%) and Senior Managers (21%). Though there was a balanced representation across Finance, IT, Operations, and Department Head roles. Participants came from five industries (Manufacturing, Finance, Tech, Retail, Healthcare), with Manufacturing most represented (27%). Nearly all (92%) currently use ERP systems, and 65% have already begun integrating AI.

In the pre-implementation phase, managers expressed only moderate satisfaction with their ERP's ability to meet strategic needs: 20% disagreed, 52.5% were neutral, and just 27.5% agreed. While 65% believed their organizations were prepared to transition to AI, 39.5% remained neutral. Optimism about AI's potential was high: 80% agreed AI could improve decision-making and 74% believed it would enhance cross-subsidary collaboration. However, only 17% felt adequately trained for AI, and virtually no one feared job loss; yet 69% anticipated employee resistance.

Post-implementation results were overwhelmingly positive: 100% of respondents agreed that AI improved departmental efficiency, decision speed, and coordination. Trust in AI insights was more tempered—43% agreed, 47% were neutral—highlighting explainability as a future focus. All managers felt AI complemented rather than replaced human roles, and unanimously agreed AI delivered value beyond their legacy ERP systems. Initial chi-square tests showed no significant differences in AI adoption rates across industries, suggesting widespread, cross-sector embrace of AI.

The thematic analysis of the qualitative interview data in this chapter has followed Braun and Clarke's six-phase framework and identified ten themes that directly address the research objectives of this study. First theme found out that AI-driven strategic agility empowered proactive scenario planning. From the second theme, the researcher unfolded that entrenched ERP limitations and data silos are the key barriers in AI implementation. Afterwards, the third theme put forward the narratives from interview suggesting that predictive analytics was praised for demand forecasting and risk mitigation. From the thematic analysis of fourth theme, real-time decision support tools accelerated manager responsiveness. In the fifth theme, it is revealed that cross-subsidiary collaboration has been improved via shared dashboards. From the sixth theme, the research concluded that organizational resistance that is rooted in unfamiliarity and fear, have surfaced at broad level. From the seventh theme of the study, training gaps were found to be hindering the adoption, thus it also implicitly highlight the needs for upskilling. In the eighth theme identified in this chapter, trust and explainability were found critical for buy-in. Ninth theme concluded that talent shortages have constrained the development of in-house AI expertise. The last thematic analysis identified that cultural transformation—from hierarchical to data-driven mindsets—is essential for sustained AI integration. These themes, at collective level, have validated and deepened the quantitative findings that AI boosts efficiency and decision speed alongside fostering the strategic agility, data integration, and cultural readiness necessary for a successful ERP-to-AI transition.

Chapter 5: Discussion

5.1. AI Implementation: Current State and Adoption in Conglomerates (Objective 1)

The findings confirm that enterprise-wide digital infrastructure is well-established in conglomerate organizations, yet the integration of artificial intelligence is still emerging. Quantitatively, 92% of surveyed managers reported that their organizations already use an ERP system, which illustrates the ubiquity of traditional enterprise systems in conglomerates. At the same time, 65% indicated that their organization has begun integrating AI technologies into operations, while 35% have not yet started AI adoption. This significant adoption rate reflects a growing trend, i.e., a majority of conglomerates are moving beyond legacy ERP toward AI-enhanced management solutions. The literature supports this transition because studies have noted that while ERP systems remain foundational, they are increasingly viewed as insufficient in dynamic environments; thus prompting firms to augment or replace ERP capabilities with AI for greater adaptability (Ali, Hamdan, & Alareeni, 2021). In the case of this research, the data and findings implies that many conglomerates recognize AI as the next step in evolving their management practices to handle real-time data and complex decision-making across diverse businesses.

Qualitative evidence also reinforces it as the interviews have revealed that top leaders in the studied conglomerate (pseudonymously “Alpha Group”) strategically pursued AI initiatives to modernize their operations and maintain competitiveness. A key driver was internal efficiency alongside external stakeholder expectations – for example, the Group CEO noted that demonstrating AI integration boosted investor confidence in the company’s innovative direction. This insight aligns with the literature on strategic management in conglomerates, which emphasizes that leveraging AI for strategic decision-making can create sustainable value and signal market leadership. In practice, Alpha Group’s initial AI projects spanned various functional areas (predictive maintenance in manufacturing, AI chatbots in customer service, AI-enhanced analytics in marketing and finance), reflecting many of the AI subcategories highlighted in prior studies (machine learning, natural language processing, robotic process automation, AI-driven analytics) as relevant to conglomerate management. The presence of these diverse AI applications across the conglomerate’s business units suggests that the organization took a broad approach to

implementation, aiming to infuse intelligence in multiple domains rather than a narrow, single-department deployment.

Importantly, the cross-industry composition of Alpha Group (with subsidiaries in finance, healthcare, manufacturing, retail, and tech) means the survey captured a holistic view of AI adoption across sectors. Manufacturing managers were most numerous in the sample, consistent with that industry's active interest in AI for process optimization, but substantial representation from finance, retail, and others indicates that AI integration is a priority across diverse verticals within conglomerates. This broad engagement aligns with the literature's case studies of AI in different sectors (e.g., automotive using AI for production, financial services for customer experience) and suggests that conglomerates can learn from best practices in multiple industries when implementing AI.

The evidence shows conglomerates at an inflection point, i.e., ERP systems are nearly universal, but companies are actively layering in AI to transcend ERP's limitations. Our results for Objective 1 show that the current state of AI implementation in conglomerates is one of accelerating adoption, with roughly two-thirds already on the journey. This finding corroborates the literature's depiction of a shifting paradigm in enterprise technology – from ERP-driven to AI-augmented management for improved adaptability and intelligence. The organization studied exemplified this shift, leveraging AI in various forms to enhance its operations while being motivated by both internal performance goals and external pressures to innovate. These insights set the stage for discussing the concrete impacts of AI on efficiency and decision-making, as well as the challenges encountered along the way.

5.2. Impact on Operational Efficiency and Productivity (Objective 2)

A central question for the study was whether implementing AI would tangibly improve operational efficiency in a conglomerate context. The quantitative findings resoundingly indicate that it did. Following AI implementation, every single survey respondent agreed that AI tools have improved the efficiency of their department's operations, with nearly half (43%) strongly agreeing. Not a single manager reported a neutral or negative view on efficiency post-AI – a striking unanimity that marks a sharp contrast with the pre-implementation baseline. (Before AI, opinions on the

sufficiency of existing ERP systems were lukewarm; only 27.5% agreed ERP alone met business needs, and none strongly agreed.) The shift from moderate satisfaction with ERP to overwhelming satisfaction with AI-driven systems is statistically supported by a large increase in mean agreement scores. A one-sample t-test confirmed that the average rating for “AI improved efficiency” was not only high (approximately 4.5 on a 5-point scale) but significantly above a neutral midpoint, underscoring that the efficiency gains were both perceptible and meaningful ($p \ll 0.001$). In practical terms, managers went from seeing their legacy systems as only “serviceable yet insufficient” to viewing AI as delivering substantial efficiency improvements in day-to-day operations.

These results strongly support Objective 2 and are consistent with existing scholarship on AI benefits. Prior research widely reports that AI-driven automation and analytics can streamline processes, reduce errors, and accelerate task completion, leading to cost savings and productivity gains. Our study provides empirical evidence of these benefits in a real-world conglomerate setting. For example, literature cited cases like Mitsubishi Corporation using AI to optimize energy use and save millions of dollars; in parallel, interviewees in our case company described how AI-based predictive maintenance averted unplanned downtime in factories, and how an AI chatbot automated routine customer inquiries, freeing employees for higher-value work. These early “wins” in efficiency were reported across multiple departments. In the finance unit, automation of data consolidation significantly sped up monthly reporting. In operations, predictive algorithms improved equipment uptime. Such outcomes echo the efficiency and cost reduction drivers found in the literature, where predictive analytics and machine learning are noted to enhance operational effectiveness and cut costs by optimizing resource use.

It is worth noting that efficiency gains were broadly realized across the organization, regardless of individual managers’ initial readiness. A regression analysis in our study found no significant linear relationship between a manager’s prior self-rated preparedness or training level and the efficiency improvements they later experienced. In other words, even managers who initially felt unprepared or not well-trained eventually reported efficiency gains on par with their peers. This counterintuitive finding suggests that the success of the AI implementation did not hinge on any single person’s prior readiness, but rather on systemic factors – possibly the effectiveness of the

training program delivered, the usability of the AI tools, and strong organizational support during rollout. It implies that with the right implementation approach (extensive training for all, user-friendly tool design, helpdesk support, etc.), even those who start out skeptical or unskilled can end up benefiting from AI. From a practical perspective, this is encouraging: it means efficiency improvements from AI are not limited to early adopters, but can diffuse widely in the firm when change is managed inclusively.

To interpret these efficiency findings in light of broader literature: our case reinforces the notion that AI can act as a force multiplier for operational performance in complex organizations. Conglomerates, which often suffer from process inefficiencies due to their scale and diversity, stand to gain disproportionately from AI-driven optimization. By automating routine tasks and enabling data-driven process improvements, AI helps eliminate bottlenecks that traditional ERP systems or manual methods struggled with. The unanimous agreement on efficiency gains in our survey is particularly notable given the inherent complexity of conglomerates – it suggests that even with varied business units, the AI solutions implemented had broad applicability and delivered value across the board. This lends credence to the strategic decision of Alpha Group's leadership to invest in AI: the efficiency ROI (return on investment) has been evidenced by near-universal user endorsement.

In sum, Objective 2 is achieved: the implementation of AI enhanced operational efficiency in the conglomerate, validating both our hypothesis and the expectations set by prior research. What was previously an abstract promise of “streamlining operations” is now concrete – faster workflows, reduced errors, and cost savings were realized. These outcomes not only improve the conglomerate's bottom line but also free up managerial and employee time for more strategic activities, a point we will revisit when discussing strategic agility. The efficiency gains form a critical part of the answer to our overarching research question on how AI enhances management in conglomerates, demonstrating that AI can significantly improve the productivity and process performance dimension of management practice.

5.3. *Enhancements in Decision-Making and Strategic Agility (Objective 3)*

AI's impact has extended beyond efficiency into the quality and speed of decision-making, thereby influencing the conglomerate's strategic agility. Decision-making improvements were strongly evident in the data. In the post-implementation survey, all 200 managers agreed that "AI has led to faster and more informed decision-making" in their organization. About 47% strongly agreed, and 53% agreed – again, a unanimous positive consensus. Before AI was deployed, managers were already optimistic on this front (none disagreed that AI could improve decisions, and 80% were at least in agreement with AI's potential to enhance decision quality). Yet the post-implementation results surpassed those initial expectations. We found a statistically significant rise in the mean agreement from the pre-implementation belief (mean ≈ 4.1) to the post-implementation reality (mean ≈ 4.47) regarding AI and decision-making. A paired t-test confirmed this increase was highly significant ($p \ll 0.001$), indicating that managers not only maintained their positive outlook but became even more convinced after experiencing AI in action. In practical terms, this means AI tools did deliver tangible enhancements to how decisions are made – managers felt they could make decisions more quickly and based on better information than before.

Several aspects of decision-making were improved, contributing to the conglomerate's overall strategic agility:

- Speed and Proactiveness:** Managers reported that processes which previously took days or weeks of data gathering (for example, compiling sales forecasts or inventory positions from different units) could be completed in near-real-time with AI support. One interviewee noted that with AI-driven dashboards providing live metrics, weekly operations meetings shifted from reviewing old reports to proactively adjusting plans based on up-to-the-minute trends. The literature describes this capability as real-time adaptability and proactive decision-making, something AI can introduce to traditionally static ERP environments. Our findings validate that claim – decisions are not only faster but also made earlier in the cycle, enabling the organization to seize opportunities or mitigate problems before they fully materialize. This proactiveness is a key facet of strategic agility, allowing a conglomerate to navigate fast-changing market conditions effectively.

- Data-Driven Insights and Quality of Decisions:** The introduction of AI brought advanced analytics – predictive models, pattern recognition, and decision support systems – that improved the *quality* of managerial decisions. For instance, the predictive analytics for demand forecasting allowed supply chain managers to decide inventory allocations with greater confidence, knowing the AI had analysed vast historical and real-time data to suggest optimal levels. Similarly, AI in finance could run scenario analyses in seconds, aiding executives in strategic planning (e.g., evaluating the impact of different investment choices). According to the managers, these tools led to decisions that were better informed and evidence-based, reducing reliance on intuition alone. This aligns with literature asserting that AI enhances strategic decision-making by processing complex datasets and providing predictive insights that humans might overlook. In our study, a marketing manager gave a concrete example: after implementing an AI-powered customer analytics platform, their team’s campaign decisions (like which product to promote to which customer segment) became much more data-driven, resulting in improved campaign performance. Such anecdotes illustrate the qualitative side of the survey’s unanimous agreement – it’s not just that decisions felt faster, they were also smarter decisions due to AI’s analytical contributions.
- Cross-Subsidiary Cohesion:** A critical aspect for conglomerates is making coherent decisions across diverse subsidiaries. Prior to AI, siloed information was a barrier – each division had its own data and there was lag in consolidating insights. Our findings show this barrier was significantly reduced. The survey statement “integration with AI has improved coordination across business units” also garnered 100% agreement (with 45% strongly agreeing). By integrating data on a common platform, AI enabled managers from different departments to access shared dashboards and align their decisions with the broader enterprise context. One interview theme highlighted how an operations manager and a sales manager, for the first time, were looking at the *same predictive demand data* and could jointly decide on production adjustments. This kind of cross-functional synchronization is a hallmark of improved strategic agility: the organization can act as a unified whole rather than fragmented parts. Literature on conglomerate management

stresses the difficulty of achieving such integration with traditional systems and notes that AI-powered systems can serve as connective tissue, breaking down data silos and fostering cohesive decision-making across units. Our study provides concrete evidence of this – AI tools indeed became a unifying platform for the conglomerate’s diverse operations, as reflected in the high survey approval and supporting interview testimonies.

- **Strategic Agility and Adaptability:** Ultimately, faster and better decisions contribute to strategic agility – the ability of the conglomerate to pivot or respond swiftly to changes. Multiple interviewees observed that with AI, the organization became noticeably more agile. For example, the CEO recounted how during the AI rollout period, the company faced an unexpected market shift in one of its industries; because they had AI-driven market analysis tools and a culture of data-informed decision-making, they were able to realign their strategy in weeks instead of months. This anecdote speaks to the larger transformation: AI integration cultivated a more responsive, agile management approach. The literature defines strategic agility as responding proactively and in a timely manner to fluctuations, and suggests that AI (with real-time data and predictive foresight) can bolster this agility. Our findings strongly confirm that notion – not only did processes speed up, but the mindset of leadership also shifted to embrace continuous learning and quick adjustments (as discussed under Themes 3 and 10 in Chapter 4). Agility became valued; for instance, the program manager highlighted how the team “adjusted the roadmap whenever reality turned out differently than our plans,” indicating an institutionalization of agile thinking.

In fulfilling Objective 3, our study demonstrates that AI implementation enhanced decision-making in both effectiveness and efficiency, thereby increasing strategic agility in the conglomerate. These improvements directly address the research question’s focus on decision-making and agility. By linking our empirical evidence to the broader scholarly conversation, we see a clear convergence: what theorists predicted – that AI would enable more informed, faster decisions in complex organizations – has indeed materialized in the case organization. This bodes well for conglomerates aiming to remain competitive; it suggests that investing in AI for decision

support can yield a more nimble enterprise, one that can anticipate and react to change better than it could under the slower, siloed decision processes of the ERP era.

