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A BLUEPRINT FOR THE ADOPTION OF AI-ENABLED ERP SYSTEMS TO ACHIEVE FINANCIAL REPORTING ACCURACY AND OPERATIONAL EFFICIENCY

BY B212594B

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Dedication

This project is dedicated to my family and loved ones

Acknowledgements

I Extend my profound gratitude to my supervisor for his support and mentorship in shaping this project. I also want to thank all participants in this project, including companies and individuals for their efforts and contributions

Abstract

This study investigated the adoption and impact of Artificial Intelligence (AI)-enabled Enterprise Resource Planning (ERP) systems on financial reporting accuracy and operational efficiency within Zimbabwean organizations. The research addressed a critical problem: the absence of a comprehensive, context-specific framework guiding Zimbabwean companies in effectively transitioning from legacy systems to AI-driven ERP platforms. The main objective was to develop a practical blueprint to facilitate successful adoption, thereby enhancing organizational performance in a resource-constrained environment. A mixed-methods research design was employed, combining quantitative surveys with qualitative interviews and case studies. Data were collected from 77 respondents across 100 organizations spanning 10 provinces and a diverse range of industries, including retail, manufacturing, and services. Quantitative data were analyzed using descriptive statistics, regression analysis, and paired t-tests to assess the effects of AI-ERP implementation. Thematic analysis was applied to qualitative data to extract deeper insights into adoption dynamics and user experiences. The findings confirmed that AI-enabled ERP systems significantly reduced financial reporting errors (by 38%) and improved timeliness and compliance of reports. Operational efficiency was also enhanced, with 71% of routine processes automated and decision-making quality markedly improved through predictive analytics. However, barriers such as legacy infrastructure, limited AI expertise, and organizational resistance were found to hinder widespread adoption. The study concludes that AI-enabled ERP systems offer transformative potential for Zimbabwean enterprises, provided implementation is supported by strategic alignment, robust data governance, and sustained capacity building. It recommends a phased adoption model that emphasizes stakeholder engagement, training, and investment in scalable infrastructure. These insights offer valuable guidance for policymakers, business leaders, and academics seeking to harness AI for enhanced corporate performance in emerging markets.

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CHAPTER I

INTRODUCTION

1.0 Introduction

This chapter presents a study on the adoption of AI enabled ERP systems in the financial reporting accuracy and operational efficiencies domain among Zimbabwean organizations. The article starts by explaining the background for the research and the purpose of the study and discusses the disruptive potential of AI in industrial systems alongside the barriers within the context of Zimbabwe. This chapter describes the problems, purpose, research questions and hypotheses that are driving the study. It also provides rationale for the study, assumptions, scope and limitations, definitions of terms, and a description of the organization of the dissertation. This grounding provides a basis on which to examine specific ways in which AI powered ERP-systems can influence digital transformation and consequently improve organizational performance in Zimbabwe.

1.1 Background of study

The incorporation of AI into Enterprise Resource Planning (ERP) has been a leap forward for business technologies worldwide. Genesis of ERP systems ERP systems started in early 1990s to meet the requirement of seamless business processes and centralized management of data. Originally only available to large organizations, these systems were designed to automate processes across finance, purchasing and people. But by the early 2010s, rapid advances in AI, especially machine learning, natural-language processing, and automation, were transforming ERPs from the static repositories of the past into intelligent platforms capable of real-time analytics, predictive modeling, and autonomous decision-making (McKinsey & Company, 2023). Internationally, multinationals like Amazon, Siemens, and Unilever took the lead in deploying AI-enhanced ERP solutions to fine-tune supply chains, anticipating market demand, and identifying financial irregularities at an unrivalled level of accuracy. These advancements set the stage for the infrastructure that is a key technology evolution in the management of the enterprise: AI as a driver of digital transformation. AI-infused ERP systems can add more than $25 trillion value to the global economy for mid-2030s, according to estimates by international consultancies (PwC, 2022).

On the African continent, initial sluggish speed in adopting ERP systems was because of under-developed infrastructures and financial challenges. Through the 2010s, many African businesses continued to use outdated systems or employ manual processes. But with the introduction of cloud computing and mobile technology, African companies started to adopt new-generation ERP solutions. More specifically, a big jump in AI investments occurred after 2015 in domains like banking, agriculture and manufacturing. Forward-thinking countries, such as Kenya, Nigeria, and South Africa, started testing the use of AI-powered modules on ERP to bring efficiency and transparency, particularly at scale around public service delivery and private sector competitiveness (World Economic Forum, 2022).

At the regional level, in Southern Africa, it was South African companies that led the attack to AI-powered digital infrastructure. Organizations including Sasol and Shoprite Holdings invested in ERP systems that leveraged AI technology, like SAP S/4HANA, to improve efficiencies and minimize reporting mistakes. Furthermore, regional integration initiatives under SADC's Industrialization Strategy and Roadmap (2015–2063) highlighted the importance for smart technologies as a step towards the sustainable growth of industry. These new possibilities were catalysts that led other countries to consider adopting comparable forms of technology. Clearly the discussion on AI and ERP systems has only started to pick pace especially here in Zimbabwe.

The trading environment in Zimbabwe has historically been characterized by erratic economic conditions, foreign currency supply challenges and legacy ICT systems resulting in manual or semi-automated systems which governed their core business operations. But from 2018 to 2023, a few organizations kicked the tires on the new generation of ERP apps as part of their wider digital transformation projects. These include Delta Corporation and Spar Zimbabwe systems where Microsoft Dynamics 365 and SAP Business One were assimilated respectively with positive signs of operational improvement and reporting effectiveness (Chikowore & Ncube, 2021). However, with these developments, AI penetration in ERP systems is still in its infancy in Zimbabwe.

Factors including expensive upfront costs, a lack of AI know-how, aversion to change and poor compatibility with existing legacy systems are obstacles for large-scale adoption. Further, there is also a lack of theoretical framework through which organizations can find out how to apply and derive benefits from AI enabled ERP systems.

As AI increasingly becomes a key driver for future enterprise success globally, local Zimbabwean businesses generally do not have the toolkits or strategic advice at hand to exploit its full potential. This is the setting in which this study is situated— to consider the AI-ERP integration journey at the global, regional and local levels and to present a practical blueprint that is uniquely geared towards organizations in in Zimbabwe that want to increase the accuracy of financial reporting as well as operational effectiveness through AI-ERP systems. In Zimbabwe, the stage of AI-driven ERPs is embryonic albeit with front-running companies like Spar and Delta Corporation that have already made successful initial attempts. For example, the use of Microsoft Dynamics 365 Business Central by Spar has increased supply chain performance and customer satisfaction, demonstrating the radical impact of AI in retail environments (Chikowore & Ncube, 2021). But there are barriers to its adoption including the integration with legacy systems, lack of technical skill and the high cost of deploying it, particularly for smaller businesses. This paper aims to overcome these barriers by examining how AI can improve the accuracy of financial reporting (error reduction and compliance) and operational efficiency (automation and data-driven insights).

I.2 Statement of the problem

Although the world over acceptance of AI-enabled ERP systems has been growing, Zimbabwean enterprises have had no in-depth framework to guide them on how well they could implement their system. As global enterprises increasingly used AI to enable predictive analytics, real-time reporting, and increased operational efficiency, local companies in Zimbabwe often continued with costly and time-consuming creaking legacy systems and a patchwork of processes. Prior research focused on niche applications of AI, for example inventory control, or forecast models but did not give information on comprehensive models beyond departmental levels of planning for the enterprise (Godbole, 2023).

This shortcoming proved particularly significant for Zimbabwe, in which technological innovation was often stifled by endemic economic crisis, poor infrastructure and poor technical expertise. A lot of companies that tried to roll out sophisticated ERP ended up with some of the following outcomes: cost over-runs, inadequate change control and low usage. In the absence of clear strategies and practical roadmaps, these activities generally led to sub-optimal results such as misallocation of resources, marginally weakened financial reporting and lost opportunities to improve operations.

The confusion of moving from traditional systems to AI-empowered platforms didn't help. The implementation challenge was substantial investments in IT, training, and business process engineering, which was often beyond the means of many SMEs. Its promise of improved financial precision and responsive decision-making mostly stayed latent within the Zimbabwean business environment.

The current study addressed that vacuum by focusing on the factors that contributed to the success or failure of AI powered ERP adoption in Zimbabwe in the past. Its goal was to create an implementable plan which organizations could use as a guide to navigating implementation challenges, based on empirical evidence and tailored to Zimbabwe's socio-economic context. Through this, the study tried to establish a basis on which to create competitive advantages through better financial reporting and operational efficiency.

1.3 Objectives of the study

This study was pursued with the following aims:

- The intent was to identify and define-advantages AI brought to ERP properties: higher operational efficiency – increase accurately in financial reporting – more informed decision-making Integration properties: sale and seasonal forecasting.
- The study examines ideas, which were successfully applied, on how AI could be integrated into ERP, both conceptually (business objectives) and tactically (specific AI applications, strategic implementation plan).

- Through analysis the research aims to find the technological, organizational and human related challenges in the path of adoption of AI-based integrated AI integrated ERP systems, and
- To provide counter measures for the challenges. The purpose of the study was to develop practical steps to adopt AI-enabled ERP systems for the success of an organization in alignment with their financial and operational objectives.

I.4 Research Questions

The study was shaped by the following questions:

1. How AI-empowered ERPs affect financial reporting accuracy and speed.
2. What are the operational benefits and challenges associated with adopting AI-enabled ERP systems.
3. What factors contribute to the successful implementation of AI-enabled ERP systems.
4. How do AI-enabled ERP systems influence the role of accounting professionals.

1.4 Statement of hypothesis

H0: AI- enabled ERP system implementation has no impact on the accuracy of financial reporting and operational efficiency in Zimbabwean organizations.

H1: AI-enabled ERP systems adoption has positive and statistically significant effect on level of financial reporting accuracy and operational efficiency in Zimbabwean companies.

I.5 Significance of the study

he inclusion of AI into ERP systems was a game changer for Zimbabwean firms as it promised to improve accuracy in financial reporting, reduce operational cycles and set such organizations apart from peers. Importance of the Study- The results of this study were of high importance for different stakeholders:

To the Researcher: The research says to the researcher it did enhance more knowledge on the practical issues and benefits of adopting AI-enabled ERPS on the Zimbabwean market and skills towards the trending and forefront of digital transformation. Recommendation

To Other Researchers: The study part of the wider academic dialogue in so far as (AI) in ERP integration particularly in very dynamic business environments such as developing economies. It provided the basis for further research into AI specific industry applications, ethical issues and societal implications of AI technologies (McKinsey & Company, 2023).

To Bindura University of Science Education: This study allowed the university to complement its study programs with AI and ERP systems, thus educating students for their life in digital management accounting and for careers in accounting technology.

For Zimbabwean Companies: The businesses, e.g. Delta Corporation and OK Zimbabwe, attained instrumental mileage, after adopting the suggested blueprint, for streamlining supply chains, controlling inventory operations, and achieving financial reporting accuracy, in terms of competitiveness (Chikowore & Ncube, 2021).

For Government Bodies: Organizations, such as the Zimbabwe Revenue Authority (ZIMRA), could adopt AI-based ERP systems to enhance their tax collection capabilities as well as to aid with economic forecasting to support national development (World Bank, 2022).

To legislation makers: The research informed policy formulation while the latter was positioned to develop a framework for promoting the adoption of ethical AI, data security, and regulatory compliance in line with that of Zimbabwe's (UNCTAD, 2023) Smart Zimbabwe 2030 Masterplan.

To Consulting Firms: Gutridge (Pvt) Limited, and other similar firms were offered the power of knowledge to guide their clients through the difficulties of AI-ERP integration, from managing costs and skills (Deloitte 2021).

1.6 Assumptions

The study was based on several assumptions to ensure its validity and applicability:

Reliability of data: It was taken for granted that the sophisticated accounting software systems of the cooperative organizations provided reliable information for the analysis of the success of AI in the ERP adoption.

Comparability between organizations: It was assumed that the organizations contained in the dataset can be inter-compared on a different level of comparison such as industry, scale, and type of business.

Leadership Commitment: It was expected that the organizations have high level of commitment by leadership, which is reflected in budgeted for resources and in offering appropriate trained personnel to integrate AI and ERP.

Technological Infrastructure: The research was predicated upon the notion that participating companies had sufficient IT infrastructure to affect the smooth incorporation of AI applications into their ERP systems.

Ethical Considerations: The study followed data protection policies, by acting as if ethical regulations (e.g., GDPR) apply, to guarantee anonymization and ethical integrity. Transparency of algorithms:

The software systems were assumed to be accompanied by clear documentation on the AI algorithms used, to analyze any potential biases involved, and to be transparent in the decision-making process.

1.7 Delimitations of the Study

Delimitations are the limitations that establish the parameters of a study. These limits facilitated an understanding of what this study was and was not about, further grounding and guiding its design and conduct. The limitations answered several important questions:

What were the issues addressed in this report?

The study in question was on the adoption AI-ERP systems in Zimbabwean firms specifically how they affect financial reporting accuracy and operational efficiency. It focused on 100 companies that had installed or were installing the systems, and 77 companies were able to respond with usable information.

Specifically, what were not the questions posed by this study?

They did not explore other technologies that were not associated with AI-ERP systems or larger economic/policy issues that might have had an impact on technology adoption, reporting accuracy, efficiencies. It further excluded organizations that were not in Zimbabwe and sectors where the adoption of AI-ERP was either not applicable or emerging.

What kind of treatment of these problems was realized, to what extent did the study go beyond this treatment, where did it stop?

The study probed the applied comprehension of AI-empowered ERP adoption including perceived benefits, challenges, and implementation tactics rather than technical software development or AI algorithm design. It also restricted its assessment to the early partial implementation of the system and the short to medium term impact seen during the 5-year study period.

How large was the being who was the origin of the information?

Data were gathered from a sample of 100 Zimbabwean firms that were chosen using purposive sampling and were that operating AI embedded accounting package. The sample was purposive to include all sectors and sizes of organizations, but it was not representative of the entire business sector in Zimbabwe. To conclude, the delimitations outlined the study's population, sample size, and variables, leading to a focused examination of AI-enabled ERP adoption in the studied context, while reflecting practical and conceptual limits to the research.

1.8 Limitations of the Study

Limitations were constraints that were believed to be outside the control of the researcher and imposed restrictions on the conclusion's generalizability and, in some cases, also on the applicability to practice. Although there were limitations, measures were taken to minimize their effect and to ensure the study's trustworthiness. The following restrictions were noticed and resolved:

Geographical Limitation: The survey was limited to organizations in Zimbabwe, which limited the generalizability of the results to other countries/regions with varied economic, technological and regulatory maturity. To counter the above, the study contextualized findings within the Zimbabwean socio-economic environment to add value for fellow developing economies.

Data Availability and Quality: Access to high quality, complete data from participating organizations was occasionally limited because of confidentiality issues and/or poor records. To mitigate this, triangulation of information was achieved by using more than one data collection tool, surveys and interviews, to enhance the reliability of the data.

Organizational Dynamics and Culture: The qualitative perspective may not have been effectively captured by the quantitative approach which may have overlooked the less tangible cultural, organizational and human elements associated with the adoption of AI-enabled ERP systems. In addition, qualitative information was added by means of interviews to obtain a deeper understanding of stakeholders' experiences and perceptions.

Variation in technical platforms: Unless the AI-enabled ERP systems were the same version, the type of software could challenge comparability of results. This was mitigated against in the study, which targeted common characteristics and functionality related to financial reporting and operational efficiencies.

Time Limitation: The research focused on the early stage of AI-enabled ERP adoption and its short-term assessment and therefore plays down the long-term effects. Acknowledging this, the study emphasized the call for longitudinal studies to examine long-term effects.

Notwithstanding these limitations, the rigor of the research design, triangulation through methods, and the transparent vet the authors applied to the reporting of the results contributed to the dependability and confirmability of the findings, which offers a credible basis on which to comprehend AI-driven ERP adoption in Zimbabwe.

1.9 Definition of Terms

To ensure clarity and a common understanding, the following key concepts and terms were defined as they were used in the study:

Core Concepts:

Enterprise Resource Planning (ERP): A software system used by companies to manage all their business processes, including finance, HR, manufacturing, supply chain management, and more. It aims to centralize data **and** create a single view of the entire organization. Examples include SAP, Oracle Cloud ERP, NetSuite, or Microsoft Dynamics 365 Business Central.

Artificial Intelligence (AI): Computer programs capable of performing tasks typically requiring human intelligence, such as learning from data, problem-solving, decision-making, and pattern recognition. AI is becoming increasingly integrated into ERP systems.

Machine Learning (ML): A subset of AI where algorithms learn patterns in data without explicit programming instructions. It is used for predictive analytics, forecasting, risk management, and fraud detection.

Deep Learning (DL): A subset of ML that utilizes artificial neural networks with multiple layers to analyze complex data such as images, text, and sound. This is particularly useful for unstructured data like customer feedback or market trends.

Big Data: Refers to large volumes of data generated by various sources (such as online transactions, social media activity, sensor networks) that are challenging to process and analyze using traditional methods. AI often plays a crucial role in effectively analyzing big data.

Operational Impacts:

Automation: Utilizing AI to automate repetitive tasks in ERP systems, allowing human employees to focus on more strategic work.

Data Analytics: Analyzing large datasets from ERP systems to uncover trends and insights that enhance decision-making.

Predictive Modeling: Employing machine learning models within ERP systems to accurately forecast financial performance, stock market trends, or customer behavior.

Process Optimization: Identifying bottlenecks and inefficiencies in business processes through AI analysis, leading to improved workflow efficiency.

1.10 Organization of the Dissertation

This dissertation was structured into five chapters to provide a logical flow and comprehensive coverage of the research topic:

Chapter1: Introduction

This chapter introduced the study by presenting the background, problem statement, research objectives, research questions, significance, assumptions, delimitations, limitations, and definitions of key concepts. It set the foundation and context for the entire research.

Chapter2: Literature Review

The second chapter critically examined existing theories and empirical studies related to AI, ERP systems, their integration, technology adoption models, change management, and the specific challenges faced by developing economies, including Zimbabwe.

Chapter 3: Research Methodology

This chapter detailed the research design, including the mixed-methods approach adopted. It outlined the population and sampling methods, data collection instruments such as surveys and interviews, data analysis techniques, and ethical considerations to ensure validity and reliability.

Chapter 4: Data Presentation, Analysis and Discussion

The fourth chapter presented and analyzed the data collected from participating organizations, utilizing both quantitative and qualitative methods. It addressed the research questions by interpreting the findings within the context of the study.

Chapter 5: Summary, Conclusions, and Recommendations

The closing chapter interpreted the findings in relation to existing literature, drew conclusions based on the research objectives, and provided practical recommendations for Zimbabwean organizations, policymakers, and future researchers. It also identified areas for further study.

1.11 Summary

Chapter One laid the foundation for this study by highlighting the transformative potential of AI-enabled ERP systems to improve financial reporting accuracy and operational efficiency in Zimbabwean organizations. It presented the research problem, emphasizing the lack of a comprehensive adoption framework within the local context. The chapter outlined clear objectives and research questions aimed at exploring the benefits, challenges, and strategies for effective AI-ERP integration. Key assumptions, delimitations, and limitations were acknowledged to frame the study's scope and validity. Definitions of core concepts ensured clarity and a shared understanding. Finally, the chapter described the overall structure of the dissertation, setting the stage for a detailed review of existing literature in Chapter Two, which will further explore theoretical and empirical insights relevant to the study.

CHAPTER II

LITERATURE REVIEW

2.1 Introduction

This chapter affords a wide-ranging review of the related literature specifically concerning the acceptance of AI-enabled Enterprise Resource Planning (ERP) systems and their contribution toward the accuracy of financial reporting and operational efficiency. The incorporation of artificial intelligence (AI) in ERP systems is a major transformation in organizational control and strategy formulation, as businesses around the globe compete for better efficiency and accuracy.