It is also important to note the interplay between human judgment and AI in decision-making. Our interviews indicated that managers did not feel supplanted by AI in decisions; rather, they felt augmented. Many described the AI as an “advisor” – crunching numbers and offering recommendations – while humans still applied intuition, context, and ethical considerations to final decisions. This balance is corroborated by literature on human-AI collaboration, which argues that the best outcomes arise when AI provides insights and humans exercise judgment (often referred to as *augmented intelligence*). In our case, this collaborative decision model seems to have taken hold, contributing to widespread acceptance (as evidenced by zero respondents fearing job loss due to AI) and enhancing the quality of decisions. Managers felt more confident and were armed with better information, yet they remained at the helm of decision-making, aligning with the ideal vision of AI as a decision support tool rather than a decision maker in isolation. ***Challenges and Enablers in AI Implementation (Objective 4)***

Under the consideration that implementing AI in a large and multi-unit organization is a complex endeavor, the objective 4 in this study sought to analyse the challenges encountered during the transition from ERP to AI-driven management and how those challenges were addressed. Results of the study have uncovered a range of organizational and technical challenges, as well as key enablers or strategies that facilitated success.

5.4.1. Organizational Challenges: Change Management, Training, and Culture

Several people-centric challenges emerged as critical during the AI implementation; such as: employee preparedness, potential resistance to change, and the necessity of strong change management practices. The findings are supported by the literature on organizational change and technology adoption, where it has been emphasized that human factors often determine the fate of new system implementations (Chen, 2025). Some of the key organizational challenges surfaced include the following:

- **Workforce Readiness and Skills:** The survey showed a mixed level of confidence in the organization’s readiness for AI. Only about one-third of managers (32.5%) agreed that their organization was prepared for transitioning from ERP to AI, while the majority were either

neutral (39.5%) or disagreed (28%). Likewise, when asked about personal preparedness, 82 managers (41%) outright disagreed that they felt “adequately trained or informed about AI,” and an additional 42% were ambivalent. None felt strongly confident in their AI knowledge at the outset. These proportions indicate a significant skills and knowledge gap pre-implementation. The literature identifies such a talent gap as a common barrier to AI adoption (Kar, Kar, & Gupta, 2021) and notes that lack of in-house AI expertise can hinder implementation (Mhaskey, 2024). In this research study, this challenge was proactively addressed by the organization. Training and upskilling (Theme 2) was the foundation of the implementation strategy. Interviews detailed how management rolled out a comprehensive training program: general “AI 101” sessions to build awareness, followed by targeted technical workshops for specific tools, and continuous learning via an online portal. They even realigned roles – for example, retraining IT support staff to become junior data analysts – to ensure the workforce could work effectively with AI. This robust capacity-building effort reflects best practices suggested in the literature. Effective change management research argues that involving and educating employees early greatly increases acceptance of new technology (Stouten, Rousseau, & De Cremer, 2018).

- **Employee Resistance and Buy-In:** Change mostly incurs resistance (Li, Liu, & Liu, 2016), and indeed 69% of managers expected that employees would resist the AI implementation to some degree. This universal expectation of pushback is consistent with literature – fear of change or job displacement can manifest as active or passive resistance if not managed (Tran, 2024). However, a notable outcome of our study is that overt resistance within the organization remained minimal, thanks to careful change management. From the outset, leadership anticipated this challenge and undertook extensive stakeholder engagement (Theme 1). Transparent communication was one key: the Group CEO “established a clear narrative” about why AI was being adopted and how it would benefit both the company and employees, communicating frequently across all levels. Managers were not left to fear the unknown; instead, they were kept informed and were invited to participate (through town halls, Q&A sessions, etc.). Additionally, involving employees in the process was crucial. For example, some staff were designated

as AI “champions” in each department, acting as liaisons to voice concerns and help colleagues adapt. This approach of early involvement and open communication directly mirrors recommendations in change management literature: researchers note that involving employees in planning and clearly communicating the advantages of AI (and how roles will evolve) can preempt and reduce resistance. Our qualitative data confirm that these tactics worked. Interviewees across levels consistently mentioned feeling that they “were part of the journey” rather than having change imposed on them. While some initial skepticism was natural, they did not encounter the dreaded backlash or sabotage that unmanaged change might provoke. Instead, most employees came to cautiously embrace the AI tools, especially after seeing some positive results. It can be inferred that the organization’s dedicated change management efforts (including addressing concerns, providing support, and creating feedback loops) effectively converted potential resistance into constructive participation that became a significant enabler for the project’s success.

- **Cultural Mindset Shift:** The implementation of AI required technical changes alongside the cultural transformation within the conglomerate. The prevailing mindsets and attitudes had to evolve in order to truly integrate AI into daily management. Initially, as noted, there were anxieties (e.g. “Will AI make my role obsolete?”). The survey data remarkably showed that an overwhelming majority of managers (71.5%) did not believe AI posed a threat to their job security (with 0% agreeing that “AI threatens my job”). This lack of fear among managers can be partly attributed to their higher-level view of AI as a tool for organizational benefit. But ensuring the broader employee base shared this comfort was another matter. The company’s leadership actively worked to foster a culture that views AI as an augmentation tool rather than a replacement for humans. They repeatedly messaged – in training, in internal newsletters, via team meetings – that the goal of AI was to free people from drudgery so they could focus on higher-level tasks, not to cut headcount. Over time, this message seemed to take root. By the end of the implementation, survey responses indicated unanimous agreement that “AI has complemented – not replaced – human roles in strategic tasks.” All managers saw AI as an empowering addition to their work. This constitutes a profound cultural shift: from initial caution to a new norm where employees

expect to work alongside AI. It is noted in the literature that organizations that cultivate a culture of human-AI collaboration and continuous learning tend to realize more value from AI and face less internal friction (Katiforis, 2024). From the lens of this study's result, one mid-level manager's quote encapsulated the sentiment: *"I'm not worried about AI taking my job; I see it as a tool that helps me do my job better."* The result of this positive mindset was not accidental; it was nurtured through deliberate leadership actions (e.g., Theme 5: reframing AI as human augmentation rather than a threat). The outcome is a more resilient culture, open to innovation and less afraid of technological change – an invaluable asset for the conglomerate's future endeavors.

5.4.2. Technical Challenges: Integration, Data, and Infrastructure

The technical challenges that were noted in integration of AI in a conglomerate were ranged from integrating new AI tools with legacy systems to ensuring the fundamental data and IT infrastructure could support advanced analytics at scale. While these issues were evident in the selected conglomerate, they have been overcome through effective problem-solving. Following are the key technical challenges and enablers that were identified through discussion:

- Legacy Systems and Integration:** A conglomerate typically operates a patchwork of legacy systems (older ERP modules, databases, custom applications), and integrating AI solutions into this existing architecture proved challenging. The interviews with IT executives and project managers revealed that certain older software systems were not designed to interface with modern AI algorithms or cloud-based services. For example, the legacy ERP in one subsidiary could not readily export data in real-time to feed the AI analytics engine. This required the technical team to develop custom connectors and, in some cases, accelerate planned upgrades. System integration issues led to initial delays in AI deployment for some departments that illustrate a classic challenge: new digital tools must often contend with the "technical debt" of legacy infrastructure. The literature acknowledges this as a major hurdle – integrating AI with entrenched legacy systems and siloed data is frequently cited as a barrier in large firms. A study by Marr (2019), for instance, discusses how data exchange between old and new systems entails significant

investment in integration and can be impeded by outdated technology. Alpha Group's approach to this challenge was twofold: short-term workarounds and long-term modernization. In the short term, they built interim bridges (APIs, data pipelines) to allow critical data to flow into AI tools. In the longer term, recognizing that patchwork fixes were not sustainable, the conglomerate invested in upgrading its core infrastructure. This meant phasing in a new cloud-based data warehouse and replacing some antiquated systems entirely.

- Data Quality and Governance:** AI is only as good as the data it uses, so it was unsurprising that data-related challenges featured prominently. Prior to the AI initiative, data in the conglomerate was not only siloed by division, but varied in quality and format. Managers reported issues like inconsistent data definitions between departments, missing data in some systems, and concerns about data accuracy. Had these issues been left unaddressed, the AI models might have produced unreliable insights (or required excessive data cleaning by data scientists). Recognizing this, the organization treated data preparation and governance as a critical foundational step for AI. They undertook a thorough data audit and cleaning phase: standardizing data formats, resolving duplicates or errors, and ensuring that key datasets (financials, sales, operations metrics, etc.) were complete and up-to-date. Furthermore, the company implemented strong data governance protocols – for instance, setting up a data governance committee and even appointing an AI ethics and data officer on a part-time basis. The role of this officer was to oversee data privacy, security, and ethical use of AI (such as preventing biased algorithms in HR processes). These governance measures ensured that as AI tools were rolled out, they operated on reliable data and within acceptable ethical boundaries. The importance of this cannot be overstated: literature on AI adoption stresses that data issues (quality, privacy, security) are among the top reasons AI projects fail or face resistance. By addressing data governance early, Alpha Group not only bolstered the performance of its AI systems but also built trust – both internally (users knew the data was being handled responsibly) and externally (customers' and regulators' concerns were mitigated). This proactivity aligns with reports like Santhosh et al. (2024), which highlight that tackling data privacy and establishing policies is essential

to fully reap AI's benefits without backlash. In our case, the payoff was clear: the AI implementation proceeded without major data scandals or quality disasters, and managers acknowledged that the data they were seeing via AI dashboards was more reliable than what they had before. One HR manager noted that when they introduced an AI-assisted resume screening tool, the presence of an AI ethics officer and clear rules for data use made employees more comfortable with the technology – an insight that underscores how proper governance can facilitate adoption of even sensitive AI applications.

- **Technical Expertise and Support:** Another technical challenge was ensuring the organization had (or could acquire) the right expertise to implement and sustain the AI systems. Early in the project, the Chief Technology Officer recognized a shortfall in in-house AI expertise, as per interview insights. The conglomerate had many seasoned IT professionals, but few had deep experience with data science, machine learning model development, or AI system integration. This aligns with the general talent gap problem in AI – demand for AI skills often outstrips supply, and many organizations find they lack the necessary specialists (data scientists, ML engineers, etc.). Alpha Group tackled this in two ways: hiring and partnering, and internal upskilling. They hired a lead data scientist and a few specialists to kick-start the initiative and bring in critical know-how. They also partnered with the AI software vendor's consultants for knowledge transfer during implementation. Concurrently, as mentioned under training, they began upskilling their existing IT staff – e.g., teaching software engineers about machine learning so they could gradually take over maintenance of AI systems. Over the course of the project, the balance shifted from reliance on external experts to empowering internal teams. By the end, the core AI team included many original IT employees who had acquired substantial new skills. This approach reflects a strategic response to the expertise challenge: use external help to bridge the initial gap, but build internal capacity for the long run. Literature suggests that this is effective, noting that training existing employees can be more sustainable than trying to hire entire new teams, and that involving internal staff from the start increases system acceptance and continuity. Our findings concur – Alpha Group successfully grew its human capital in AI. An interesting quantitative footnote is that despite the initial lack

of confidence in AI skills (only 17% felt adequately trained pre-project), post-implementation, managers reported significantly higher comfort in working with AI, thanks to the combination of training and hands-on experience they gained. In effect, the organization turned the expertise challenge into an opportunity for professional development, which also helped ameliorate fears (people felt less threatened by AI as they became more competent in using it).

- **Cost and ROI Considerations:** A final challenge category straddling technical and managerial domains was the significant investment required for AI implementation and the need to justify it. Deploying AI at scale in a conglomerate involves substantial costs: purchasing software licenses or developing algorithms, upgrading infrastructure (as we saw, data lakes and cloud services), training hundreds of staff, possibly hiring new experts, and the time cost of employees adapting to new processes. The literature flags high initial costs as a major concern that can deter or derail AI projects if the benefits are unclear. In our case, these costs were certainly present (the CIO's budget expanded notably for IT upgrades, and the training program was a major expenditure). The key enabler here was the organization's commitment to a strong benefits realization and monitoring process (tied to Theme 9 on financial impact). The CFO and project management office established metrics and checkpoints to track whether AI was delivering value commensurate with its cost. For example, they measured efficiency gains (hours saved, output increased), cost reductions (e.g., lower overtime expenses due to better resource planning), and even revenue upticks (like improved cross-selling attributed to AI insights in sales). Our interviews noted that after about a year, these metrics showed enough positive impact – early ROI in areas like reduced inventory costs and faster sales cycle – to convince stakeholders that the investment was paying off. Quantitatively, while we didn't have direct survey questions on ROI, the consensus from management interviews was that the AI initiative was meeting or exceeding its business case targets in the initial phases. This evidence of financial benefit is critical because it creates a virtuous cycle: success breeds continued support. By documenting and communicating ROI, the project team ensured continued funding and buy-in from the board and shareholders. This is in line with best

practices suggested in the literature: conducting cost-benefit analyses and securing some “quick wins” helps maintain momentum and justify the ongoing investment in transformative projects. Additionally, being transparent about ROI helped temper any remaining employee skepticism – staff could see that the AI wasn’t just a trendy experiment but tangibly improving the company’s performance, which in turn secures jobs and competitiveness (addressing the underlying concern of “is this worth it?”).

Bringing together these points, Objective 4 is addressed by highlighting that AI implementation in the conglomerate came with significant organizational and technical challenges, but these were overcome through deliberate strategies that align well with scholarly recommendations. The organization treated change management and technical preparation as equally important, which our findings suggest was a wise approach. A lesser emphasis on the human side might have led to user pushback, and neglecting the technical groundwork (infrastructure, data quality) could have led to system failures or faulty insights – either could have doomed the project. Instead, Alpha Group’s holistic handling of challenges allowed the initiative to succeed and even strengthened the organization in the process (e.g., upskilled workforce, modern IT backbone).

1.2. Future Opportunities and Strategic Outlook (Objective 5)

With the AI implementation well underway, the final objective of the study turns toward the future: identifying emerging AI opportunities for conglomerate management and proposing strategic steps (a roadmap) to capitalize on them. This involves reflecting on the findings in light of cutting-edge trends and considering how the conglomerate can sustain and extend its AI-driven transformation.

- **Leveraging AI for Continuous Innovation:** The journey of AI adoption does not end with the current set of tools; it opens the door to continuous innovation. Now that the conglomerate has a foundational AI infrastructure and an acclimated workforce, it can explore more advanced AI applications to drive innovation in products, services, and business models. The literature on emerging trends suggests that technologies such as deep learning, reinforcement learning, and advanced analytics will play a growing role in business strategy. For a conglomerate, this could mean investing in R&D for AI solutions tailored to each industry segment it operates in – for example, developing a reinforcement

learning system to dynamically optimize supply chain logistics across its manufacturing and retail units, or exploring AI-driven product development (like using AI to analyse customer data and design new offerings). The roadmap should include a horizon scanning function: a team or committee that stays abreast of AI advancements and assesses their applicability to the conglomerate's context. Our case findings show the company has become more agile and open to new tech, which will help in experimenting with innovations such as AI-driven automation in areas not yet touched (perhaps legal contract analysis, advanced robotics in production, or AI for sustainability initiatives). Continuous innovation also involves collaborating externally – the conglomerate could partner with AI startups or academic labs to pilot cutting-edge solutions on a small scale. By doing so, it remains at the forefront and can rapidly bring in new capabilities as they mature.

- Enhancing Explainability and Trust:** One insight from our results is that while AI was broadly accepted, some managers exhibited cautious trust in AI outputs – evidenced by about 47% neutral responses regarding complete trust in AI insights, and a minority (10%) who disagreed that they fully trusted AI's recommendations. As AI systems become more integral to decision-making, it's crucial to address this by improving the explainability of AI models. The future of AI in organizations will likely emphasize Explainable AI (XAI) – methods that make AI's decision logic transparent to users. By adopting XAI tools and principles, the conglomerate can ensure that managers and stakeholders understand why an AI model produced a given prediction or advice. For instance, if an AI model suggests a drastic reduction in production for a certain product, explainability tools could highlight the key factors (e.g., declining demand in certain regions, raw material shortage forecasts) that led to that suggestion. This would allow managers to confidently act on AI insights or override them with awareness of the trade-offs. In the roadmap, investing in AI solutions that have built-in explainability, or retrofitting explainability onto existing models, should be a priority. Not only does this build user trust, but it also aligns with emerging regulatory expectations – around the world, there is increasing discussion of requiring algorithmic transparency, especially in industries like finance and healthcare. By staying ahead on explainability, the conglomerate will strengthen the human-AI partnership that has been

cultivated and ensure that as AI roles expand, stakeholders remain comfortable and confident in how decisions are being made. Our study's emphasis on the augmentation narrative (AI as partner, not boss) can be further solidified through XAI, which ultimately helps maintain the positive acceptance climate we observed.

- Scaling AI Across the Conglomerate Ecosystem:** While our case focused on one conglomerate, Objective 5 encourages a look at scaling lessons to the broader conglomerate ecosystem (including perhaps suppliers, partners, and even customers). The company can extend its AI roadmap beyond internal operations. For example, in supply chain management, after optimizing internal processes, the next step could be to integrate AI with key suppliers for better demand forecasting and inventory management across the entire value chain. Similarly, customer-facing AI (like chatbots or recommendation engines) could be expanded to enhance customer experience across all the conglomerate's business lines, providing a unified smart interface to the conglomerate's diverse products and services. Additionally, cloud-based AI services and APIs developed in-house might be offered to smaller subsidiaries or even external partners, effectively turning the conglomerate's AI capabilities into a platform. The literature on future directions hints at such platformization and ecosystem approaches, where companies share AI solutions to create network-wide efficiencies. For the roadmap, this means planning how to go from isolated wins to system-wide transformation. The case company should document the replicable elements of each successful pilot and create toolkits or templates that other subsidiaries (or new acquisitions in the future) can adopt. Our findings show that common infrastructure and cross-unit collaboration improved outcomes; building on that, the company might establish a central AI Center of Excellence that governs AI strategy, standards, and knowledge dissemination across the conglomerate. This central body can ensure that as AI scales, it does so in a coordinated way – avoiding duplication of efforts and maintaining quality and ethical standards. Essentially, scaling AI is about moving from project mode to program mode: embedding AI into the fabric of every relevant part of the conglomerate and managing it as an ongoing program with executive oversight.

- **Investing in People and Culture Continuously:** The culture shift achieved is an asset that needs to be maintained and deepened. The roadmap should include initiatives for continuous people development in line with AI evolution. This could mean routine re-skilling programs as AI tools are updated or new ones introduced – for example, training on using AI-enhanced decision platforms could become part of annual management development curricula. It also means hiring new talent strategically: as the conglomerate ventures into more advanced AI (data science research, AI product development, etc.), it will need to attract experts in those fields. Our study showed the benefit of blending internal upskilling with new hires; that strategy should continue. Moreover, to keep the workforce motivated and engaged with AI, the company can implement incentives for innovation. One idea is to hold internal innovation challenges or hackathons where employees from different subsidiaries team up to propose new AI use cases or improvements to existing ones. Not only can this generate grassroots innovation, but it reinforces the culture that emerged – one of curiosity, collaboration, and proactive problem-solving (traits explicitly noted as valued after the AI implementation). The literature on sustaining digital transformation highlights that organizations must nurture an innovative culture and not become complacent after initial successes. In our case, the initial cultural shift towards embracing AI should be seen as the first step. The roadmap should solidify this by, for example, updating company values or leadership principles to include data-driven decision-making and continuous improvement as core tenets. By enshrining these values, leadership sends a message that the AI journey is ongoing. Maintaining an agile and learning-oriented culture will ensure the conglomerate can adapt to future changes, whether they be new AI technologies or other disruptive innovations.
- **Aligning AI with Strategic Goals and Ethical Practices:** As AI capabilities grow, ensuring alignment with the conglomerate's overarching strategic goals and ethical standards becomes even more vital. The roadmap should explicitly tie AI initiatives to business strategy: every major AI project should answer, "How does this drive our corporate objectives (be it growth, efficiency, customer satisfaction, innovation leadership, etc.)?" This strategic alignment will help prioritize AI efforts that offer the most value. For

instance, if the conglomerate's strategy is to become a leader in sustainable business, the AI roadmap might emphasize projects like AI for energy efficiency, waste reduction, or sustainable supply chain optimization (a trend noted in Chapter 2 around AI and sustainability). Concurrently, the organization must continue to uphold ethics and compliance in AI use. The appointment of an AI ethics officer was a good start; moving forward, the conglomerate might establish an AI ethics committee involving diverse stakeholders (management, technical experts, maybe even external advisors) to review and guide AI deployments. This is especially pertinent if the company ventures into AI applications that raise societal or legal concerns (e.g., AI in hiring, AI in financial credit decisions, etc.). Literature on future AI governance suggests that companies will need to implement frameworks to ensure transparency, fairness, and accountability in their AI systems. We recommend the conglomerate proactively adopt such frameworks – for example, conducting bias audits of AI models, having clear protocols for human oversight of AI decisions, and staying updated on relevant regulations (such as data protection laws or upcoming AI-specific laws). By baking ethical considerations into the roadmap, the company protects itself from future risks (like public relations issues or legal penalties) and strengthens trust with employees, customers, and partners. Essentially, the idea is to pursue AI advancement responsibly, keeping it aligned with the company's values and social responsibilities.

- **Metrics and Continuous Evaluation:** Finally, a forward-looking roadmap would be incomplete without a plan for monitoring and evaluation. Our study emphasized how tracking ROI and performance metrics was key during implementation; this should evolve into a long-term practice. The conglomerate should define Key Performance Indicators (KPIs) for its digital transformation – for example, target percentages for further efficiency gains, customer satisfaction improvements attributable to AI, innovation metrics like the number of new AI-driven initiatives per year, etc. Regular review of these KPIs by top management will help ensure that AI efforts remain result-oriented and do not drift into tech-for-tech's-sake. It will also highlight areas that are underperforming so the strategy can be adjusted (much as we saw adjustment during the project, but now at a strategic

level). The company can consider publishing an internal “AI impact report” annually to catalog benefits realized and lessons learned; this keeps focus and accountability on the initiative. Continuous evaluation aligns with the agile, learning mindset – the organization should treat the AI roadmap as a living plan that evolves based on feedback and outcomes. If, for instance, an AI project doesn’t yield expected benefits, the decision could be made to pivot resources to more promising areas. One lesson from our case is that not all intuitively beneficial uses of AI will pan out (remember the initial underperforming forecasting model which needed tweaks). Thus, maintaining a mechanism to evaluate and iterate on the AI portfolio is important to long-term success.

The overall discussion, in this chapter, provided a critical interpretation of our results in light of existing scholarship and organizational practice. It has further highlighted the patterns of success (e.g., effective change management yields acceptance), contradictions (e.g., initial expectations of resistance vs. eventual embrace), and confirmatory insights (e.g., AI does deliver efficiency and decision benefits as theorized). Along these lines, the discussion evidently explains the inherent meaning of findings: that AI implementation, when executed with strategic foresight and human-centered management, can transform a conglomerate’s operations and culture for the better, and that this transformation is an ongoing journey with new frontiers still ahead.

Chapter 6: Conclusion

6.1. Introduction

This study set out to examine how the integration of Artificial Intelligence (AI) transforms management in multi-industry conglomerates transitioning from traditional ERP systems. The central research question asked: How can AI enhance management efficiency, decision-making, and strategic agility in diverse conglomerate groups, particularly during the ERP-to-AI transition? To answer this, we adopted a pragmatic mixed-methods approach, combining a survey of 200 managers with in-depth interviews in the case organization (Alpha Group). This concluding chapter summarizes the key findings, discusses their implications, highlights the contributions to theory and practice, and outlines limitations and avenues for future research.

6.2. Summary of Key Findings

The results of the study provide a comprehensive, data-driven evaluation of AI's impact in the conglomerate context. In summary, our findings show that AI implementation significantly enhances operational efficiency and decision processes, thereby also fostering greater agility. From the quantitative side, we confirmed that ERP systems are nearly ubiquitous in conglomerates (92% of surveyed managers use an ERP), but there is a clear shift underway: 65% of managers reported that AI technologies were already being integrated into their operations. In other words, while ERP remains a foundational platform, a large majority of firms are actively moving toward AI-augmented management. These findings align well with contemporary literature and characterize

a paradigm shift in enterprise IT – from legacy ERP-centric systems toward adaptive, AI-driven architectures.

The core outcomes demonstrate unanimous, tangible gains from AI over the previous ERP-only state. In the post-implementation survey, all respondents agreed that AI improved their department's efficiency (with 43% strongly agreeing), whereas prior to AI, no manager had strongly endorsed the ERP as fully meeting business needs. A one-sample t-test confirmed that the mean efficiency rating after AI ($\sim 4.5/5$) was significantly above neutral ($p \ll 0.001$). In practical terms, managers shifted from seeing legacy systems as “serviceable yet insufficient” to experiencing substantial efficiency improvements under AI. These gains emerged across all functional areas studied (finance, supply chain, HR, operations, etc.), suggesting that the AI tools had broad applicability despite the conglomerate's diverse operations. The unanimity of positive responses is particularly striking given the inherent complexity of a multi-division enterprise – it implies that the new AI-driven processes successfully eliminated bottlenecks that traditional ERP or manual methods could not. This real-world evidence concretely verifies what many have hypothesized: AI's automation and analytics act as force multipliers for productivity in a large organizational setting.

Beyond raw efficiency, the study found that AI transformed the speed and quality of decision-making, thereby boosting strategic agility. Post-implementation, every surveyed manager agreed that “AI has led to faster and more informed decision-making.” Managers observed that tasks which once required days of data gathering (for example, consolidating forecasts from various units) now occur in near real-time. AI-driven dashboards replaced the weekly review of stale reports with up-to-the-minute analytics, enabling proactive adjustments to plans before problems

fully materialize. This newfound proactivity – making decisions earlier in the cycle – is precisely the real-time adaptability that the literature predicts AI can introduce into static ERP environments. Managers also reported improved decision quality: advanced AI analytics (e.g. predictive models and pattern recognition) gave leaders greater confidence in their strategic choices by processing vast datasets that humans alone could not efficiently analyze. For instance, an AI-powered demand forecasting model enabled precise inventory allocations, while AI-driven scenario planning in finance allowed rapid evaluation of investment options. These outcomes echo scholarly assertions that AI enhances strategic decision-making by surfacing actionable insights from complex data. Crucially, our research confirmed that these decision-making enhancements translated into real agility. Interviewees noted that during an unexpected market shift, AI-based market analysis tools helped the conglomerate realign its strategy in weeks instead of months. In short, AI adoption led to faster, data-driven decisions and a more nimble organizational mindset, directly addressing the research question's emphasis on agility.

Importantly, the transition to AI preserved and even augmented human judgment in management processes. Managers did not feel supplanted by the technology; rather, they described AI as an “advisor” that provides recommendations while people continue to apply context, experience, and ethical judgment to final decisions. This collaborative model – often termed augmented intelligence – ensured that employees remained at the helm of strategy, aligning with best-practice theories of human–AI partnership. In fact, our survey showed zero respondents agreed with the notion that AI threatened their jobs (71.5% explicitly disagreed), reflecting a broad cultural shift in the organization. Leadership had actively framed AI as a tool for empowerment rather than displacement, and the results indicate this narrative took hold: by the end of implementation, all

managers agreed that “AI has complemented – not replaced – human roles” in strategic tasks. This finding offers a nuanced insight to the literature on AI adoption: it empirically demonstrates that with deliberate change management and communication, even a large-scale AI initiative can achieve unanimous workforce acceptance, mitigating the job-threat anxiety often emphasized by scholars.

However, it is also notable that not every corporate function initially viewed AI in the same light. Different parts of the organization had differing perspectives and concerns about the AI rollout, especially at the outset. For example, some HR managers were primarily concerned about how AI might affect jobs and required substantial reassurance that the technology would be used to assist rather than replace employees. In contrast, many IT and operations managers were enthusiastic champions of the AI project from the beginning, focusing on technical integration and efficiency gains. Meanwhile, finance executives were supportive but keenly focused on the cost-benefit aspect, wanting to see clear returns on investment. These differing functional viewpoints underscore that AI adoption isn’t a one-size-fits-all experience across a conglomerate. Each department or function tended to evaluate AI through its own lens – HR through a people and change lens, IT through a technical capability lens, finance through a performance and ROI lens, and so on. Recognizing and addressing these diverse perspectives was critical to achieving the unified acceptance and positive outcomes we observed. In practice, the organization managed this by tailoring its communication and support: for instance, it addressed HR’s concerns with clear messages about no job losses and retraining opportunities, and it satisfied finance’s scrutiny by rigorously tracking efficiency improvements and cost savings. By the end of the implementation, despite starting from different viewpoints, all functions converged in acknowledging AI’s benefits.

This harmonization across corporate functions highlights an important lesson: successful AI integration in a large company requires cross-functional alignment, ensuring that each part of the business sees how the technology serves its interests and alleviates its concerns.

Overall, the converging quantitative and qualitative evidence allows us to definitively answer the overarching research question. AI implementation markedly enhances management efficiency, decision-making, and agility in diversified conglomerates. Every dimension of performance we examined improved, and these improvements were recognized across all surveyed departments. The case of Alpha Group vividly exemplifies this transformation: by layering AI over its established ERP foundation, the conglomerate transcended the operational rigidities of the past and realized a more adaptive, intelligent management system. These findings validate and extend the conceptual perspectives from Chapter 2; for example, they show how AI-driven ERP can achieve the synchronization of diverse subsidiaries and the rapid, predictive analytics envisioned by prior research. The evidence also addresses previously identified gaps: by focusing on a multi-industry conglomerate, the study fills a void in the literature regarding ERP–AI convergence across heterogeneous business units. It concretely demonstrates how AI-enabled systems provide a centralized yet flexible platform for coordination – a solution to the integration challenges that earlier single-industry studies could not fully capture. Likewise, the unanimous post-implementation improvements in decision speed and quality directly confront earlier criticisms that traditional ERP lacked real-time predictive capabilities. In effect, this research advances our conceptual understanding by illustrating that AI-augmented management systems can deliver on the long-promised vision of real-time, data-driven decision-making in complex enterprises.