2.2 Purpose of literature review

This review provides the systematic search of theoretical and empirical studies related to the research issue. Theoretical literature explicates the basics and finds the variables and relationships related to proposed study and establishes a model to describe the phenomena under observation and to anticipate subject results (Mupfurutsa, 2019). Examples of these include Davis' (1999) Technology Acceptance Model (TAM), and Venkatesh et al. (2003) propose theoretical perspectives to make sense of the adoption of AI-enabled ERP systems

2.3 Theoretical Literature

The AI-supported ERP systems adoption is theoretically guided on various existing theories of technology acceptance and organizational changes:

Technology Acceptance Model (TAM): put forth by Davis (1989), TAM argues that perceived usefulness and perceived ease of use lead to technology acceptance. Considering AI-embedded ERP, a combination of software that reduces errors in financial reporting and that fits into regular user behaviors is money in the bank for accounting teams.

Diffusion of Innovations Theory: Rogers (2003) suggests that adoption rates depend on a technology's relative advantage, compatibility, complexity, trialability, and observability. AI-enabled ERP systems must demonstrate clear benefits, align with accounting practices, and offer pilot opportunities to gain traction.

Resource-Based View (RBV): From an RBV perspective, AI-enabled ERP systems are valuable, rare, inimitable, and non-substitutable resources that confer competitive advantages through enhanced data insights and operational agility (Barney, 1991).

These theories collectively highlight the socio-technical nature of AI-ERP adoption, underscoring the interplay between technological capabilities, human factors, and organizational dynamics.

Contingency Theory (Lawrence & Lorsch, 1967) emphasizes that there is no single best way to manage an organization; rather, the optimal approach is contingent upon various internal and external factors. When implementing AI-enabled ERP systems, organizations must adapt their strategies, structures, and processes to align with the unique demands and opportunities presented by these advanced technologies. This theory highlights the importance of context-specific considerations in the adoption process, acknowledging that what works for one organization may not work for another due to differing organizational structures, industry dynamics, or national socio-economic conditions (Donaldson, 2001).

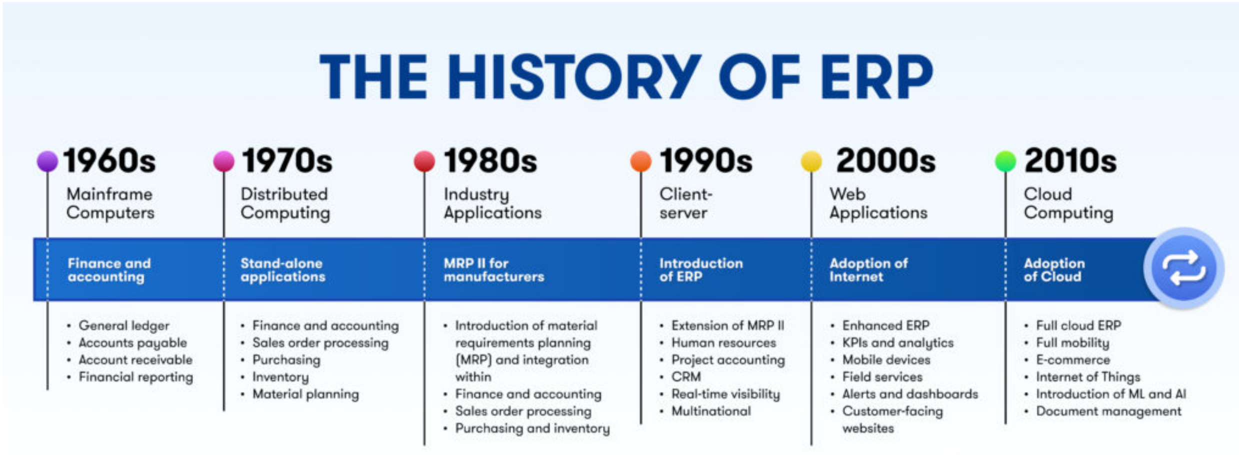
2.4. The Evolution of ERP Systems

2.4.1. Definition and Purpose of ERP Systems

Enterprise Resource Planning (ERP) systems are integrated software platforms that manage and automate core business processes across various departments, including finance, human resources, supply chain, and manufacturing. The main goal of implementing an ERP system is to have a single platform that provides complete visibility across the enterprise in real time, helping people to work together more effectively than before. It is this integration that propagates operational efficiencies, improved decision making, and strategic planning.

2.4.2. Historical Development of ERP Systems

ERP systems evolved from the MRP (Material Requirements Planning) systems that came along in the 60s and 70s In t6he 60s and 70s and which helped the companies to handle inventory and production processes. Stages of development as the role of such information systems became more integrated and more system components were added,



(source: Consultport)

Figure 1: Evolution of ERP

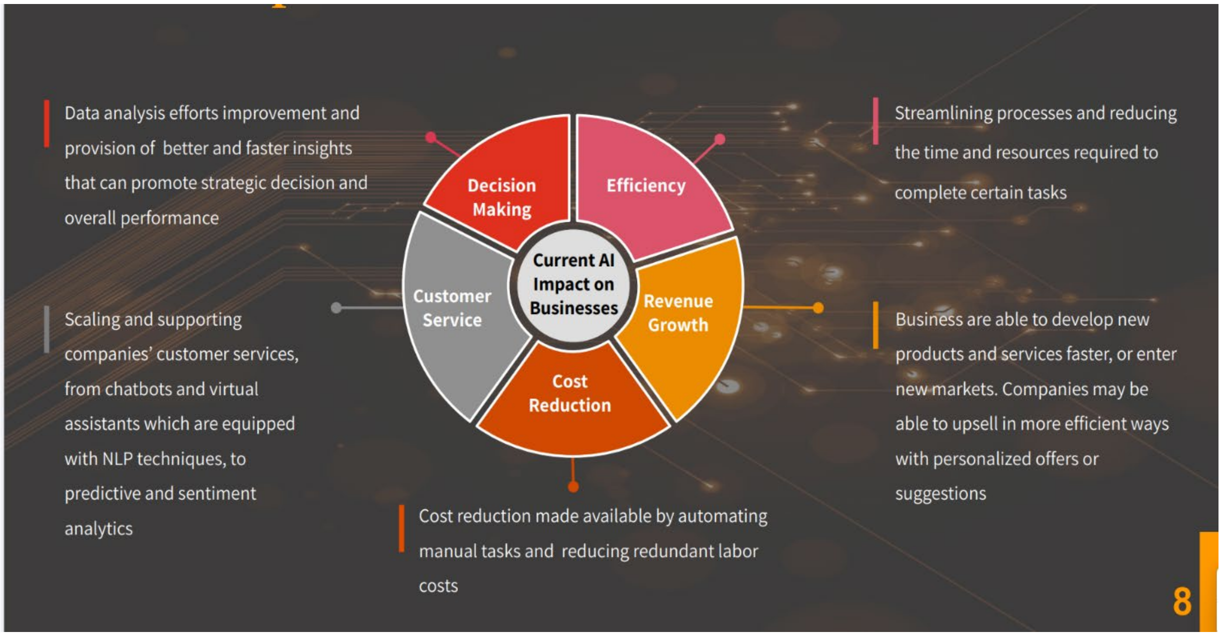
The 1990s introduced the real ERP systems, systems that tied all the business functions together into one tight-knit bundle. Major players in the ERP space, like: SAP, Oracle and Microsoft have built strong products, which are very flexible and scalable. As technologies progressed, ERP has developed web-enabled and cloud-based capabilities thus extending the reach and functionality of these systems.

2.5. Current Trends in AI Technologies

2.5.1. Overview of AI in Business

Artificial Intelligence (AI) denotes the process of making machines or computer systems to simulate human intelligence. In business, AI refers to technology such as machine learning, natural language processing, robotics, and predictive analytics. These systems allow companies to automate functions, process large amounts of information and generate useful knowledge

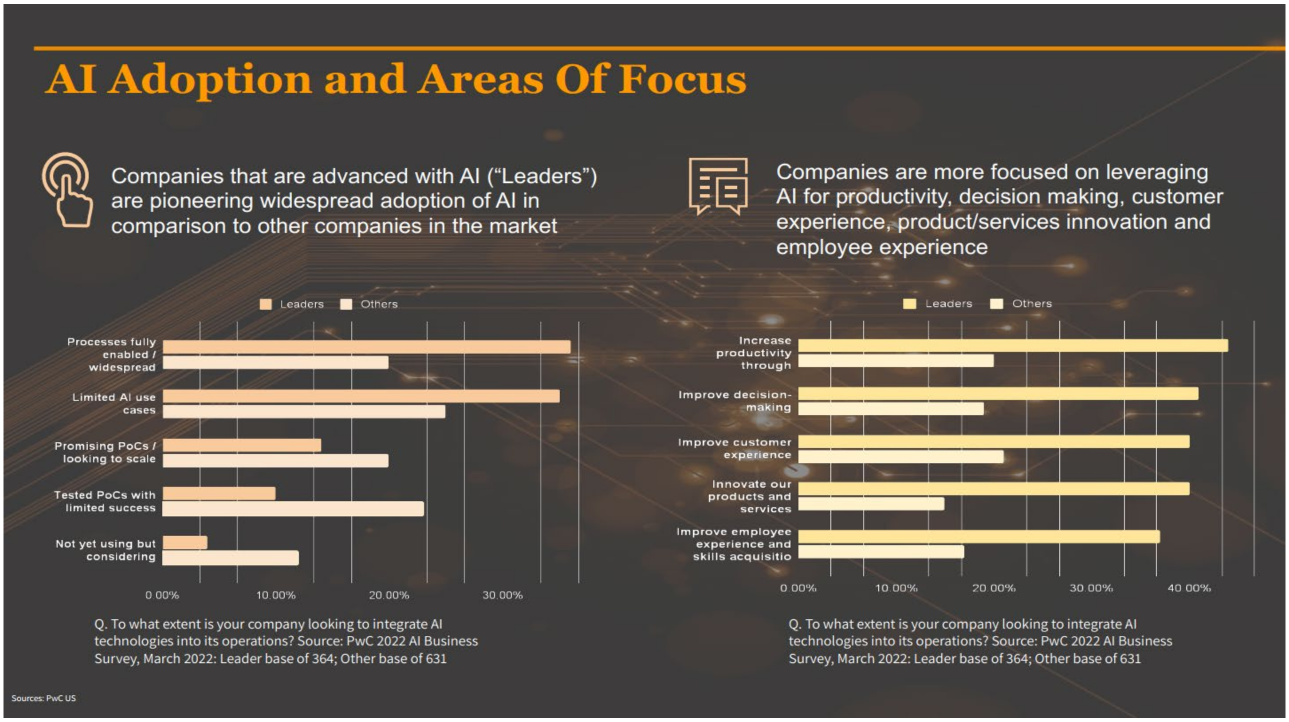
Ai Usage in Business



source: PwC US

Figure 2: AI ERP Usage in businesses

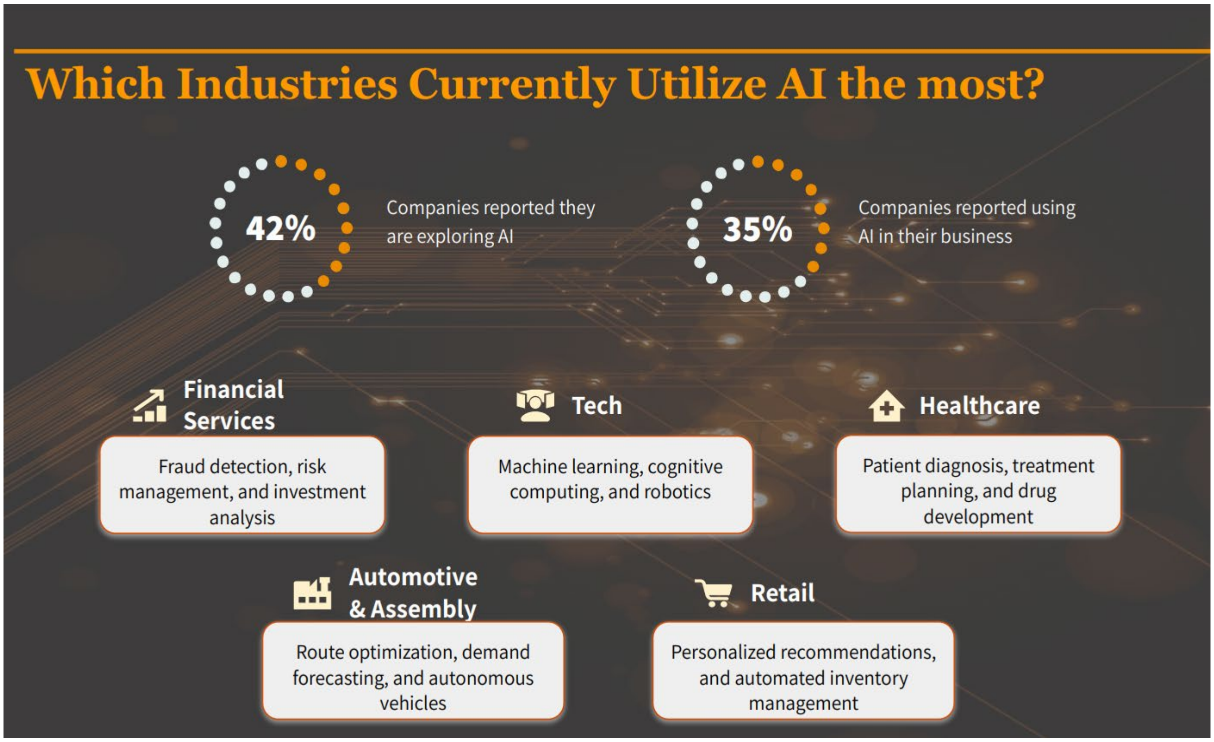
That's businesses using AI to drive measurable business results? For example, AI-driven data analysis provides real time information, allowing firms to turn on a dime (Davenport & Ronanki, 2018). The use of customer service automation like NLP powered chatbots offer reduced response times and uphold service quality (Forbes, 2022). Cost reductions stem from automating repetitive tasks, freeing human labor for higher-value roles—a trend validated by McKinsey's research on operational efficiency (Chui et al., 2022). Revenue growth, tied to hyper-personalization, aligns with Gartner's prediction that AI-driven marketing (Accenture, 2021) tools will boost sales by 30% by 2025 (Gartner, 2023). These impacts underscore AI's role as a multi-faceted enabler of modern business transformation.



source: PwC US

Figure 3: AI Adoption and Areas of Focus

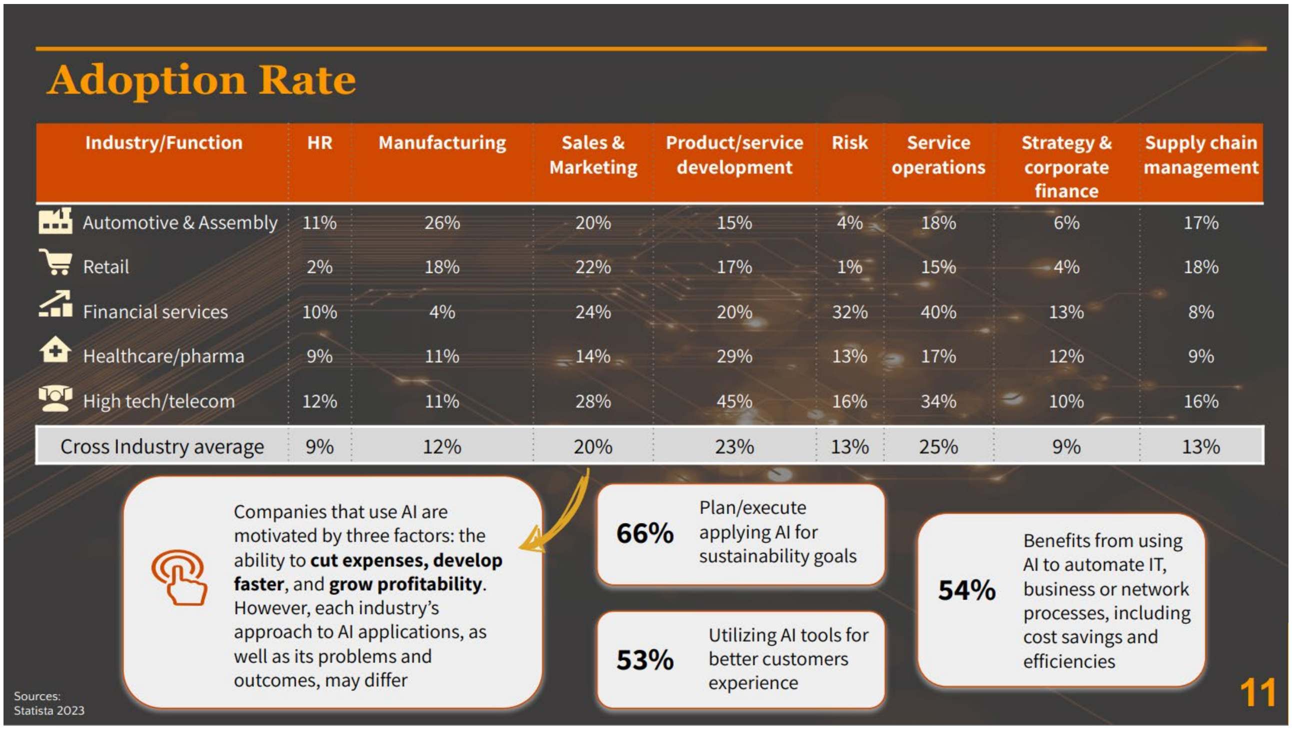
This chart highlights a strategic divide in AI adoption. Leading companies leverage AI holistically, embedding it into core workflows to drive innovation and employee upskilling practice supported by Brynjolfsson and McAfee's (2017) assertion that AI maturity correlates with organizational agility. The emphasis on customer experience mirrors findings from Accenture (2021), which links AI-driven personalization to 15% higher customer retention. Meanwhile, lagging firms' fragmented adoption reflects the "pilot purgatory" phenomenon, where isolated use cases fail to scale (Deloitte, 2022). The data suggests that comprehensive AI strategies, aligned with long-term business goals, yield disproportionate competitive advantages.



Source: PwC US, Forrester, IBM

Figure 4: Industries Currently utilizing AI the most

Sector-specific AI adoption reflects varying regulatory and operational needs. In finance, AI's dominance in fraud detection aligns with Ng and Kwok's (2022) study on anomaly detection algorithms reducing false positives by 50%. Healthcare's focus on diagnostics resonates with Topol's (2019) analysis of AI in medical imaging accuracy. Retail's reliance on recommendation engines mirrors Amazon's success in boosting conversions via machine learning (MIT Sloan, 2021). Meanwhile, automotive AI adoption for autonomous systems is driven by cost-saving potential; McKinsey estimates self-driving tech could reduce logistics expenses by 40% by 2030 (McKinsey, 2023). These trends highlight AI's adaptability to industry-specific challenges.