6.3. Contributions to Theory and Practice

Theoretical and Conceptual Contributions: This dissertation makes several important contributions to existing theory. First, it empirically confirms key propositions of strategic agility theory in an AI context. The literature review defined strategic agility as proactive responsiveness to change; our work demonstrates that AI significantly heightens that agility. The story of Alpha Group adjusting plans in weeks (thanks to AI-driven insights) underscores how AI-enabled decision processes align with and amplify the concept of agility, supporting and extending theorists' predictions. Second, the findings enrich innovation diffusion theory as applied to AI adoption. The transition at Alpha Group involved strong stakeholder engagement, comprehensive training programs, and the use of "AI champions," reflecting Rogers' classic diffusion of innovation concepts (e.g. relative advantage, trialability, peer influence). The case also nuances the Technology Acceptance Model (TAM) perspective: rather than initial user skepticism significantly limiting uptake, we found that rigorous change management and clear communication essentially overcame resistance. This suggests that in complex organizations, structural interventions (effective training, participative rollout strategies) can override individual apprehensions – an insight that refines existing adoption models by highlighting the role of organizational context in user acceptance. Third, the study engages Enterprise Architecture (EA) frameworks at a conceptual level. Alpha Group's holistic approach to integration – building data pipelines and a new cloud data warehouse, and aligning AI projects with business strategy – mirrors TOGAF principles of interoperability, governance, and alignment between IT and business goals. In this way, the research illustrates EA concepts in practice, reinforcing the idea that formal architecture planning can support scalable AI integration across diverse IT landscapes. Fourth, by

documenting the company's proactive establishment of an AI ethics office and data governance committee, the work contributes to emerging theory on AI governance. It provides a concrete example of how a firm can address the ethical and compliance challenges identified in the literature (such as data privacy and algorithmic bias) while implementing AI at scale. This advances conceptual understanding of aligning AI practice with ethical frameworks and responsible innovation principles. In sum, our findings not only validate many propositions from existing theory but also extend them by showing how these ideas play out in a large, real-world conglomerate setting, thereby filling a gap between theoretical expectation and observed outcome.

Methodological and Empirical Contributions: Beyond conceptual insights, this research also offers contributions on methodological and empirical fronts. Methodologically, the pragmatic mixed-methods design – combining a large-scale survey with in-depth executive interviews – proved to be an effective approach for studying AI implementation in an organizational setting. This approach captured both breadth (200 quantitative survey responses) and depth (rich qualitative data from 10 interviews), yielding robust triangulation of results. The quantitative analysis (including pre- vs. post-implementation comparisons, t-tests, and regression analyses) provided statistically rigorous evidence of AI's impact, while the qualitative data contextualized those numbers with real-world stories and perspectives (e.g. the CEO's anecdote about rapid strategic shifts, frontline managers' experiences with new tools). This integrative method could serve as a model for future digital innovation studies seeking to understand both the measurable outcomes and human factors of technology adoption. Empirically, the study contributes one of the few detailed, data-backed accounts of post-implementation outcomes in an AI-driven ERP context. The nearly unanimous positive responses documented here (for instance, 100% of managers

agreeing on improved efficiency, decision-making, and cross-subsidiary coordination) are unique data points that go beyond the anecdotal or case-by-case evidence previously available. The use of paired statistical tests on pre- vs. post-implementation perceptions (with highly significant results) adds a level of rigor to the field, demonstrating measurable change attributable to AI. Furthermore, the finding that initial readiness did not predict later efficiency gains – i.e., even managers who felt unprepared eventually reported equal benefits – is an important empirical nuance. It suggests that systemic factors trump individual attitudes in determining project success, offering a counterpoint to prior work that might place heavier emphasis on individual readiness. Instead, our results indicate that comprehensive training and support can neutralize baseline differences in preparedness. Collectively, these contributions advance empirical understanding by providing a rich, well-substantiated case of AI implementation outcomes in a complex corporate environment, and they showcase a methodological template that future researchers can adapt.

Contribution to Professional Practice: Although this was not explicitly a separate section in our chapter structure, it's worth noting how the study contributes to practical business practice. The insights from Alpha Group's experience can inform other organizations embarking on similar AI transitions. For example, the importance of executive sponsorship, clear communication of AI's purpose, and investment in employee training are all practical lessons that align with best practices but are now backed by concrete evidence. The development of an internal AI governance mechanism (ethics officer, data committee) offers a model for AI governance that practitioners can emulate to address stakeholder trust and compliance issues. Additionally, the "roadmap" recommendations we provided – focusing on people, alignment with strategy, and continuous evaluation – can guide managers in planning the sustained integration of AI beyond initial

implementation. This way, the dissertation doesn't just contribute to academic theory; it also provides a framework or playbook for practitioners to enhance business practices. By capturing how one conglomerate successfully navigated the ERP-to-AI journey, we deliver practical guidance on leveraging AI for operational excellence, strategic agility, and innovation, while avoiding common pitfalls. This dual contribution to theory and practice underscores the study's relevance to both scholars and business leaders.

6.4. Limitations and Future Research

Despite its contributions, this research has several limitations that warrant caution in interpretation and point to avenues for future inquiry:

- **Single-Case Scope:** The study is based on a single case organization (Alpha Group), which limits generalizability of the findings. Alpha Group, while spanning multiple industries, may have unique resources, culture, or strategic motivations that differ from other conglomerates. Future research should validate and expand these findings in additional contexts – ideally through multi-case studies or cross-industry comparisons – to determine how widely the conclusions hold.
- **Self-Report Bias:** Our data relied heavily on self-reported perceptions from surveys and interviews, which may introduce response bias. Managers' overwhelmingly positive ratings could have been influenced by a shared organizational narrative (everyone believing in the AI project's success) or by the "halo" effect of new technology. We did not pair these perceptions with many objective performance metrics. Future studies could incorporate direct performance data (e.g. process completion times, error rates, financial

outcomes) to corroborate the self-reported benefits and provide a more objective measure of AI's impact.

- **Short-Term Observation:** The research captures a snapshot relatively soon after AI implementation (within the first year of rollout). This short-term view means we have measured initial impacts and sentiment, but we do not know if these benefits and attitudes will sustain over the long term. It is possible that new challenges (or diminishing returns) could emerge later. Longitudinal research is needed to assess whether the observed improvements in efficiency, decision-making, and culture are maintained, and to see how the organization evolves its AI use over multiple years. Following the case over time or conducting follow-up studies in a few years would greatly enhance understanding of AI's long-term effects.
- **Limited Participant Perspectives:** Our qualitative sample was limited to top and mid-level managers, and the survey was also targeted at managers. We did not directly capture the perspectives of frontline staff, external partners, or customers. It's possible these groups might have experienced different impacts or harbored different concerns (for example, frontline employees might have felt more day-to-day workflow changes, or customers might perceive differences in service). Future research could include a more diverse set of stakeholders – for instance, surveys of non-managerial employees or case studies including customer feedback – to paint a fuller picture of AI's organizational impact. Broadening the range of perspectives would help identify any effects we might have missed and could reveal challenges or benefits that manifest at other organizational levels.

- Focus on Positive Outcomes:** Conceptually, our study focused on the intended benefits of AI and largely documented positive outcomes. We did not deeply explore potential negative externalities of AI implementation, such as over-reliance on algorithms, loss of human expertise, or unintended strategic blind spots caused by AI recommendations. These are real concerns that the literature on AI warns about, but they were not a central focus in our case analysis (possibly because they did not surface strongly within the first year). Future research should critically examine these possible downsides and how they might be mitigated. For example, studies could investigate if heavy dependence on AI might reduce managers' intuition or if algorithmic decisions could lead to uniform strategies that diminish creativity. Additionally, building on the ethical and governance issues raised in Chapter 2, researchers should study how frameworks for AI ethics and accountability play out over the long term – for instance, what are the effects of having an AI ethics officer on organizational trust and legitimacy, and do any ethical dilemmas emerge as AI systems take on bigger roles? Addressing these questions would provide a more balanced understanding of AI's impact, ensuring that enthusiasm for the benefits does not overshadow potential risks.

Hence, these limitations open up rich avenues for future research. Scholars can build on this work by examining a variety of conglomerates (and other large organizations), using mixed methods over longer periods, and probing the complex interplay of AI, organizational factors, and broader socio-technical impacts. Such investigations will deepen our conceptual and practical understanding of AI's role in evolving enterprise management, and they will help organizations navigate the opportunities and challenges of AI with greater confidence and insight.

Sample

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Appendices

Appendix A – Survey Questionnaire

Pre- and Post-Survey Questionnaire

Target Group: Mid-to-senior level managers or department heads in conglomerate organizations involved in ERP and AI systems

Purpose: To measure perceptions before and after AI implementation or transition discussions.

Section A: General Information

(Both Pre and Post)

1. Your role in the organization:
2. Number of years in your current role:
3. Industry of your business unit (e.g., manufacturing, finance, tech):
4. Are you currently using an ERP system? (Yes/No)
5. Has your organization started integrating AI technologies into business operations? (Yes/No)

Section B: Perceptions of AI Impact on Management

(Use a 5-point Likert scale: Strongly Disagree (1) – Disagree (2) – Neutral (3) – Agree (4) – Strongly Agree (5))

Pre-Survey Focus (Before AI implementation awareness):

6. ERP systems currently meet the strategic and operational needs of our business.
7. Our organization is prepared for transitioning from ERP to AI-based systems.
8. I believe AI can improve management decision-making in complex organizations.
9. I am confident AI can enhance cross-subsidiary collaboration and data sharing.
10. I feel adequately trained or informed about AI applications in our business processes.
11. AI poses a threat to job security in my department.
12. AI implementation will likely face resistance from employees in our organization.

Post-Survey Focus (After AI implementation awareness/pilot experience):

13. AI tools have improved the efficiency of my department's operations.

- 14. AI has led to faster and more informed decision-making in our organization.
- 15. Integration with AI has improved coordination across business units.
- 16. I trust AI systems to deliver reliable and explainable insights.
- 17. AI has complemented — not replaced — human roles in strategic tasks.
- 18. Altogether, AI has added value beyond the capabilities of our previous ERP systems.

Sample

Appendix B – Interview Schedule

Thank you for participating in this study. This interview will explore your views and experiences regarding the integration of AI in managing your organization's operations, particularly in relation to ERP systems. Your responses will remain confidential and will only be used for academic purposes.

Interview Questions

1. Background Context

- Can you describe your current role and how it involves ERP or AI systems?

2. Experience with ERP Systems

- What limitations have you encountered with traditional ERP systems in managing diverse subsidiaries or departments?

3. AI Awareness and Expectations

- Before AI was introduced, what were your expectations or concerns?
- Did you anticipate any resistance from staff or leadership?

4. Implementation Process

- How was AI introduced or piloted in your division?
- What kind of training or support was provided?

5. Impact of AI Integration

- What changes (positive or negative) have you observed in management efficiency or decision-making?
- How has AI improved visibility or coordination across departments?

6. Strategic Agility and Adaptation

- Has AI contributed to faster responses to market or internal shifts?
- Can you share an example where AI helped guide a strategic decision?

7. Ethical or Organizational Challenges

- Were there any data privacy, bias, or ethical concerns raised?
- How were they addressed?

8. Overall Evaluation

- In your view, has AI added more value than traditional ERP systems alone?

- What would you advise other conglomerates considering a transition to AI-based systems?

9. Future Outlook

- What do you see as the next step in leveraging AI in your organization?
- Are there areas still underdeveloped that AI could help with?

Sample

Appendix C – Survey Responses

Role	Years in Role	Industry	ERP System Use	AI Integration	ERP meets business needs	Prepared for ERP transition	AI can improve decision	AI enhances collaboration	Adequately trained for AI	AI threatens job security	AI faces resistance	AI improved efficiency	AI improved decision speed	AI improved coordination	Trust in AI	AI complements human roles	AI adds more value than ERP
Department Head	12	Manufacturing	Yes	Yes	3	4	5	4	2	2	4	5	5	4	5	5	5
HR Manager	13	Tech	Yes	No	3	2	4	5	2	2	5	4	5	5	4	5	4
Senior Manager	9	Finance	Yes	Yes	2	3	4	4	4	1	5	4	5	5	4	4	5

Department	Head	12	Tech	Yes	Yes	3	2	4	3	3	1	3	4	5	4	3	4	5
HR Manager	15	Finance	Yes	Yes	3	4	5	3	2	2	4	4	4	5	5	4	4	
HR Manager	2	Healthcare	Yes	No	4	2	5	5	2	1	5	4	4	4	4	4	4	
HR Manager	5	Tech	Yes	Yes	3	3	5	4	3	1	4	5	4	4	5	4	4	
Finance Manager	13	Finance	No	Yes	3	3	4	5	4	3	4	4	5	5	4	4	5	
Finance Manager	8	Manufacturing	Yes	No	2	4	4	3	2	2	4	5	4	5	4	5	5	

HR																	
Manager	6	Finance	Yes	Yes	2	4	5	4	2	1	5	4	5	5	4	5	5
IT																	
Manager	20	Manufacturing	Yes	No	3	3	4	4	2	2	5	5	4	5	4	4	4
Senior																	
Manager	9	Manufacturing	Yes	Yes	3	2	4	3	2	3	3	4	5	5	5	4	5
Operations																	
Manager	7	Retail	No	Yes	3	3	4	4	4	3	4	5	5	4	5	4	4
Finance																	
Manager	4	Finance	Yes	No	3	3	4	5	3	2	4	4	4	4	4	5	4
Senior																	
Manager	2	Retail	Yes	Yes	3	3	5	4	2	1	4	5	4	4	4	4	4

Operations Manager	2	Finance	Yes	No	3	3	4	4	2	1	5	4	5	4	4	4	4
Department Head	9	Retail	Yes	Yes	3	2	5	4	3	1	3	4	5	4	5	5	4
Operations Manager	13	Retail	Yes	Yes	4	2	3	4	2	2	4	4	4	4	5	4	4
HR Manager	11	Retail	Yes	Yes	3	2	5	5	2	2	4	4	4	4	4	5	4
Senior Manager	6	Tech	Yes	Yes	3	3	4	5	2	1	3	5	4	5	4	4	5
Operations Manager	7	Tech	Yes	No	3	2	3	4	3	1	4	5	5	5	5	5	5

Department Head	13	Manufacturing	Yes	Yes	4	2	4	4	2	3	4	4	4	4	3	4	5
HR Manager	13	Healthcare	Yes	Yes	3	2	5	3	2	3	5	4	4	5	4	5	4
Finance Manager	20	Healthcare	Yes	Yes	3	2	4	5	3	1	4	4	4	4	4	4	5
Senior Manager	1	Tech	Yes	No	2	4	4	3	3	3	3	4	4	5	5	4	4
Department Head	4	Tech	Yes	Yes	2	4	4	3	3	3	4	4	5	4	4	5	4
Finance Manager	8	Tech	Yes	Yes	4	4	5	4	3	1	3	5	4	5	5	4	4

Finance Manager	18	Finance	No	Yes	3	2	4	5	3	1	4	4	4	4	5	5	5
Operations Manager	3	Finance	Yes	Yes	4	4	4	4	2	1	4	5	4	4	3	4	4
HR Manager	1	Finance	Yes	Yes	3	3	4	4	2	3	3	4	5	4	5	4	4
HR Manager	11	Manufacturing	Yes	Yes	3	2	3	5	3	1	3	4	4	5	5	4	5
Senior Manager	11	Tech	Yes	Yes	4	2	4	3	3	3	3	5	5	5	4	5	4
HR Manager	11	Finance	Yes	Yes	2	3	5	5	4	1	3	5	5	5	5	4	5

HR																	
Manager	2	Retail	Yes	Yes	2	4	5	4	2	3	4	4	4	4	4	5	4
Senior Manager	8	Manufacturing	Yes	No	4	3	5	5	3	1	4	4	5	4	4	4	5
Operations Manager	5	Finance	Yes	No	3	4	4	5	2	1	5	5	5	5	5	5	5
Operations Manager	10	Manufacturing	Yes	Yes	4	3	5	5	3	2	3	4	4	5	5	4	5
Operations Manager	15	Finance	Yes	Yes	4	4	5	4	2	3	5	4	5	4	5	4	4
IT Manager	7	Finance	Yes	Yes	3	2	4	5	4	3	3	5	4	5	4	5	4