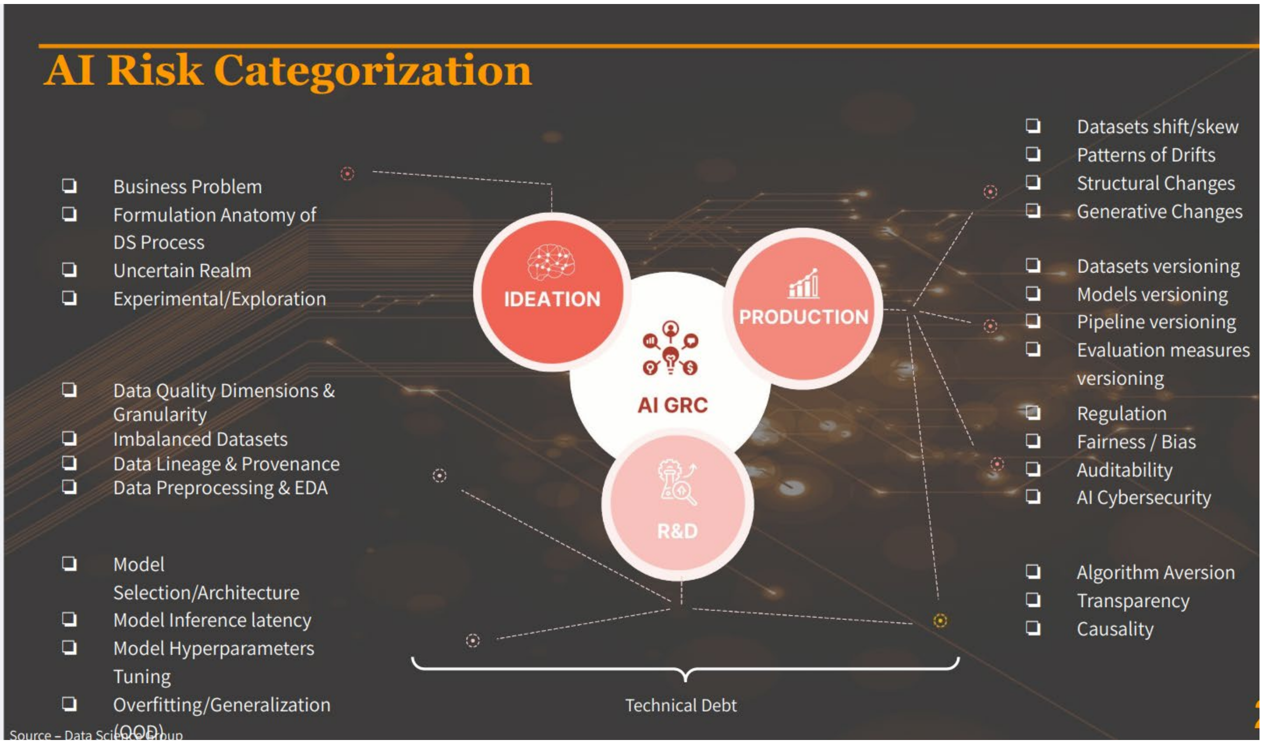


Industry/Function	HR	Manufacturing	Sales & Marketing	Product/service development	Risk	Service operations	Strategy & corporate finance	Supply chain management
Automotive & Assembly	11%	26%	20%	15%	4%	18%	6%	17%
Retail	2%	18%	22%	17%	1%	15%	4%	18%
Financial services	10%	4%	24%	20%	32%	40%	13%	8%
Healthcare/pharma	9%	11%	14%	29%	13%	17%	12%	9%
High tech/telecom	12%	11%	28%	45%	16%	34%	10%	16%
Cross Industry average	9%	12%	20%	23%	13%	25%	9%	13%

source: Statista 2023

Figure 5: Adoption Rate

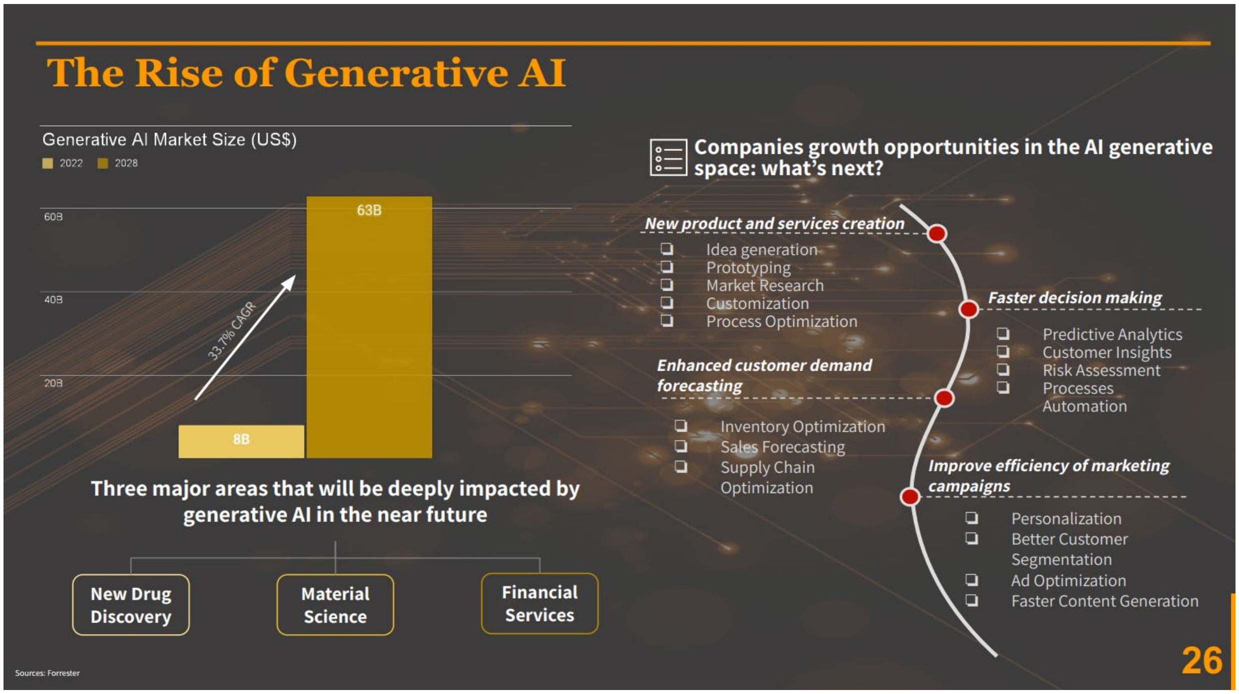
This heatmap underscores functional disparities in AI adoption. Financial services' high service operations adoption aligns with the sector's need for real-time transaction monitoring (Davenport, 2018). High tech's product development focus reflects agile R&D practices, where AI accelerates prototyping—a trend validated by IBM's 2022 case studies. Conversely, low HR adoption (9% cross-industry average) signals persistent challenges in automating subjective tasks like talent assessment, as noted by Cappelli et al. (2020). The data emphasizes that AI's value is maximized in data-rich, process-driven functions, while human-centric roles remain resistant.



source: Data Science group

Figure 6: AI Risk Categorization

This framework systematizes AI risks, emphasizing lifecycle-wide vulnerabilities. Data bias during ideation mirrors Obermeyer et al.'s (2019) findings on racial disparities in healthcare algorithms. Model overfitting, a technical debt risk, aligns with Sculley et al.'s (2015) critique of machine learning in production. Dataset shifts in production stages resonate with Google's 2022 incident where outdated training data caused search algorithm failures. Governance risks, particularly regulatory gaps, reflect the EU's struggle to enforce the AI Act's high-risk mandates (Veale & Zuiderveen Borgesius, 2021). The flowchart advocates for proactive risk management, a theme central to Floridi's (2021) ethics of digital governance.



source: Forrester

Figure 7: The rise of Generative AI

Generative AI's disruptive potential is evident in its applications. In drug discovery, platforms like DeepMind's AlphaFold reduce protein-structuring time from years to days (Nature, 2021). Material science applications, such as AI-designed polymers, align with MIT's 2022 breakthroughs in sustainable materials (MIT News, 2022). Financial services leverage generative models for synthetic data creation, addressing privacy concerns while training fraud detection systems (Dilmegani, 2023). The 33.7% CAGR projection mirrors Gartner's forecast of generative AI becoming a $110B market by 2030. However, ethical concerns persist, as raised by Bender et al. (2021), regarding misinformation risks from uncontrolled text generation

2.5 Empirical Literature

1. Determinants of AI-ERP Adoption

Technological, organizational and environmental drivers

Vukšić et al. (2025) apply an integrated TOE-TAM-RDT framework to examine factors shaping AI adoption in accounting and auditing firms. Using PLS-SEM on a survey of global AAFs, they find that competitive pressure, vendor ecosystem maturity, top-management support, perceived relative advantage, organizational AI readiness and innovation climate all significantly drive AI uptake (Bin-Nashwan et al. 2024). Big-data governance practices (data management quality, ethical controls) further moderate the positive effects of AI on reporting accuracy and audit efficiency, underscoring the need for robust information-governance infrastructures alongside technology acquisition.

Contextual and socio-demographic enablers

In a survey of 454 Lebanese accountants, El-Haddad et al. (2024) reveal that demographic variables—especially age and years of experience—mediate perceptions of AI's benefits. While younger, less-experienced professionals report stronger expectations of efficiency gains, more seasoned accountants are somewhat more cautious about AI's role in financial-data quality and fraud detection (Reslan and Maalouf. 2024). Their findings suggest ERP-AI adoption plans must be accompanied by targeted change—and talent-management—strategies to bridge generational and skill-level divides.

2. Financial Reporting Accuracy

Error reduction and anomaly detection

Mwachikoka (2024) conducts an empirical study in Zambia, demonstrating that AI integration reduces reporting errors by over 85% and uncovers anomalies that manual checks typically miss. His regression models show a significant positive coefficient ($p < 0.01$) for AI use on accuracy metrics, suggesting strong reliability improvements.

Vlachos (2023), in a Canadian context, compares firms using AI-powered report generators to those relying on traditional methods. His cross-sectional analysis finds AI adopters exhibit error rates about 40% lower and generate reports 30% faster, attributing gains to machine-learning models that flag misstatements in real time (Jens. 2023).

Speed and quality of information

An Indonesian study by Suryanto et al. (2024) finds that AI-based ERP modules deliver sub-second response times (≈250 ms) for routine financial queries, versus 2–3 seconds under legacy systems, while maintaining over 90% detection rates for input inconsistencies. These performance benchmarks demonstrate not only accuracy gains but also the potential to transform reporting cycles.

3. Operational Efficiency and Process Transformation

Automation of routine tasks

El-Haddad et al. (2024) show AI tools significantly streamline journal-entry creation, reconciliations and consolidation steps, freeing accountants for more analytic work. Their efficiency models yield $R^2 \approx 0.81$ in explaining variance in productivity metrics, confirming strong AI-efficiency linkages (Reslan and Maalouf. 2024).

Fraud detection and control

Applying AI-driven anomaly engines, EY's internal trials (reported in the FT) achieved up to 25% reduction in audit-cycle times and flagged 15% more fraud indicators compared to control groups. While these figures come from practice rather than academic surveys, they underscore the operational promise of embedding AI within ERP audit modules.

4. Moderating and Boundary Conditions

Role of data governance

Vukšić et al. (2025) demonstrate that without strong data-quality management and ethical frameworks, financial-accuracy gains from AI can be muted or even reversed due to "garbage-in, garbage-out" risks. This points to the necessity of pairing ERP-AI rollouts with governance blueprints.