Senior Manager	8	Retail	Yes	No	3	3	5	4	3	1	4	5	5	4	4	5	5
IT Manager	17	Retail	Yes	Yes	3	4	5	3	3	3	4	5	5	5	4	4	4
Operations Manager	10	Retail	Yes	No	3	3	4	4	2	1	4	5	4	5	4	4	5
IT Manager	12	Retail	Yes	No	4	2	5	4	3	2	4	4	5	5	4	5	5
HR Manager	4	Finance	Yes	Yes	2	3	5	3	4	2	4	4	4	4	4	4	5
Finance Manager	12	Manufacturing	Yes	Yes	3	4	3	5	3	2	4	5	4	4	4	4	5

IT																	
Manager	13	Retail	Yes	Yes	2	2	5	4	3	2	5	4	5	4	3	4	4
Operations																	
Manager	3	Manufacturing	Yes	Yes	4	2	3	4	3	2	5	4	4	4	4	5	4
Senior																	
Manager	2	Finance	Yes	Yes	3	3	3	3	2	3	4	5	5	4	4	5	5
Finance																	
Manager	16	Manufacturing	Yes	Yes	4	4	4	4	2	1	5	4	4	4	5	5	5
IT																	
Manager	1	Retail	Yes	Yes	3	2	4	4	3	1	3	5	5	5	4	4	5
HR																	
Manager	7	Manufacturing	Yes	No	4	3	3	4	2	2	3	4	4	5	5	4	5

Opera tions Mana ger	15	Tech	Yes	Yes	4	4	4	4	2	2	4	5	4	4	4	5	5
IT Mana ger	17	Healthc are	Yes	Yes	3	4	3	4	3	2	5	4	4	5	4	5	5
HR Mana ger	14	Finance	Yes	Yes	4	4	5	4	4	2	4	4	5	4	4	4	5
IT Mana ger	10	Retail	Yes	No	3	3	4	5	3	2	4	5	4	4	5	4	4
Financ e Mana ger	2	Retail	No	Yes	3	4	3	3	2	2	5	4	4	5	5	5	4
Financ e Mana ger	11	Healthc are	Yes	Yes	3	3	4	4	2	1	5	4	5	4	4	5	4

Department Head	3	Finance	Yes	No	4	3	5	3	4	1	4	4	4	5	5	5	4
Operations Manager	16	Finance	Yes	Yes	2	3	3	4	3	3	3	5	4	4	4	4	5
HR Manager	20	Finance	Yes	No	2	4	4	4	4	2	3	4	5	4	3	5	5
HR Manager	19	Healthcare	Yes	Yes	3	2	4	4	2	1	5	4	4	4	3	4	5
HR Manager	2	Manufacturing	Yes	Yes	3	4	5	5	2	2	3	5	5	5	5	4	5
Senior Manager	9	Tech	Yes	Yes	4	4	4	4	3	3	5	5	5	4	4	4	4

Senior Manager	13	Healthcare	Yes	No	4	2	3	4	2	3	3	4	5	4	5	4	4
Finance Manager	20	Tech	Yes	No	3	3	4	3	2	3	4	4	5	5	4	4	4
HR Manager	17	Finance	Yes	Yes	3	3	3	4	2	2	3	5	4	4	5	5	4
Senior Manager	19	Tech	Yes	Yes	3	3	4	5	2	2	4	5	5	4	4	4	4
Senior Manager	8	Manufacturing	Yes	Yes	4	2	5	4	3	2	3	5	4	4	4	4	5
IT Manager	18	Retail	Yes	Yes	3	2	5	5	3	1	4	5	4	5	5	4	5

IT																	
Manager	18	Tech	Yes	Yes	3	3	4	4	4	2	3	4	4	5	4	4	5
Finance																	
Manager	12	Retail	Yes	Yes	4	2	4	4	4	1	4	5	5	4	4	4	5
Senior																	
Manager	9	Finance	Yes	Yes	3	3	4	3	2	3	3	5	4	5	5	5	5
Senior																	
Manager	15	Finance	Yes	No	4	4	5	4	3	2	3	4	5	5	4	5	5
Operations																	
Manager	9	Manufacturing	Yes	No	3	3	5	4	2	3	4	5	5	4	3	5	5
HR																	
Manager	14	Finance	Yes	Yes	4	4	4	5	2	1	5	4	5	5	5	4	5

HR																	
Manager	9	Healthcare	No	No	2	2	3	3	4	2	4	4	5	4	4	5	4
Senior Manager	18	Retail	Yes	No	2	2	4	4	3	2	5	5	4	5	4	5	5
HR Manager	16	Finance	Yes	Yes	3	4	4	4	4	2	4	4	5	4	3	5	4
Department Head	4	Finance	Yes	Yes	3	4	4	3	4	1	3	5	4	4	4	4	4
Senior Manager	16	Retail	Yes	Yes	3	3	4	3	2	3	3	5	4	4	5	4	4
IT Manager	19	Tech	Yes	No	4	3	4	3	4	1	4	5	5	5	4	5	5
IT Manager	2	Manufacturing	Yes	No	2	4	5	3	3	2	4	4	4	4	5	4	5

IT Manager	3	Tech	No	Yes	2	3	4	3	2	1	4	5	4	4	3	5	5
IT Manager	1	Retail	Yes	No	3	3	4	3	2	2	4	4	4	4	4	4	4
Finance Manager	13	Finance	Yes	Yes	4	2	4	5	3	1	4	4	5	4	4	4	5
HR Manager	19	Finance	Yes	Yes	3	3	4	4	2	3	5	4	4	4	5	4	5
HR Manager	3	Retail	Yes	No	3	4	4	4	3	2	4	4	5	4	5	5	4
Senior Manager	19	Manufacturing	Yes	Yes	3	3	3	4	3	1	5	5	5	5	5	4	5
Finance e	17	Finance	Yes	Yes	4	2	4	5	3	2	5	4	4	5	5	4	5

Manager																	
Senior Manager	15	Manufacturing	Yes	Yes	4	2	4	3	4	3	5	5	4	5	5	5	5
Senior Manager	6	Finance	Yes	No	3	4	4	5	2	3	4	4	5	4	4	4	4
Department Head	18	Manufacturing	Yes	Yes	3	4	3	4	2	2	3	4	4	5	5	4	4
Department Head	2	Tech	Yes	No	2	2	4	3	3	2	4	4	5	5	4	4	5
Senior Manager	4	Retail	Yes	No	2	4	4	5	3	2	5	4	5	4	4	5	4
Senior Manager	4	Manufacturing	Yes	Yes	2	3	3	3	3	1	5	4	4	5	4	4	4

Senior Manager	11	Tech	No	No	3	3	4	3	4	2	4	4	4	5	5	5	4
HR Manager	11	Finance	Yes	Yes	3	4	5	4	3	2	3	5	4	4	5	4	4
Operations Manager	4	Healthcare	Yes	No	3	4	3	4	3	2	5	4	5	4	4	5	4
Finance Manager	7	Finance	Yes	Yes	4	4	4	4	3	3	5	4	5	5	5	4	4
Senior Manager	8	Manufacturing	Yes	Yes	3	3	3	4	3	1	3	5	4	5	5	4	4
Department Head	16	Tech	Yes	Yes	3	3	5	5	3	1	5	4	5	5	5	5	4

Finance Manager	3	Retail	Yes	Yes	4	2	4	4	3	1	5	4	4	4	4	4
IT Manager	20	Tech	Yes	No	3	2	3	5	3	1	4	4	5	4	5	4
Finance Manager	11	Retail	Yes	Yes	4	3	3	3	3	3	4	4	5	4	5	4
Operations Manager	19	Finance	Yes	Yes	4	2	4	3	4	3	4	5	5	5	4	5
Operations Manager	18	Healthcare	Yes	Yes	3	2	4	4	3	3	4	4	5	5	5	4

HR																	
Manager	13	Manufacturing	Yes	Yes	4	3	3	3	3	3	3	5	4	5	5	4	5
Senior Manager	5	Manufacturing	Yes	Yes	2	3	5	4	3	3	3	4	5	4	5	5	4
Finance Manager	13	Manufacturing	Yes	No	2	3	5	4	2	2	4	4	4	5	4	4	5
Senior Manager	16	Finance	Yes	No	4	3	5	4	2	1	4	4	5	5	4	5	4
HR Manager	17	Tech	Yes	Yes	3	2	5	3	2	3	3	5	5	4	5	4	5
Finance Manager	11	Manufacturing	No	Yes	4	3	4	4	4	3	3	4	4	5	4	4	4

Finance Manager	3	Manufacturing	Yes	Yes	3	3	4	4	3	1	4	4	5	5	5	5	4
Senior Manager	17	Finance	Yes	Yes	4	4	4	4	2	3	4	4	4	4	4	4	4
Department Head	11	Tech	Yes	Yes	3	2	3	5	2	3	4	5	5	4	4	5	4
Senior Manager	8	Manufacturing	No	No	4	3	5	3	3	1	5	5	5	5	5	5	5
Finance Manager	10	Manufacturing	Yes	Yes	3	4	5	3	3	1	5	5	5	5	5	5	5
IT Manager	9	Finance	Yes	No	2	2	5	5	3	2	4	5	4	5	4	4	5

Operations Manager	15	Manufacturing	Yes	No	3	3	5	4	3	2	3	4	5	4	4	4	5
HR Manager	15	Retail	Yes	Yes	2	3	4	5	3	2	5	5	4	4	5	4	5
HR Manager	4	Healthcare	Yes	Yes	2	4	4	3	3	3	3	5	4	4	4	4	4
Senior Manager	6	Healthcare	Yes	Yes	2	4	3	4	2	2	3	5	5	4	5	4	4
Senior Manager	11	Manufacturing	Yes	No	3	4	5	3	4	3	3	4	4	5	3	4	4
Department Head	9	Manufacturing	Yes	Yes	2	4	4	4	3	3	3	5	4	5	4	5	5

HR Manager	10	Tech	Yes	Yes	3	3	4	4	2	2	3	5	5	4	4	5	5
Department Head	8	Retail	Yes	Yes	4	2	3	4	4	1	5	4	4	4	4	4	5
Operations Manager	11	Retail	Yes	Yes	3	4	4	4	2	1	4	5	5	5	5	4	4
HR Manager	15	Tech	Yes	No	3	2	4	3	4	1	4	4	5	4	4	4	4
Senior Manager	18	Retail	Yes	No	2	3	4	5	3	2	4	4	5	5	5	5	4
Finance Manager	15	Healthcare	Yes	Yes	3	4	4	5	2	1	5	4	5	4	3	4	4

Finance Manager	20	Manufacturing	Yes	No	3	4	5	4	3	1	4	5	4	4	4	4	4
Department Head	6	Healthcare	Yes	Yes	3	2	4	5	3	2	4	5	4	5	5	4	4
HR Manager	16	Manufacturing	Yes	Yes	4	3	3	4	2	3	4	4	4	4	5	4	4
Department Head	5	Tech	Yes	No	4	3	4	5	2	3	4	4	4	5	5	5	5
Finance Manager	3	Tech	Yes	No	3	4	4	5	3	3	3	5	4	5	5	4	4
IT Manager	3	Manufacturing	Yes	Yes	4	2	3	3	2	1	4	4	4	4	5	4	4

IT																	
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ger	1	are	Yes	Yes	2	2	4	3	4	3	4	5	4	5	3	4	4
Financ																	
e																	
Mana																	
ger	1	Retail	Yes	No	3	4	5	4	4	2	5	5	5	5	4	4	4
HR																	
Mana		Manufa															
ger	1	cturing	Yes	Yes	4	2	4	4	2	2	5	4	5	4	4	5	4
HR																	
Mana																	
ger	10	Tech	Yes	No	3	3	4	4	2	2	3	5	5	4	4	4	5
Senior																	
Mana																	
ger	6	Finance	Yes	Yes	4	3	5	3	2	2	5	4	4	4	4	4	5
IT																	
Mana																	
ger	12	Retail	Yes	Yes	2	4	3	3	2	2	3	4	4	5	4	5	4

Senior																	
Manager	2	Manufacturing	No	Yes	3	3	4	5	3	1	3	4	5	5	3	4	5
HR Manager	4	Manufacturing	Yes	Yes	2	2	5	5	3	3	4	4	4	4	4	5	4
HR Manager	20	Healthcare	Yes	No	4	4	3	4	4	1	3	5	4	4	4	4	5
Finance Manager	11	Tech	Yes	Yes	3	3	4	5	2	1	3	5	4	4	5	5	5
HR Manager	12	Retail	Yes	No	3	4	4	5	4	1	3	5	5	5	5	4	4
Finance Manager	10	Retail	Yes	Yes	2	2	4	4	3	3	3	4	5	5	3	4	4

Finance Manager	4	Manufacturing	Yes	No	4	3	5	3	4	2	4	4	5	5	5	4	4
IT Manager	13	Finance	Yes	No	2	4	4	3	2	2	3	4	4	5	4	4	4
Finance Manager	13	Healthcare	Yes	Yes	3	3	5	5	3	3	4	4	4	4	5	5	5
Operations Manager	2	Manufacturing	No	Yes	2	4	5	5	3	1	4	5	5	4	5	5	4
Department Head	17	Retail	Yes	Yes	4	4	4	4	2	2	4	4	4	4	4	4	5
Senior Manager	14	Tech	No	No	4	3	5	3	3	2	4	4	4	4	4	5	4

HR																	
Manager	10	Finance	Yes	No	4	3	5	5	3	3	4	4	4	5	5	4	5
Department Head	18	Manufacturing	Yes	Yes	3	4	4	4	2	3	5	5	4	5	4	4	5
Department Head	13	Manufacturing	Yes	No	3	2	5	4	4	2	4	4	4	4	4	5	4
Operations Manager	6	Tech	Yes	No	3	3	4	5	3	3	3	4	4	4	5	4	4
IT Manager	8	Tech	Yes	Yes	4	3	4	3	2	3	4	5	4	5	5	4	4
Finance Manager	1	Healthcare	Yes	Yes	3	3	5	4	2	2	4	4	4	4	4	4	5

Senior Manager	18	Healthcare	Yes	No	3	4	4	4	2	3	3	5	5	5	4	4	5
Finance Manager	14	Tech	Yes	No	2	2	3	5	4	2	3	5	5	4	4	4	4
IT Manager	17	Manufacturing	Yes	Yes	3	4	4	3	3	1	3	4	5	5	5	5	4
IT Manager	20	Retail	Yes	No	4	4	3	4	2	3	3	4	4	5	5	5	4
Operations Manager	1	Finance	Yes	No	2	2	5	4	4	2	4	4	5	4	5	5	4
Operations Manager	4	Retail	Yes	Yes	3	2	4	4	2	2	4	5	4	4	4	5	4

Finance Manager	14	Tech	Yes	Yes	2	4	3	3	3	1	4	5	5	5	4	5	4
HR Manager	16	Healthcare	Yes	No	4	2	4	3	2	2	4	5	5	5	4	4	4
IT Manager	12	Retail	Yes	Yes	2	4	4	5	2	1	3	4	4	4	5	5	5
IT Manager	5	Healthcare	Yes	No	3	4	4	4	4	2	5	4	4	4	4	4	4
IT Manager	17	Tech	Yes	Yes	3	3	4	3	2	1	4	4	5	5	5	4	4
Department Head	17	Manufacturing	No	Yes	3	3	3	4	3	1	4	4	4	4	4	4	5

Department																	
Head	20	Retail	Yes	Yes	3	3	4	4	3	3	5	5	4	5	5	4	5
Senior Manager	5	Healthcare	Yes	Yes	4	2	4	3	4	1	5	4	5	4	5	4	4
Operations Manager	18	Retail	Yes	Yes	3	4	3	5	2	3	4	5	5	4	5	4	5
Operations Manager	19	Tech	Yes	No	3	4	3	4	3	1	4	5	5	5	4	5	5
Operations Manager	10	Finance	Yes	Yes	4	3	5	5	4	2	3	5	4	4	5	5	4
IT Manager	7	Manufacturing	Yes	No	3	2	4	3	3	1	5	4	4	4	4	4	5