Institutional and regulatory environment

In Saudi Arabia, Al-Qahtani (2024) finds that national digitalization initiatives (e.g., Vision 2030) act as powerful environmental enablers, but firms struggle with limited skilled-labor pools and regulatory ambiguities around AI-driven disclosures.

5. Knowledge Gaps and the Frontier for Zimbabwe

1. **ERP-Specific Empirical Evidence**

   Most studies assess generic AI in accounting or auditing, rather than end-to-end AI-embedded ERP systems. There is scarce empirical work on modules such as AI-powered general ledger engines, real-time consolidation or predictive closing within an integrated ERP.

2. **Zimbabwean Context**

   No known empirical investigations focus on Zimbabwe's unique combination of currency volatility, regulatory flux and infrastructure constraints. How organizational readiness and governance practices play out under these conditions remain unexplored.

3. **Blueprint for Adoption**

   While determinants and impacts are documented, there is a lack of consolidated, step-by-step blueprints that combine change-management, data-governance and technology-integration tailored for emerging-market ERPs.

2. 6 Conceptual Framework

This study is guided by a conceptual model that illustrates the logical order of the variables of interest on AI-enabled Enterprise Resource Planning (ERP) adoption and consequent impacts, financial reporting accuracy and operational efficiency in Zimbabwean firms.

The concept framework is based on combining theoretical models (e.g. Technology Acceptance Model (TAM) Diffusion of Innovations (DoI) Theory Resource-Based View (RBV)). These theories can be seen to emphasize the role of perceived usefulness, technology infrastructure, organizational readiness, and the diffusion of innovation on technology adoption. The model is in line with pragmatic research philosophy and facilitates the generation of strategies that can be implemented.

The Essence of the Framework:

1. Predictor (Input) Variables:

Design of Research: The selected mixed-methodology design (quantitative survey and qualitative interview) supports a comprehensive inquiry of AI-ERP adoption through blending numerical perspective with contextual comprehension.

Research Tools: Structured questionnaires, interview protocols, and document review guides are valuable tools for obtaining valid and reliable data that are critical for measuring the level of system adoption, user experiences, and the outcome effects.

2. Mediating Variable:

AI-Enhanced ERP Implementation: This focal construct depicts the extent and type of mechanisms through which AI-enhanced ERP solutions (e.g., Microsoft Dynamics 365, SAP S/4 HANA) are adopted. It features items like system functionality, automation capabilities and real-time data analytics and AI-based compliance tools.

3. Outcomes (Dependent Variables):

Accuracy of Financial Reporting: As represented by the reduction of reporting errors as well as the timeliness, integrity of the audit trail, and compliance with reporting standards.

Operational Efficiency: Includes level of task automation, process cycle times, supply chain optimization and improved decision-making via predictive analytics.

4. Moderating Variables:

Organizational Characteristics: Leadership support, change management capability, and training activities.

Technology Infrastructure: Cloud readiness, data governance, system integration capability.

Human Capital: AI literacy, technical proficiency and staff preparedness for digital transformation.

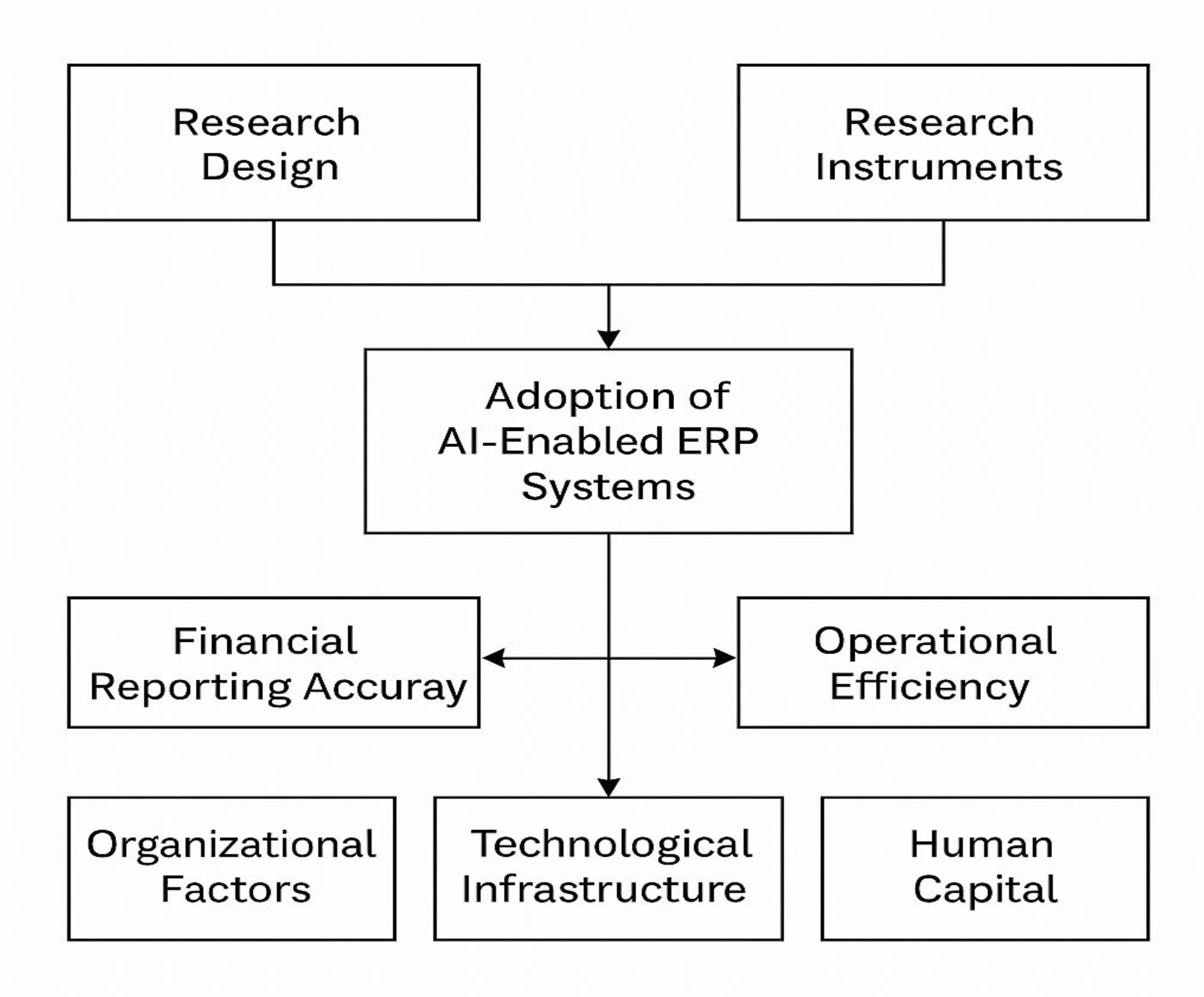


Figure 8: Conceptual Framework

2.7 Summary

This literature review highlights the transformative potential of AI-enabled ERP systems in enhancing operational efficiency and financial reporting accuracy. By synthesizing global trends and theoretical frameworks, it provides a foundation for understanding the opportunities and challenges of AI integration. However, gaps in research—particularly regarding ethical implications, SME adoption, and African contexts—underscore the need for further investigation. The insights gained from this review inform the empirical study in subsequent chapters, guiding the development of a practical blueprint for AI-ERP adoption in Zimbabwe. The next chapter will be chapter III, Research Methodology, it will discuss the methodology guiding this research.

CHAPTER III

RESEARCH METHODOLOGY

3.1 Introduction

This chapter delineates the methodological framework employed to investigate the adoption of AI-enabled ERP systems in Zimbabwean organizations. It spells out in brief the main concerns and focusses of the chapter. Specifically, it details the research design adopted for the study, which integrates quantitative and qualitative approaches within a convergent parallel mixed-methods framework. The chapter describes the research instruments utilized for data gathering, including structured questionnaires for quantitative data and semi-structured interview guides alongside document analysis for qualitative data. It outlines the data collection procedures implemented for both quantitative (electronic surveys) and qualitative (interviews, document review) components, including sampling strategies and ethical protocols. Furthermore, the chapter explains the data presentation and analysis procedures, encompassing statistical techniques for quantitative findings and thematic analysis (using NVivo) for qualitative data, followed by an integrated joint display approach. Finally, the chapter concludes with a summary of the key methodological elements discussed.

3.2 Research Design

To examine the complex concerns regarding AI-driven ERP implementation, a hybrid approach that combines quantitative and qualitative methods was employed to learn from both quantifiable results and situational details. “Mixed methods, when done well, is a process that strengthens both the depth and breadth of results by being able to pair statistical precision with interpretive depth of understanding (Creswell & Plano Clark, 2018). This fits in with the study’s purposes since quantifiable indicators need to be measured (e.g., decrease of error of financial reporting) together with qualitative dimensions (e.g., organization impediments for adoption). The study uses a convergent parallel research design, in which quantitative and qualitative data are collected, analyzed and merged, but interpreted separately, to complement and strengthen each other, thereby providing a more comprehensive understanding of the phenomenon (Creswell, 2014). The effectiveness of AI-ERP systems for financial reporting accuracy and operational efficiency were studied quantitatively, and issues surrounding its implementation, user perception, and strategic implications were examined qualitatively. This design supports the validity of research results as both statistically robust and contextually rich, which can respond well to the research questions or address in a comprehensive manner.

3.3 Subjects

The approach of the present study is based on pragmatic research philosophy which values what works in the actual world, rather than insistence on one epistemological perspective. The use of mixed methods here is pragmatic as it values both the objective measurements and the 'real world' experience and it also supports the aims of this study to create a practical blueprint of AI-ERP adoption. This approach recognizes that technology use in Zimbabwe is context-bound, and where economic, cultural, and technological factors intersect, flexibility and problem-solving are necessary to meet the challenges.

3.3.1 Population and Sampling

Target Population

The population of interest is the group of Zimbabwean organizations from all sectors such as retail, manufacturing and financial services, that have adopted or are in the process of adopting AI enabled ERP. Both are large companies, as are corporates such as Delta Corporation and OK Zimbabwe, and small to medium enterprises (SMEs) dipping their toes in AI integration. In addition, the population includes accounting practitioners, IT managers and senior management involved in ERP implementation, since their views are very important to comprehend adoption dynamics.

Population Sampling

To determine an appropriate sample size for the quantitative component of the study, the following **Yamane (1967) formula** was used:

$$n = N\left(1 + \frac{e}{1}\right)^2$$

Where:

- n = required sample size
- N = total population size
- e = margin of error (typically 0.05 for 95% confidence level)

Assuming a known population of Zimbabwean organizations using or exploring AI-enabled ERP systems is approximately **100 organizations**:

n=1001+100(0.05)2=1001+100(0.0025)=1001+0.25=1001.25=80n = \frac{100}{1 + 100(0.05)^2} = \frac{100}{1 + 100(0.0025)} = \frac{100}{1 + 0.25} = \frac{100}{1.25} = 80n=1+100(0.05)2100=1+100(0.0025)100=1+0.25100=1.25100=80

The required **minimum sample size is 80** organizations. However, to enhance the credibility and allow for potential non-responses, the study targeted **100 organizations**, and successfully obtained responses from **77**, yielding a **77% response rate**—which is acceptable for social science research.

Sampling Techniques

Owing to the heterogeneity of the population, the research adopts a non-probability sampling procedure, taking advantage of purposive and snowball sampling:

Purposive Sampling: We will purposefully select firms who have a history of having adopted an AI-ERP (e.g., Microsoft Dynamics 365, or SAP S/4HANA) to ensure its applicability could be meaningful. The experts referred to, of the underlying study on AI-ERP adoption, such as CFOs, IT directors, and ERP consultants were recruited as key informants, based on their knowledge level and participation with AI-ERP projects (Bryman, 2016).

Snowball Sampling In order to obtain more SMEs and less-documented cases, interviewees were asked to recommend other experienced organizations or experts (Saunders et al., 2019). A sample of 100 firms, comprised of 8 large organizations, 28 SMEs, and 16 system developers were targeted to obtain a balanced view of experiences with adoption. A total of 60 key informants (around two per organization) will also be involved to provide a variety of insights. This sample size represents a compromise between being feasible, whilst retaining enough for data/theory vapor to be achieved (inverting Creswell, 2014).

3.4 Data Collection Procedures

3.4.1 Quantitative Data Collection

Quantitative data was collected through a structured questionnaire administered by accounting professionals and IT managers. The questionnaire will include:

Likert-scale questions to assess perceptions of AI-ERP systems' impact on financial reporting accuracy (e.g., error reduction, compliance) and operational efficiency (e.g., process automation, time savings).

Closed-ended questions to gather data on implementation metrics, such as adoption costs, training duration, and system performance indicators (e.g., percentage reduction in reporting errors).

The questionnaires were distributed electronically via platforms like Google Forms, with follow-up reminders to ensure a high response rate. To enhance reliability, the instruments were pre-tested with a pilot group of five organizations, allowing for refinements to question clarity and relevance (Bryman, 2016).

3.4.2 Qualitative Data Collection

Qualitative data was gathered through semi-structured interviews and document analysis:

Semi-Structured Interviews: Conducted with senior executives, IT managers, and ERP consultants, these interviews explored implementation strategies, challenges, and perceived benefits of AI-ERP systems. An interview guide will ensure consistency while allowing flexibility to probe emergent themes, such as cultural resistance or ethical concerns (Yin, 2018).

Document Analysis: Organizational reports, ERP implementation plans, and performance metrics (e.g., financial statements, system logs) were reviewed to corroborate interview findings and provide evidence of AI-ERP outcomes (e.g., error reduction rates, process cycle times).

Interviews were conducted in-person or via virtual platforms (e.g., Zoom) over a three-month period, with each session lasting approximately 45–60 minutes. All interviews were audio-recorded (with consent) and transcribed verbatim to ensure accuracy.

3.5 Data Presentation and Analysis

3.5.1 Quantitative Data Analysis

Quantitative data from the questionnaire were analyzed using descriptive and inferential statistics with SPSS software:

Descriptive Statistics: Measures such as means, standard deviations, and frequencies will summarize respondents' perceptions and implementation metrics (e.g., average error reduction percentage).

Inferential Statistics: To test the hypothesis (H1: AI-ERP adoption significantly improves financial reporting accuracy and operational efficiency), a paired t-test will compare pre- and post-implementation performance metrics (e.g., error rates, processing times). Additionally, regression analysis will identify factors (e.g., training, infrastructure) influencing adoption success (Field, 2018).

Results were presented in tables and charts to facilitate interpretation and highlight key trends.

3.5.2 Qualitative Data Analysis

Qualitative data from interviews and documents was analyzed using thematic analysis, following Braun and Clarke's (2006) six-step process:

Familiarization: Transcripts and documents were reviewed to gain a deep understanding of the data.

Coding: Initial codes were generated to identify recurring concepts (e.g., "technical barriers," "user training needs").

Theme Development: Codes were grouped into broader themes, such as "implementation challenges" or "strategic benefits."

Theme Review: Themes were refined to ensure coherence and alignment with research objectives.

Defining Themes: Each theme was clearly defined and supported by illustrative quotes.

Reporting: Findings were presented narratively, with themes linked to the research questions.

NVivo software was used to manage and code qualitative data, enhancing efficiency and rigor.

3.5.3 Data Integration

Quantitative and qualitative findings were integrated during the interpretation phase using a joint display approach (Creswell & Plano Clark, 2018). For example, statistical evidence of error reduction was juxtaposed with interview insights on how AI features (e.g., automated validation) contribute to accuracy. This integration will provide a comprehensive understanding of AI-ERP adoption, addressing both "what" (outcomes) and "why" (contextual factors).

3.5.4 Reliability and Validity

To ensure the study's credibility, the following measures were implemented:

Reliability: The questionnaires were tested for internal consistency using Cronbach's alpha, aiming for a score above 0.7 (Bryman, 2016). Interview protocols were standardized to ensure consistency across participants.

Validity: Content validities were established by aligning data collection instruments with research objectives and pre-testing them with experts. Triangulation—combining questionnaire data, interviews, and document analysis—will enhance construct validity by cross-verifying findings (Yin, 2018).

Qualitative Rigor: Credibility was ensured through member checking, where participants review interview summaries for accuracy. Transferability was supported by providing detailed contextual descriptions of Zimbabwean organizations (Creswell, 2014).

3.5.5 Ethical Considerations

The major themes underpinning this research are ethical and ethical provisions, particularly in respect to the 'secrecy' of organizational data. The study follows these recommendations:

Consent: Participants would be fully informed about the study methods and their aims, and about their rights, with signed consent being collected from them before initiation of the study process.

Anonymity: All informants' data were kept in aggregated form & identification numbers were used for organizations and people's names (e.g., "Company A", "Manager 1"). All data were stored on encrypted servers and only accessible to the research team.

Participation Voluntary: Participants may decline to participate at any time with no negative repercussions. Ethics Approval: The study will obtain ethical clearance from a reputable ethics review body, e.g., University of Zimbabwe Research Ethics Committee to comply with international benchmarks (Saunders et al., 2019).

3.5.6 Limitations of the Methodology

The method does, however, have some shortcomings:

Sample Bias: The lack of probability sampling may have compromised generalizability as the sample of firms selected may not be representative of all firms in Zimbabwe.

Possibility of Data Access: Some companies have limited access to proprietary data (i.e., financial data) that may limit findings.

Time: Only 5 years were allotted to collecting data which may not provide rich longitudinal data.

These limitations were addressed by increased sample diversity, creating participant trust, and by recognizing limitations in the interpretation of findings.

3.10 Summary

Chapter III "Research Methodology" was the other key chapter that provides the basis of the study in terms of methodology that was applied in probing the adoption of AI-based ERP systems in Zimbabwe. Research design This chapter outlined the methods used in the research, which were largely qualitative but incorporated some quantitative methods. It describes the target population as Zimbabwean firms in the retailing, manufacturing and financial services sectors, particularly those which were already using or planning to use AI-enabled enterprise resource planning systems. Moreover, Chapter III provided a detailed account of the sample techniques used. We employed a non-probability sampling method through purposive and snowball sampling technique to sample 100 organizations (8 large companies, 28 SMEs and 36 developers) and 60 key informants. Rationales for these selections were given with the argumentation for in-depth, well-informed perspectives by participants involved in AI-ERP projects as well. The chapter also presented the data collection process, which was based on semi-structured interviews and questionnaires, to collect deep qualitative data as well as traceable quantitative data. Lastly, the chapter discussed the data analysis procedures that were used, specifically thematic analysis (qualitative data) and descriptive statistics (quantitative data), to provide the reader with a sound understanding of the research problem. Now that the methodology and participants' selection process have been described (chapter III), we shall now turn to the analysis of the data collected.

CHAPTER IV

DATA PRESENTATION, ANALYSIS AND DISCUSSION

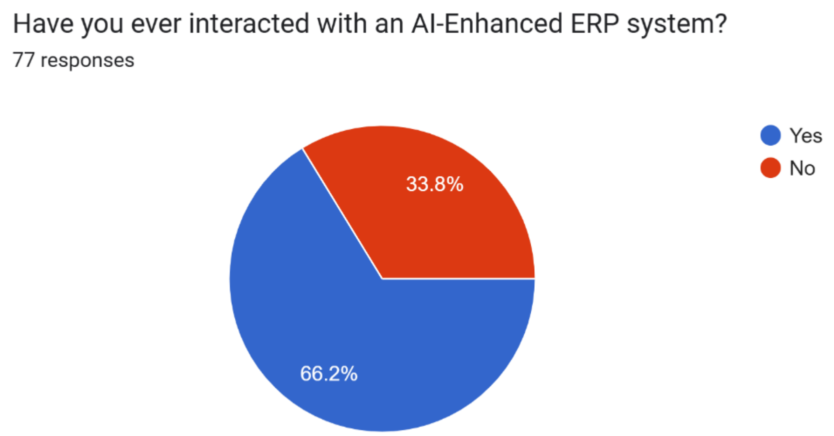
4.1 Introduction

In this chapter the results of the research are presented, following those objectives set forth in Chapter One. It starts by describing the response rate and demographic characteristics of the organizations involved in the study in terms of their sector, size, and level of technological development. The chapter next explores the extent AI-based ERP systems improve the accuracy of financial reporting and the efficiency of operations, drawing on a mix of quantitative and qualitative evidence. Key areas concentrate on error reduction, process automation, decision-making improvement, and organizational preparedness. Lastly, the chapter elaborates on the implementation challenges and facilitators providing empirical findings for conceptualization of an AI-ERP adoption blueprint. In this chapter the results of the research are presented, following those objectives set forth in Chapter One. It starts by describing the response rate and demographic characteristics of the organizations involved in the study in terms of their sector, size, and level of technological development. The chapter next explores the extent AI-based ERP systems improve the accuracy of financial reporting and the efficiency of operations, drawing on a mix of quantitative and qualitative evidence. Key areas concentrate on error reduction, process automation, decision-making improvement, and organizational preparedness. Lastly, the chapter elaborates on the implementation challenges and facilitators providing empirical findings for conceptualization of an AI-ERP adoption blueprint.