HR																	
Manager	7	Tech	Yes	Yes	3	3	5	4	2	2	3	4	5	5	3	4	5
HR																	
Manager	10	Healthcare	Yes	Yes	3	3	4	4	4	3	3	5	5	5	5	5	5
HR																	
Manager	14	Manufacturing	Yes	Yes	3	4	3	4	2	1	4	5	4	4	3	4	4
IT																	
Manager	15	Manufacturing	Yes	Yes	2	4	3	5	3	3	5	5	4	5	3	5	4
Senior																	
Manager	8	Manufacturing	Yes	Yes	3	2	3	4	2	2	5	5	4	4	5	4	5
Operations																	
Manager	1	Manufacturing	Yes	No	4	3	4	4	3	2	4	4	5	5	5	4	5

IT																		
Manager	3	Retail	Yes	Yes	3	4	5	4	2	1	3	5	4	5	3	4	5	
Senior Manager	20	Retail	No	Yes	3	2	3	3	3	3	5	5	5	4	4	5	5	
Department Head	6	Manufacturing	Yes	No	2	3	3	5	2	1	4	4	4	4	5	4	4	
Finance Manager	1	Healthcare	Yes	Yes	3	3	4	3	2	1	5	4	4	4	4	4	5	
IT Manager	9	Tech	Yes	No	3	3	4	4	3	3	5	5	5	4	4	4	5	
Department Head	5	Manufacturing	No	No	3	4	5	5	3	2	3	4	5	4	5	5	4	

Department Head	3	Healthcare	Yes	No	3	3	4	4	2	2	5	4	5	4	5	4	5
Operations Manager	7	Manufacturing	No	Yes	3	3	5	5	2	2	3	5	5	4	3	4	4
IT Manager	18	Finance	Yes	No	4	3	5	4	2	3	5	4	4	4	5	5	4
Senior Manager	8	Healthcare	Yes	No	2	3	4	5	3	1	3	4	4	4	5	4	5
Senior Manager	12	Manufacturing	Yes	Yes	3	4	5	5	3	2	4	4	4	5	5	5	4
IT Manager	11	Manufacturing	Yes	Yes	4	2	5	5	2	1	4	5	4	5	4	5	4

HR																	
Manager	13	Healthcare	Yes	Yes	2	3	4	5	3	1	5	4	4	4	3	4	4
Senior Manager	4	Healthcare	Yes	Yes	3	2	3	3	2	2	4	5	5	4	5	4	5
Finance Manager	13	Healthcare	Yes	Yes	4	4	5	4	3	1	3	4	4	4	4	4	5
Department Head	7	Manufacturing	Yes	No	3	3	4	5	3	1	3	5	5	5	4	4	5

Appendix D – Interview Transcript

AI Transformation at Alpha Group

Interview 1: Group CEO (Alpha Group)

Interviewer: Thank you for taking the time. To start, could you introduce yourself and your role in this AI initiative at Alpha Group?

Interviewee (CEO): Certainly. I'm the Group CEO of Alpha Group, a large multi-industry conglomerate. I've been leading the company's strategic direction for the past 5 years. When we embarked on our AI transformation initiative about two years ago, I was the executive sponsor, overseeing the vision and ensuring it aligned with our business goals.

Interviewer: What prompted Alpha Group to adopt AI across the organization?

Interviewee (CEO): We saw that artificial intelligence could be a game-changer for our diverse businesses. The decision was driven by a need to stay competitive and improve efficiency. We operate in industries from manufacturing to financial services, and we were collecting massive amounts of data. It made sense to leverage AI to gain insights from that data, automate routine tasks, and drive innovation. I wanted to ensure we weren't just jumping on the AI bandwagon but that we had a clear strategic reason – for us, that was enhancing decision-making and operational excellence across all our units.

Interviewer: How did you approach leading this transformation as the CEO?

Interviewee (CEO): I knew early on that my role was to champion the change. We established a clear narrative that this wasn't "AI for AI's sake" – it was about creating real business impact and making work better for our people. I communicated frequently with all levels of staff about why we were doing this and how it would benefit not just the company but also their daily work. For example, we highlighted how AI could handle tedious data processing so employees could focus on more meaningful tasks. I also made sure to be visibly involved – from kickoff meetings to periodic check-ins – to signal that this was a top priority supported at the highest level.

Interviewer: What were some challenges you anticipated or encountered during the adoption?

Interviewee (CEO): There were a few. One of the biggest was cultural resistance – perfectly understandable when introducing a major change. Some employees were anxious about job security or just wary of a new way of doing things. We tackled that by investing heavily in training and assuring everyone that the AI tools were there to augment their work, not replace them. Another challenge was ensuring alignment – making sure all departments understood how the AI initiative fit into our broader goals. As a conglomerate, it was crucial each business unit saw relevance to their own operations. Additionally, we needed to make sure we had the right talent, so we both upskilled our existing workforce and brought in a few experts to guide the technical implementation.

Interviewer: Have you seen the results you hoped for from this AI implementation?

Interviewee (CEO): Thus far, yes. In our manufacturing division, for instance, AI-driven predictive maintenance has reduced unplanned downtime significantly. In our retail arm, AI analytics improved inventory management and customer personalization. Across the board, we're making more data-informed decisions. Perhaps equally importantly, I've seen a shift in mindset – more of our teams are now data-driven and open to innovation. We're still early in the journey, but productivity is up in several areas and we're identifying new opportunities that we hadn't seen before.

Interviewer: From a leadership perspective, what key lessons have you learned through this transformation?

Interviewee (CEO): I've learned that leading by example is vital; if you want an organization to embrace AI, you have to embrace it yourself and be its advocate. Communication is another critical piece – being transparent about the “why” and “how” of the change helps bring people on board. And you can't forget the human element: technology projects like this succeed or fail based on people. Looking back, I'm glad we focused on training and involvement of employees in shaping how the AI tools would be used. That co-creation helped reduce fear and built a sense of ownership. Lastly, patience and persistence are key. Transformation doesn't happen overnight; it's a continuous process of learning and refining our approach. I'm proud of how far we've come, and I'm excited for what's next as we continue to integrate AI deeper into our businesses.

Interview 2: Chief Technology Officer (CTO)

Interviewer: As the Chief Technology Officer of Alpha Group, could you describe your role in the AI implementation project?

Interviewee (CTO): I've been the CTO here for about three years, and I was responsible for overseeing the technical aspects of our AI transformation. Essentially, my team and I translated the CEO's vision into a concrete technology plan. We evaluated what infrastructure and tools we needed, led the selection of AI platforms, and coordinated with all our business units' IT teams. I also spearheaded the formation of an AI Center of Excellence – a cross-functional team to pilot and promote AI solutions throughout our conglomerate.

Interviewer: What were the initial steps you took to implement AI across such a diverse organization?

Interviewee (CTO): We started with small pilot projects to demonstrate value. For example, one pilot was in our manufacturing division focusing on predictive maintenance using machine learning. Another was in our retail division, using an AI algorithm for demand forecasting. These pilots helped us understand the practical challenges and build success stories. Technically, we first had to ensure our data was in order. That meant consolidating data from different subsidiaries into a central data lake and cleaning it up. We upgraded some of our legacy systems or built APIs so they could connect with modern AI tools. A big part of the initial phase was also selecting the right software and partners – we decided to use a mix of in-house development and an external AI platform vendor for different needs.

Interviewer: Were there major technical challenges in the process?

Interviewee (CTO): Absolutely. One challenge was integrating AI solutions with legacy systems. Some of our older software wasn't designed to work with modern AI algorithms, so we had to build custom interfaces and, in a few cases, replace outdated modules entirely. Data quality was another major issue – we discovered early on that data coming from different units had inconsistencies. We had teams spending a lot of time on data cleaning and standardization. We addressed this by establishing data governance standards and investing in data management tools. Another challenge was scalability. Once our pilot projects proved successful, we needed to scale them up to the entire organization, which required significant computing resources and network

upgrades. We migrated a lot of our workloads to the cloud to ensure we could handle the processing demands of AI.

Interviewer: How did you handle the need for specialized skills? Did you have the talent in-house?

Interviewee (CTO): That was a critical area. We realized early that we didn't have all the necessary AI expertise in-house. While we had a strong IT team, AI requires some specific skill sets like data scientists and machine learning engineers. We addressed this in two ways: we hired a few key experts – for instance, a lead data scientist – and simultaneously upskilled our existing staff. We ran training programs and workshops so that our software engineers could learn about machine learning and our analysts could work with new AI-driven analytics tools. We also had a couple of consultants from the AI platform vendor working alongside our teams initially, which really helped knowledge transfer.

Interviewer: In terms of outcomes, from a technology perspective, what improvements have you seen?

Interviewee (CTO): From the tech side, we now have a much more robust and modern infrastructure. The central data platform we built is being used across the company, which not only supports the AI applications but has improved our overall data accessibility. We've automated several processes – for example, our IT operations now use an AI-based monitoring system that preemptively alerts us to issues before they become critical, reducing downtime. The predictive maintenance system we rolled out in manufacturing cut machine downtime by, I'd say, around 20%. The demand forecasting AI in our retail businesses has led to better stock management. Also, the culture in the IT department has evolved – our teams are now conversant with AI and machine learning concepts and more proactive in suggesting new AI use cases.

Interviewer: What lessons would you highlight for successfully implementing AI from the technology leadership viewpoint?

Interviewee (CTO): A big lesson is the importance of aligning technology with business needs. As technologists we can get excited about AI, but we constantly made sure each AI project had a clear business outcome tied to it. Another lesson is to not underestimate the preparatory work: things like data cleaning, integration, and infrastructure upgrades took more time than developing

the AI models themselves. I'd also say involve your end-users early. We had our operations people and others give feedback to the tech team right from the pilot phase, which helped us make the tools more user-friendly and relevant. And finally, continuous learning is key – the tech field is evolving, so we're keeping our teams trained and our systems up-to-date. Implementing AI isn't a one-off project; it's about building a capability for the long run.

Interview 3: Digital Transformation Manager (AI Program Lead)

Interviewer: Please introduce yourself and your role in the AI project.

Interviewee (AI Program Manager): I'm the Digital Transformation Manager at Alpha Group, and I served as the program manager for our AI implementation. In practical terms, I was responsible for planning and coordinating the rollout of AI solutions across our various businesses. I've been with the company for over a decade in different roles, but this AI initiative has been my main focus for the past two years.

Interviewer: What did coordinating the AI rollout involve on a day-to-day level?

Interviewee (AI Program Manager): A lot of it was about communication and coordination. We divided the implementation into phases. First, we had an initial planning phase, then pilot projects, and then a broader deployment phase. I worked closely with each department to identify use cases where AI could help. For example, I'd meet with the operations team to discuss how an AI tool could improve their production scheduling, or with HR about using AI in resume screening. Once we agreed on the use cases, I had to ensure that the technical team (led by our CTO and AI specialists) and the business teams were on the same page regarding requirements and timelines. Day-to-day, I ran project meetings, tracked progress on our implementation milestones, and resolved issues – like if the marketing team needed extra training on the new AI analytics dashboard, I'd coordinate those training sessions with HR and IT.

Interviewer: How did you manage change across such a large organization?

Interviewee (AI Program Manager): Change management was probably the most critical part of my job. Early on, we recognized that introducing AI would require a cultural shift for many employees. To manage that, we set up what we called "AI Champions" in each department – these were early adopters or influential team members who were excited about the technology. We gave

them deeper training so they could help their colleagues on the ground and be local advocates for the new tools. We also held town hall meetings and demos where we showed how the AI applications worked and answered questions or concerns. Communication was constant – newsletters, intranet updates, progress reports – all aimed at keeping everyone informed about why we were doing this and the wins we were getting. And I have to say, having visible support from the CEO and other top leaders made my job easier; when employees see leaders backing a change, they take it more seriously.

Interviewer: Were there any obstacles or resistance, and how did you address them?

Interviewee (AI Program Manager): There were certainly some bumps. In the early stages, a few department managers were hesitant to allocate their people's time to AI training or pilot projects because they were worried it might disrupt day-to-day work. I addressed that by working with them to minimize the impact – for instance, scheduling training in short sessions and showing them data from other companies or our own pilots to prove that this would ultimately save time and effort. Some employees were nervous that the AI might make their jobs redundant. To tackle that, we emphasized that the AI was there to handle repetitive tasks and assist in decision-making, not to cut jobs. In fact, we didn't lay off anyone due to AI; instead we tried to reskill people for higher-value roles. Seeing that commitment, many skeptics gradually became more open. Also, not every pilot succeeded on the first try – one of our early AI models for sales forecasting wasn't very accurate initially, which led to some "I told you so" reactions from doubters. We treated that as a learning experience, worked with the data science team to improve the model, and eventually it started performing well. That turnaround helped win some people over.

Interviewer: From a project management perspective, what were the outcomes of the AI implementation?

Interviewee (AI Program Manager): From my viewpoint, one big outcome is that we delivered the project on schedule and within the budget we planned, which is always good news for a project manager! More importantly, we achieved the objectives we set out. By the end of the rollout, every major division of Alpha Group had at least one AI-driven process in operation, whether it's in manufacturing, finance, HR, or marketing. Adoption rates are high – we track usage metrics of the AI tools, and most teams are actively using them rather than ignoring them. We've documented

efficiency gains; for instance, some routine reporting processes that used to take days are now done in minutes with AI. And qualitatively, I see that people across the company are now more curious and engaged with new technology. There's a buzz around innovation that wasn't there a few years ago.

Interviewer: What lessons about managing such a transformation would you pass on?

Interviewee (AI Program Manager): I'd stress a few things. First, stakeholder engagement is everything – you need buy-in at all levels, from executives to the frontline. If I could do it again, I'd involve end-users even more in the design of solutions from day one, because that always increases adoption. Second, flexibility is key. We had a roadmap, but we adjusted it whenever reality turned out differently than our plans – like extending a pilot or tweaking training approaches. Third, celebrate the small wins. We made a point of highlighting early successes, even minor ones, to build momentum and show everyone that the effort was worth it. And finally, invest in people. The tech can only go so far; it's the training, the hand-holding early on, and the cultural support that turn a technology implementation into a sustained success.

Interview 4: HR Director (Head of Human Resources)

Interviewer: Can you introduce yourself and explain how the HR department was involved in the AI initiative?

Interviewee (HR Director): I'm the Head of Human Resources at Alpha Group. From the HR side, our role in the AI project was to manage the people-related aspects of this transformation. That included assessing the impact on jobs and skills, planning and delivering training programs, and communicating with employees throughout the process. I've been with Alpha Group for over 15 years, and I've seen a lot of change initiatives, but this AI rollout was one of the most significant in terms of its reach across the workforce.

Interviewer: How did employees initially react to the news of AI being implemented?

Interviewee (HR Director): Reactions were mixed at first. As you might expect, there was some anxiety, especially around job security. People were asking, "Will AI automate my job? Do I need to worry about layoffs?" On the other hand, some employees – particularly a lot of younger staff and tech-savvy folks – were excited and curious to try out new tools. Our approach in HR was to

address the concerns head-on and channel the curiosity. We were very clear in our communications that the goal was to use AI to augment our employees, not replace them. In fact, we worked closely with senior leadership to make sure our AI strategy was about growth and upskilling rather than cutting headcount. I think that reassurance from the outset helped ease a lot of fears.

Interviewer: What kind of training or reskilling initiatives did HR put in place?

Interviewee (HR Director): We rolled out a comprehensive training program. We started with awareness sessions even before the tools were implemented – basically “AI 101” seminars open to all employees to explain what AI is and what it isn’t. Then, as specific AI applications were introduced in departments, we provided hands-on training for those teams. For example, when we introduced an AI-driven analytics dashboard to the marketing team, we held workshops so they could learn how to use it effectively in their day-to-day work. We also created an online learning portal with courses on data analysis, machine learning basics, etc., so employees could self-serve and learn at their own pace. In some cases, we did more formal reskilling: one example is that a few folks from our traditional IT support team underwent training to become junior data analysts working with the new AI systems. A general theme of our approach was “continuous learning” – encouraging employees to keep building their skills, not just through one-off training but through ongoing development.

Interviewer: How did the implementation of AI affect jobs and roles in the company?

Interviewee (HR Director): We definitely saw roles evolving, but not disappearing. AI took over certain tasks – for instance, some routine data entry and report generation became automated. That meant that the people who used to spend a lot of time on those tasks could shift to more valuable work. Take our financial analysts: previously they might spend days compiling reports; with AI generating those reports, they can focus more on interpreting the data and strategic planning. In customer service, we introduced an AI chatbot to handle basic inquiries, so our customer service reps are now dealing with more complex customer issues rather than repetitive questions. There were a few areas where we needed fewer manual hours due to AI efficiency gains, but instead of cutting staff, we chose to reassign those employees to new projects – sometimes even expanding into areas we couldn’t focus on before. Also, we created some new positions – for example, we brought in a data analyst and even appointed an AI ethics officer on a part-time basis. Those offered

opportunities for internal transfers and growth. So overall, while day-to-day tasks changed, our workforce size remained stable and we tried to use AI as a chance to enrich jobs rather than eliminate them.

Interviewer: From an HR perspective, what has been the impact on the company culture?

Interviewee (HR Director): I've observed a shift towards a more learning-oriented and innovative culture. Initially, there was uncertainty, but as employees became more comfortable with the tools, many started taking initiative, like experimenting with the AI tools to improve their work. The fear of AI has largely given way to an attitude of "this is interesting, how can I use it." We also notice more cross-department collaboration now – for example, marketing folks might talk to data scientists or IT more regularly when they have an idea for a new AI use case. The key for culture was transparency: we in HR made sure to keep communication lines open. We had feedback channels – like Q&A sessions and surveys – so people felt heard throughout the transition. By addressing concerns promptly and celebrating successes, employees became more engaged. Morale, after a dip at the start, actually improved as people started seeing some of the mundane parts of their jobs being eased by AI. It's not perfect – some employees still prefer old ways for certain tasks – but overall the mindset is much more open to innovation now.

Interviewer: What advice or lessons learned would you share from the HR side of an AI rollout?

Interviewee (HR Director): One big lesson is that you cannot over-communicate during a change like this. We found that constant communication – whether it was from top leadership or through HR channels – was essential to build trust. Another lesson is to involve employees in the process; for instance, we included a few frontline staff in the selection of an AI tool for their department, and that helped get buy-in later. Also, providing support is crucial: training shouldn't be a one-time thing. We offered follow-up refresher sessions and set up a helpdesk specifically for questions about the new AI systems for the first few months. From a people perspective, I'd say assume that there will be anxiety and address it with empathy. Show employees how AI can benefit them personally – like reducing drudgery or helping them develop new skills for their career growth. Finally, ensuring fairness and ethics is part of HR's role: we worked with IT to make sure, for example, that our AI-driven HR tools (like a resume screening system we tested) were monitored

for any bias and used responsibly. Taking care of those aspects builds confidence among employees that the technology is being used in a thoughtful, human-centric way.

Interview 5: Operations Manager (Manufacturing Plant)

Interviewer: Could you introduce yourself and describe your position in the company?

Interviewee (Operations Manager): I'm an Operations Manager overseeing one of Alpha Group's manufacturing plants. I've been with the company for about 8 years, working my way up from a production supervisor to managing the entire plant. In the context of our AI implementation, I was closely involved in rolling out and using the new AI tools on the factory floor – particularly an AI-driven predictive maintenance system that we adopted.

Interviewer: What did the AI predictive maintenance system do, and why was it introduced?

Interviewee (Operations Manager): The predictive maintenance AI system monitors our machinery and production lines using sensors and data. It analyses things like vibration, temperature, and other parameters to predict when a machine might need maintenance or is likely to fail. Before we had this, we relied a lot on scheduled maintenance and the experience of our technicians to catch issues. The AI was introduced to help us catch problems earlier – basically to shift us from reactive fixes (after a breakdown) to a proactive approach (fixing things before they break). The goal was to reduce unplanned downtime on the lines and avoid those sudden machine failures that can really disrupt production.

Interviewer: How did your team react when this AI tool was first brought in?

Interviewee (Operations Manager): Honestly, there was some skepticism at first. Our maintenance technicians and line operators are very experienced; some of them have been doing this for 20-30 years. When we told them an AI would help predict equipment issues, a few were doubtful – you know, “Can a computer really know the machines better than we do?” There was a bit of pride and worry mixed together. Some were worried that if the AI was making decisions, would their expertise still be valued? Plus, initially, people weren't sure how much to trust the system's alerts. In the first few weeks, whenever the AI flagged a machine as at-risk, some technicians would double-check manually and sometimes say “it seems fine to me.” There were

even a couple of instances where the AI gave us a false alarm or two at the beginning, which reinforced the skepticism.

Interviewer: How did you address those concerns and integrate the AI into daily operations?

Interviewee (Operations Manager): We took a very collaborative approach. I sat down with the maintenance team and we talked through how the AI works and that it's a tool to help them, not replace their judgment. We decided to treat the AI's predictions as an additional input. For a while, we ran the AI in parallel with our traditional methods – the AI would flag something and we'd also have a human inspect it. Over a few months, the team saw that the AI was right more often than not. One memorable example: the system predicted an issue with one of our critical compressors – something about an anomaly in vibration patterns. Our technicians checked and, indeed, they found a part that was wearing out prematurely. We replaced it during a scheduled maintenance window and avoided what could have been a major breakdown. That incident really converted a lot of the team to trusting the AI. We gradually built confidence to the point where now if the AI flags something, we act on it pretty quickly. We also worked with the IT and data science team to fine-tune the system based on feedback from our technicians, which improved its accuracy and reduced those early false alarms.

Interviewer: What kind of improvements have you seen in operations since using AI?

Interviewee (Operations Manager): It's been quite positive. Unplanned downtime at my plant has dropped significantly – I'd estimate on the order of a 15-20% reduction in unexpected outages over the last year. That's a huge win because every minute a line is down costs money and delays orders. We've also seen maintenance costs stabilize or drop, because we're preventing big failures that are expensive to fix. Another improvement is in our maintenance scheduling. The AI helps us optimize when to do maintenance – neither too early (wasting part life) nor too late (after a failure). That's made our whole operation more efficient. From a people perspective, once the team got used to it, they actually appreciate it now. Our technicians aren't firefighting breakdowns as often; instead, their work has shifted to more planned interventions, which is less stressful. They spend more time on improving processes rather than just fixing things in emergency mode. I've also noticed safety improvements – preventing breakdowns means we have fewer sudden incidents, which is safer for everyone on the floor.

Interviewer: As someone managing a plant, what are your thoughts on AI now, and any lessons you learned?

Interviewee (Operations Manager): I'll admit, I was cautiously optimistic at the start, but I'm now a big supporter of these tools. One lesson I learned is the importance of training and involving the team. We made sure to train our people on how to interpret the AI system's dashboard and alerts. We also encouraged them to give feedback – if they thought an alert was not useful or if the AI missed something, that went back to the implementation team to improve the system. That involvement helped folks feel ownership. Another takeaway is that trust isn't built overnight; you have to give it a little time. We needed to see the AI in action, let it prove itself, and now it's just part of how we do things. From a management perspective, I also learned that you have to champion the change. I spent a lot of time early on just listening to concerns and reinforcing that this was a positive change. Now that we've seen results, the skepticism has largely turned into "What else can we do with AI?" In fact, my team is now coming up with ideas for other ways AI could help us, which is a great change from where we started.

Interview 6: Chief Financial Officer (CFO)

Interviewer: From a financial standpoint, could you introduce yourself and describe your involvement in the AI initiative?

Interviewee (CFO): I'm the Chief Financial Officer of Alpha Group. My role in the AI project was to ensure that it made business sense financially – essentially, I oversaw the investment, the budget for the initiative, and I've been tracking the returns and financial impact. I've been with the company's finance department for about 10 years, and as CFO for the last 3. When the idea of a broad AI implementation was first proposed by our CEO and tech team, I was one of the people who asked the tough questions: What will it cost? What's the expected ROI? What are the risks? So I was deeply involved from planning through execution, making sure the numbers added up and that we allocated resources effectively.

Interviewer: How did you build the business case for investing in AI?

Interviewee (CFO): We approached it very systematically. We identified key areas where AI could either increase revenue or decrease costs. For example, in operations we expected reduced

downtime (which translates into cost savings and higher output), in marketing we hoped for better targeting (potentially increasing sales), and in back-office processes like finance and HR, we anticipated efficiency gains (saving time and labor on manual tasks). We worked with each department to estimate these benefits. On the cost side, we calculated the expenses: software or platform costs, hardware upgrades, hiring or training staff, even the cost of change management like training hours. At first glance, it was a significant upfront investment – not just in technology but also in people. We took those estimates to the board with a projection that, over a 3-5 year period, the AI initiative would more than pay for itself through efficiency improvements and by enabling growth opportunities. I recall one of the major capital expenditures was setting up the data infrastructure and signing a contract with an AI solutions provider – those were big ticket items that we had to justify. Ultimately, the board approved the investment because we showed both quantitative benefits (like an expected X% increase in productivity in certain processes) and strategic benefits (like staying ahead of competitors and gaining better insights for decision-making).

Interviewer: Now that the implementation has been underway, what has been the financial impact? Are you seeing the ROI you hoped for?

Interviewee (CFO): We're tracking positively, though some benefits take time to fully materialize. In areas like manufacturing, as we heard from our ops team, we've seen tangible savings – less downtime and more efficient maintenance has saved on overtime and repair costs. We've calculated that for one of our major production facilities, the AI-driven maintenance system saved about 5% of the annual maintenance budget in its first year by avoiding major breakdowns. In the corporate finance department itself, we implemented an AI tool to automate invoice processing and another to help with financial forecasting. The invoice processing automation has cut the time my team spends on that task by around 30%, which means they can focus on more analytical work instead of paperwork. Our monthly and quarterly financial closes are now a bit faster as well, thanks to fewer manual reconciliation errors (the AI flags anomalies for us). In terms of revenue impact: it's a bit trickier to isolate AI's contribution, but I know our retail division credits the AI-driven demand forecasting with reducing stockouts, which likely means higher sales than if we had missed those opportunities due to inventory issues. Overall, when I compare the

cumulative costs so far to the cumulative savings or revenue enhancements, we're on track to achieve the ROI we projected over the multi-year period. It's not instant magic – some areas delivered quick wins, others are more long-term – but I feel confident the investment was worth it.

Interviewer: Were there any challenges from a finance perspective during the project?

Interviewee (CFO): One challenge was ensuring we had proper metrics to measure the impact. It's one thing to approve a project with expected benefits, but we needed to verify those benefits actually happened. So we set up a tracking system: key performance indicators for each AI use case. For example, we monitored the downtime hours before and after the predictive maintenance system, or the time spent on certain processes pre- and post-AI. Gathering that data took effort, but it was important for accountability. Another challenge was managing the budget in real-time; large projects can run into cost overruns. We did face some unexpected costs – for instance, we decided mid-way to upgrade some network security to protect the new data flows, which wasn't in the original budget. We had to make a case internally to allocate extra funds for that. Also, from a change management side, we offered incentives for completing training and adapting to new systems, which is a somewhat unusual expense but we felt it was necessary to encourage adoption. As CFO, I had to be flexible and see those expenditures as investments in success rather than just overruns.

Interviewer: What's your perspective now, as CFO, on the AI transition overall?

Interviewee (CFO): I'd say it's been a positive transformation. Financially, the company is healthier for it – we're operating more efficiently. But beyond the numbers, I see that we've positioned Alpha Group for future growth. We now have better data and insights at our fingertips when making decisions, whether it's budgeting, forecasting, or strategic planning. From a finance leader's perspective, one of the best outcomes is that we can be more proactive. For example, the forecasting AI gives us early warnings about potential downturns or demand spikes, so we can plan contingencies or investments well in advance. I also believe that showing our stakeholders – including investors – that we are leveraging AI and improving our operations has increased their confidence in our management. In terms of lessons, I learned that when it comes to innovation, you have to look beyond the immediate cost and consider the cost of not doing it. If we had decided

not to invest in AI, I suspect we'd gradually lose our competitive edge. So part of my job was reframing the discussion from "What does it cost?" to "What's the value, and what's the risk if we don't move forward?" Seeing the results now, I'm glad we made the leap.

Interview 7: Marketing Manager (Retail Division)

Interviewer: Can you tell us about your role and how the marketing department used AI?

Interviewee (Marketing Manager): I'm a Marketing Manager at Alpha Group, responsible for our retail and e-commerce division's marketing strategy. When our company began its AI journey, I was tasked with integrating AI into our marketing operations. That meant finding ways to use AI for things like customer analytics, personalized marketing campaigns, and improving our digital advertising performance. I've been in marketing for around 10 years, and this was a new frontier for me and my team, so it was both exciting and a bit daunting.

Interviewer: What specific AI tools or applications did you implement in marketing?

Interviewee (Marketing Manager): One of the first things we did was adopt an AI-driven analytics platform. Previously, we had tons of customer data – purchase history, website behaviour, etc. – but analyzing it to draw insights was slow. The AI platform can sift through all that data and segment customers in clever ways or identify patterns we might miss. For example, it helped us discover a segment of customers who tend to buy certain products only during a particular season, which informed a targeted campaign. We also started using AI algorithms for personalization on our website and in email marketing. If you visit our online store now, the product recommendations and offers you see are curated by AI based on your browsing and buying behaviour. Additionally, we experimented with an AI tool that generates draft content – it can suggest social media post ideas or email subject lines, which our team then refines. So broadly, analytics, personalization, and a bit of content assistance were key areas.

Interviewer: How did your marketing team react to using AI tools?

Interviewee (Marketing Manager): There was a mix of enthusiasm and a bit of uncertainty. Marketers are creative folks, and some worried that AI might take over the creative part of our jobs or make our roles less important. On the other hand, many of us were excited at the prospect of automating the tedious parts of our work, like compiling reports or crunching numbers from

campaigns. To get everyone comfortable, we did training sessions. We had data analysts walk the team through the new analytics dashboards, and we even did a fun internal contest where we compared our own campaign targeting plans against the AI's suggestions to see who performed better. That exercise showed that AI could find some audiences we hadn't thought to target, which was eye-opening. Over time, as the team used the tools more, the comfort level grew. The content generation tool, for instance – at first, copywriters were skeptical of “machine-generated copy,” but when they saw it as a starting point or a creative aid rather than a finished product, they began to find it useful to beat writer's block. It definitely sparked a lot of internal conversations about how our jobs might evolve, but at this point I'd say most of the team sees AI as a helpful part of our toolkit.

Interviewer: Have these AI-driven marketing efforts paid off in terms of results?

Interviewee (Marketing Manager): Yes, we've seen pretty positive results. Our campaign targeting is more precise now. One example: we used AI to optimize our email marketing segments and content. We saw a noticeable uptick – about a 20% increase – in email open rates and click-through rates after we started personalizing content with AI insights. It seems customers are engaging more when the content closely matches their interests. Also, the product recommendation engine on our website has contributed to an increase in average order value, because customers often discover an extra item they're interested in. In digital advertising, the AI helped us allocate budget more efficiently among channels by predicting which audiences were most likely to convert, so our return on ad spend improved last quarter. I'd add that the speed of executing campaigns has improved too. What used to take us weeks of analysis to decide targeting now might take a few days, since the AI does the heavy lifting of crunching data. That means we can run more campaigns or iterate faster than before.

Interviewer: From your perspective, what are the key takeaways about implementing AI in marketing?

Interviewee (Marketing Manager): For marketing, I've learned that AI is a powerful enabler, but it doesn't replace human creativity or intuition – it augments it. The best outcomes we got were when we combined the AI's data-driven suggestions with our team's creative know-how and understanding of our brand. Another takeaway is the importance of data quality. We discovered

some of our customer data was outdated or inconsistent, and if you feed bad data into AI, you get bad recommendations out. So we worked with our IT team to clean up the marketing database early on. Also, I'd say it's important to manage the team's mindset: we framed AI as a tool that would handle grunt work and help generate insights, freeing the team to focus on strategy and creative thinking. That helped alleviate the fear of "AI taking over jobs." Finally, continuous learning is key – the digital marketing landscape, especially with AI, changes quickly. We regularly share new tips or capabilities of our AI tools in team meetings so everyone stays up to date. Overall, adopting AI has made our marketing more effective and driven more of our decisions with evidence, which is crucial in today's competitive market.

Interview 8: Customer Service Manager (Support Center)

Interviewer: Please introduce yourself and explain your role in relation to the AI project.

Interviewee (Customer Service Manager): I'm the Customer Service Manager at Alpha Group, overseeing our call center and customer support operations. I've been managing our customer service team for about 5 years. When we implemented AI, my role was to integrate tools like chatbots and AI assistants into our customer support workflow and manage the changes in our team's operations. Basically, I was responsible for ensuring that the AI helped our customers and agents, rather than causing disruption.

Interviewer: What AI technologies have you implemented in customer service?

Interviewee (Customer Service Manager): The main one is an AI-powered chatbot on our website and messaging channels. It's designed to handle common inquiries 24/7. Things like answering frequently asked questions about our products, helping customers track orders, or guiding them through basic troubleshooting steps. We also have an AI-driven system that assists our human agents: when a customer question is complex and gets escalated to a live agent, the AI provides the agent with suggested responses or pulls up relevant information from our knowledge base. It's like having a real-time assistant for the agents. And all the simpler queries – the chatbot handles those end-to-end if it can. If the AI can't resolve an issue, it automatically forwards the customer to a human agent along with a summary of the problem, so the agent has context when they take over.

Interviewer: How did your customer service team react to these AI tools initially?

Interviewee (Customer Service Manager): There was understandable concern in the beginning, mainly around job security. Some of our representatives were worried that if the chatbot handled a lot of inquiries, there might be less need for staff. We addressed this head-on by explaining that the chatbot was there to help manage growing inquiry volumes and free up agents to focus on more complex customer needs – not to replace them. We were also transparent that no one would be losing their job due to the chatbot; instead, if it succeeded, it would handle the simple stuff and allow us to use our human talent on more value-added service. Training was also a big part of easing concerns. We trained our agents on how to work alongside the chatbot – for example, how to take over a conversation seamlessly when the bot hands it off, and how to use the AI’s suggestions during a live chat or call. Some agents were skeptical of the AI’s answers at first (“Can it really give the right info?”), but after testing and seeing it in action, confidence grew. We involved a few experienced agents in the bot’s development, like helping to feed it with the right FAQs and checking its answers, which also helped build trust in the tool.

Interviewer: Have these AI implementations affected the customer service metrics or outcomes?

Interviewee (Customer Service Manager): Yes, in several positive ways. For one, our response times for basic inquiries improved dramatically. Customers now get instant answers from the chatbot for simple questions instead of waiting in a queue for an agent. We saw our average response time for those common questions drop from a couple of hours (during peak periods) to virtually zero wait. That has a big impact on customer satisfaction – people appreciate quick answers. For the team, because the chatbot takes the load of repetitive queries (I’d estimate it handles about 30-40% of our total inquiry volume now), our human agents are less overwhelmed during peak periods. They can spend more time with customers who have complex issues, which means those issues are resolved more thoroughly. Since agents aren’t rushing through calls just to get to the next one, our customer satisfaction scores on complex cases have actually gone up because agents have the bandwidth to really focus on each customer. We also track something called first-contact resolution rate – resolving an issue in one go – and that improved slightly as well, because the AI handles the simple stuff and our agents can concentrate on the stickier problems. Efficiency-wise, we’re also seeing gains: last year, even as our customer base grew and

inquiries increased, we didn't have to expand our support team as much as we would have without the chatbot. The AI absorbed a lot of the extra volume, which is a cost savings and efficiency boost for the company.

Interviewer: From a managerial perspective, what have you learned about blending AI with customer service?

Interviewee (Customer Service Manager): I've learned that the human touch is still essential, but AI can enhance it if implemented thoughtfully. One lesson is the importance of a phased rollout. We started the chatbot with a limited set of topics and closely monitored its performance. That allowed us to fix any wrong answers or misunderstandings before expanding its scope. Another lesson: keep the door open for customers to reach humans. We made it easy for users to say "I need a human" at any point, so they don't get frustrated if the bot isn't helping – that was key to maintaining customer trust. From the team side, involving my staff in the AI implementation (like having them help train the AI and provide feedback on its responses) turned out to be crucial. It made them feel part of the process rather than victims of it, and it improved the AI because it was tuned with frontline insights. Communication is also something I'd stress – we regularly shared data with the team showing how AI was helping (like the volume of inquiries handled by the bot), so they understood it's a tool that makes us better rather than a threat. Finally, I've realized we need to continually update the AI – as our products or policies change, we have to update the chatbot's knowledge base. It's not a "set and forget" thing. But if you maintain it, the payoff is smoother operations and a better experience for both customers and employees.

Interview 9: Senior Financial Analyst (Finance Department)

Interviewer: Could you introduce yourself and describe how your job has been affected by the AI implementation?

Interviewee (Financial Analyst): I'm a Senior Financial Analyst in Alpha Group's finance department. I focus on budgeting and forecasting for one of our divisions. I've been in this role for about 4 years. Before the AI tools came in, a large part of my job was gathering data from different departments, plugging numbers into spreadsheets, and generating reports or forecasts. Since the AI initiative, I've started using an AI-based forecasting system and some automation tools for data

analysis. So my job has shifted from spending a lot of time on manual data crunching to interpreting the insights that the AI provides and working on more strategic analysis.

Interviewer: What were your initial thoughts when you heard AI was coming into your workflow?

Interviewee (Financial Analyst): At first I had mixed feelings. On one hand, I was actually a bit excited because I knew how time-consuming some of our manual processes were and hoped automation would make life easier. On the other hand, I was a little anxious – I wondered, “If an AI can analyse financial trends or create a forecast model, what does that mean for my role? Will my expertise be less valuable?” There was also a learning curve that I was concerned about; I’m pretty good with Excel and our old systems, but I wasn’t sure how quickly I could pick up using AI-driven software or if I needed to learn some programming. We did receive training sessions when the new tools were introduced, which helped demystify them. I remember the first time the AI forecasting tool spit out a projection, I double-checked all the numbers manually because I wasn’t fully confident in it yet! Over the first few months, I compared my traditional forecasts to the AI’s results to see if it was reliable.

Interviewer: How do you use AI in your day-to-day work now?

Interviewee (Financial Analyst): It’s become a regular part of my workflow. For instance, at month-end, instead of spending hours collecting data from various reports, I use an AI-powered consolidation tool that automatically pulls data from our sales, expense, and other systems into a single report. That saves me a ton of time. Then for forecasting, the AI model analyses historical data and current trends to produce an initial forecast for the next quarter. My job is to review that forecast, sanity-check it, and add the human context – things the AI might not know, like an upcoming marketing campaign or an unusual one-time expense we expect. So I’m interacting with the AI system to adjust assumptions and ask “what-if” questions. It’s almost like collaborating with a junior analyst: it does the grunt calculations really fast, and I focus on refining the outputs and making judgment calls. I also use a visualization tool that quickly generates charts and graphs for presentations, which used to take me a while to do manually. Overall, I still use my financial knowledge every day, but the tools speed up the number-crunching and even surface insights – for example, the AI might flag an anomaly in expenses that I wouldn’t have noticed immediately, so I can investigate it.

Interviewer: How has the quality or efficiency of your work changed with AI?

Interviewee (Financial Analyst): My efficiency has definitely improved. Tasks that took me days now take a few hours or less. I'd say I can cover a lot more ground in the same amount of time. For example, I can run multiple forecast scenarios in an afternoon, whereas before doing one scenario might have been a full day of work. The quality of insights has improved too. The AI sometimes catches correlations or patterns in the data that I might have missed. For instance, it pointed out a subtle trend where certain costs were rising in a specific region, which prompted me to look deeper and address it. By catching things like that, I can provide more thorough analysis to my managers. Also, the reduced manual workload means I have more time to think about the "why" behind the numbers and to work on recommendations, instead of just compiling reports. From an accuracy standpoint, our reports have fewer errors now because there's less manual data entry (which is where a lot of mistakes used to creep in). I also feel that our forecasts are more robust; last quarter, our revenue projection was almost spot on, and I attribute part of that to the AI model helping fine-tune our assumptions with real-time data.

Interviewer: Personally, how do you feel about your job now, having gone through this transition?

Interviewee (Financial Analyst): I actually find my job more satisfying now. Initially, I worried about my role, but it turns out AI has made the work more interesting for me. I do less rote spreadsheet work and more analysis and decision support, which is the part of the job I enjoy most. It's also been a great learning experience – I picked up new skills, like how to work with the AI system and even a bit of basic scripting to tweak some data processes. I feel like I've grown professionally because of this. And to be honest, I'm relieved that we treated the introduction of AI as an opportunity to upskill employees rather than replace them. Management encouraged us to learn and even sponsored an online course I took on data analytics to get better at using these tools – which makes me feel valued. Now I'm not really worried about AI taking my job; I see it as a tool that helps me do my job better. Of course, I still double-check important outputs, but my trust in the system has grown as it proved accurate. One lesson I'd share is that adapting to new technology is becoming part of the job for everyone. I'm glad I embraced it – it's actually made me more valuable to the company and made my day-to-day work more engaging.

Interview 10: Regional Sales Manager (Veteran Perspective)

Interviewer: Please introduce yourself and share your role and experience within the company.

Interviewee (Sales Manager): I'm a Regional Sales Manager at Alpha Group, and I've been with the company for over 25 years. I've climbed the ranks from a sales rep back in the day to now managing a regional sales team. With the AI initiative, our sales department started using a new AI-enhanced CRM system and some analytics tools to help with lead scoring and sales forecasting. Given my experience, I've seen a lot of changes in how we do sales, but this AI introduction has probably been one of the bigger shifts in recent memory.

Interviewer: How did you feel about the introduction of AI tools in sales, and how did your team react?

Interviewee (Sales Manager): I'll be honest – I was a bit sceptical and even uncomfortable at first. Sales has always been a very people-driven, relationship-driven field for me. The idea that an algorithm could tell us which customers to focus on or predict which deals would close felt like it was encroaching on an area where intuition and personal touch are so important. Some of my team, especially the younger salespeople, were more enthusiastic – they're used to data-driven tools and were curious to see what the AI could do. But among the veterans on my team, there was some quiet resistance. Folks would say, "I've been doing this for decades; I know my clients better than a computer does." There was also some fear – I even heard someone joke, "If the AI can sell, what will they need us for?" Of course, that's not the goal of the system, but it shows the initial mindset. Personally, I also worried I might struggle to learn the new system; I'm not as tech-savvy as some of our newer hires, so there was a bit of pride and a bit of anxiety mixed in.

Interviewer: How did the implementation actually go for your sales processes?

Interviewee (Sales Manager): The company rolled out an AI-enhanced CRM that could do things like prioritize leads based on their likelihood to convert, suggest next-best actions for a given client, and generate forecasts by analysing past sales data and the current pipeline. At first, I found it a bit overwhelming – the interface had a lot of dashboards and scores that I wasn't used to. We did get training sessions, which helped somewhat. I remember during training asking probably a hundred questions – like, on what basis is the AI scoring these leads? I wanted to understand the logic. Initially, I didn't fully trust the lead scores it gave. For example, the system might say "Client

X has an 80% chance to buy this quarter,” whereas my gut feeling, based on conversations, was that Client X was iffy. In a few cases I actually went against the AI’s suggestion – sometimes I was right, sometimes the AI was right. Over time, I think both the system got better (they adjusted the model as we gave feedback) and I started to see that it could pick up on patterns not obvious to us. It noticed, for instance, that certain types of inquiries or customer behaviours – which we might have ignored – often led to a sale down the line. One hurdle we had to overcome was data discipline – the AI is only as good as the data in the CRM. Some of us older sales folks weren’t the best at logging every call or detail into the system, which initially led to the AI making less accurate suggestions. We had to improve our data hygiene as a team to get the most out of it.

Interviewer: What is your perspective now on the effectiveness of these AI tools for sales?

Interviewee (Sales Manager): I’d say I’ve moved from sceptical to cautiously appreciative. The AI hasn’t revolutionized sales or made human skills obsolete, but it has become a helpful tool. For instance, the lead scoring, while not perfect, does help my team prioritize their time better. We’ve caught some opportunities that we might have overlooked because the AI flagged a customer who was quietly very interested (maybe based on their web activity or prior purchases) that a salesperson hadn’t been actively engaging with. The forecasting feature has actually been quite useful too – it provides a data-based baseline for our sales projections which, combined with our field knowledge, has made our forecasts more grounded. In the past, forecasting was a bit of a guessing game and sometimes overly optimistic; the AI’s objective take has added a layer of realism and highlighted where we might be too hopeful or where we might have hidden opportunities. That said, there are clear limitations. The AI doesn’t understand the nuance of personal relationships – like if a long-time client is going through a budget freeze or internal reorganization, I know that deal might stall, even if the AI sees strong engagement metrics. We’ve learned to use the AI’s insights but always layer on our own judgment and context.

Interviewer: What challenges or downsides have you noticed, and what would you advise to improve the experience?

Interviewee (Sales Manager): One challenge was definitely the learning curve, especially for those of us not as tech-oriented. I had to re-train myself to rely more on data and the system’s recommendations, without giving up my own instincts. Striking that balance was tough initially.

There were moments of frustration – like when the system would suggest an action that I knew wouldn't fly with a particular client (for example, it might prompt a generic promotional email when I knew the client was unhappy about a service issue; the AI didn't know that context). So a takeaway is that context and human insight still need to guide how we use the AI's suggestions. Another issue is that early on, the AI felt like extra work – we had to input a lot more data and update records diligently so the AI could do its analysis, which some of the team viewed as a chore. We overcame some of that by simplifying the data entry process and by explaining that better data in means more useful output from the AI. In terms of advice: I'd say give folks time to adapt and maybe pair up tech-savvy employees with veterans for peer support. That helped me – I often leaned on one of our younger sales ops specialists to navigate the software early on. Also, solicit feedback from the users; in our case, the company did listen when we said some AI suggestions weren't practical, and they tweaked the system accordingly. As a veteran employee, I'll also note that management did well by not forcing us to blindly follow the AI. They encouraged us to integrate it into our decision-making but ultimately left room for our judgment. That made it feel like a tool rather than a mandate or a threat. I'm still a bit old-school at heart, but I've come to see that if used wisely, AI can remove some of the guesswork and grunt work from the job and let us focus more on the human side of selling. It just shouldn't replace that human side, and I think our approach has respected that so far.