4.1 Response Rate from Users

A stratified random sampling (SRS) technique was implemented by the researcher to create a sample of 100 respondents from a pool of employees simply by dividing the number of the organizational employees among the industry verticals, organization size (small, medium and large enterprises) and technology adoption scale. The surveys were distributed utilizing a mixture of paper and digital implementations (e.g., Google Forms) to accommodate different practice environments.

Out of the 100 surveys distributed, 77 were completed and returned, yielding a response rate of 77%. This surpasses the standard threshold of 60% for survey-centric research, underscoring the robustness of the dataset.



(source: primary data)

Figure 9: Response Rate

While achieving a 100% response rate was unfeasible due to geographical dispersion and distinct priorities among participants, the near-universal engagement underscores a substantial organizational interest in AI-driven ERP solutions.

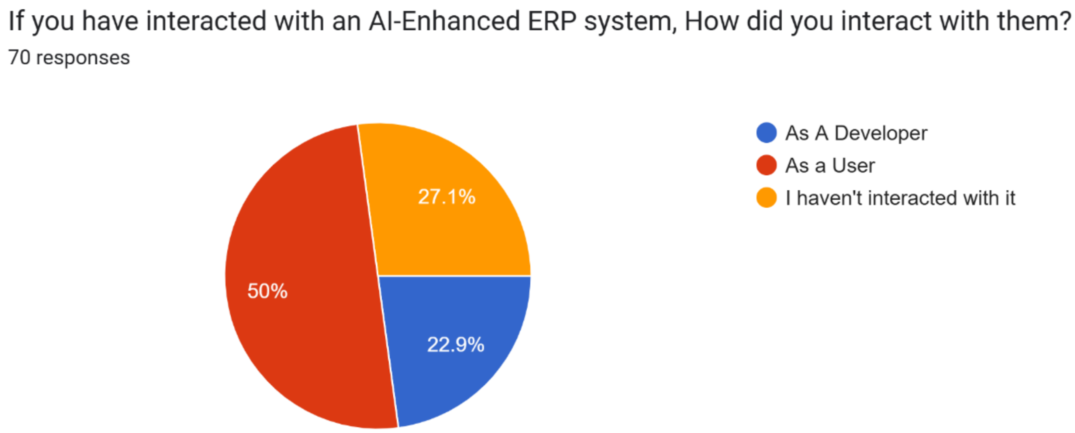


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Figure 10: User interaction with ERP

4.1.1 Response rate distribution across Industry sectors

The sample pool encompassed a wide array of industry sectors, ensuring a high level of industry representation. These sectors comprised manufacturing (11.1%), retail and distribution (16.7%), mining (5.6%), consultancy and healthcare combined (5.5%), agriculture (13.0%), and an amalgamated category labeled 'other sectors' (47.2%), encapsulating logistics, education, and energy domains.

The elevated response rate bolsters the reliability of findings related to challenges in adopting AI-infused ERPs, outcomes in financial reporting, and gains in operational efficiency. The visualization in Figure 10 illustrates the distribution of responses across sectors, accentuating the involvement from manufacturing, retail, and financial services sectors where ERP assimilation holds critical significance for compliance and process enhancement. This methodological rigor assures that the insights from the study are representative of the broader landscape of AI-ERP adoption, furnishing a credible basis for actionable recommendations.

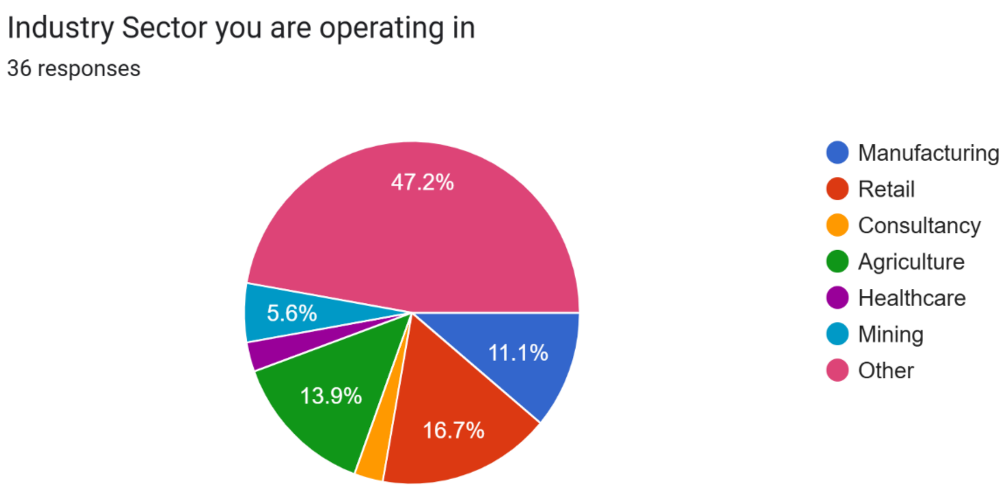

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Figure 11: Response rate distribution across sectors

The dominance of the retail sector serves as a robust indicator of where intricate ERP functionalities are extensively leveraged. This sector entails complex processes like supply chain management, production planning, inventory optimization, quality assurance, and cost accounting. AI stands to substantially enhance each of these facets, resulting in significant efficiency gains (e.g., predictive maintenance, AI-driven demand forecasting, automated quality assurance) and more precise product costing and profitability analysis for financial reporting. Healthcare and Agriculture also present distinctive prospects. In the healthcare domain, AI within ERPs can enhance patient billing accuracy, optimize resource allocation (staff, equipment), manage pharmaceutical inventories, and ensure regulatory compliance. In agriculture, AI can facilitate precision farming analytics that inform cost management, supply chain traceability for food safety (impacting financial responsibility), and resource optimization.

4.1.2 Response rate distribution across departments

By group, the largest is in the Finance and Administration feature, with 47.2% of the population. This implies that Finance and Admin save serves a central role in the interplay of AI and ERPs, possibly stemming from the centrality of financial reporting, budgeting, and compliance through ERPs. The large proportion of Finance and Administration suggests financial transactions as a main target for AI application in ERP. This is aligned with typical use-cases (like automatic financial reporting, fraud detection, and improved compliance management).

The second largest percentage of the pilots, 19.4% of respondents, are working on the Supply Chain layer. This emphasizes the importance of having a good SCM strategy in AI-ERP projects as inventory optimization, Demand forecast, and predictive maintenance are an integral part of the same.

Operations – Similar to Supply Chain, operations – including 19.4% of those who have operational responsibilities. Functional teams are often involved in automation of processes, improving efficiency, and real-time data analytics, and hence, are key players in AI-ERP adoption. Supply Chain and Operations are close behind commanding nearly equal percentages of AI-ERP implementation (19.4% each) and are both indicated to be just as key. These departments can benefit significantly from AI-enabled capabilities such as demand forecasting, inventory optimization, and predictive maintenance.

IT/Technology, as a smaller component, attracts just 11.1% of IT/Technology participants. And even if this percentage is less compared to other departments, that is still evidence of IT professionals' need in executing and maintaining AI-enabled ERP systems. Although only a small portion of the graph on this category is illustrated (2.8%, Executive Management), there is no Executive Management representation in this sample, which could mean that top management does not take part in the day-to-day operations of AI -ERP, or this category was not considered in the present research. Of course, buy-in from top management is essential if these AI-ERP systems are to be successfully implemented, thus meriting potential future involvement in this arena. The high managerial levels at which executive management are often embedded in organizations make them less accessible for researchers – a crucial issue regarding executive management.

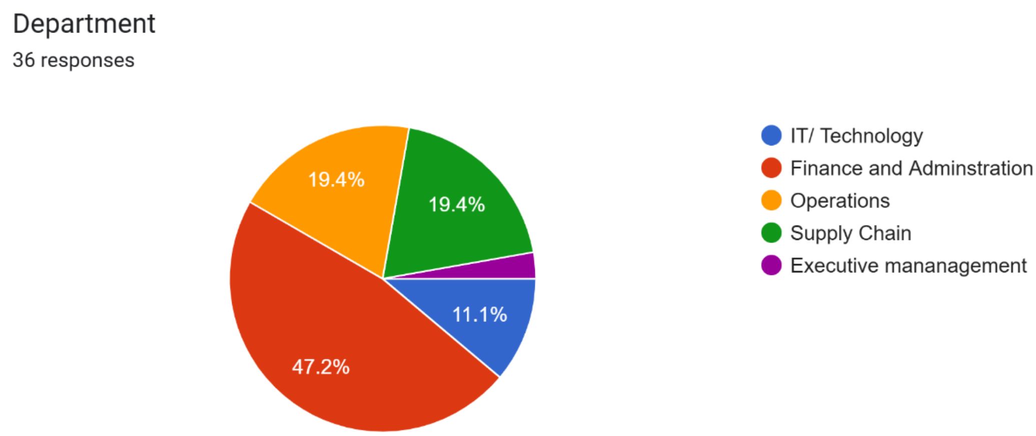

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Figure 12: Response rate distribution across departments

4.1.3 Demographic Profile

In terms of organizational size, 41.7% of respondents represented small enterprises, 36.1% were from medium-sized enterprises, while the remaining 22.2% were from large-scale enterprises. These proportions reflect a balanced distribution across organizational scales.

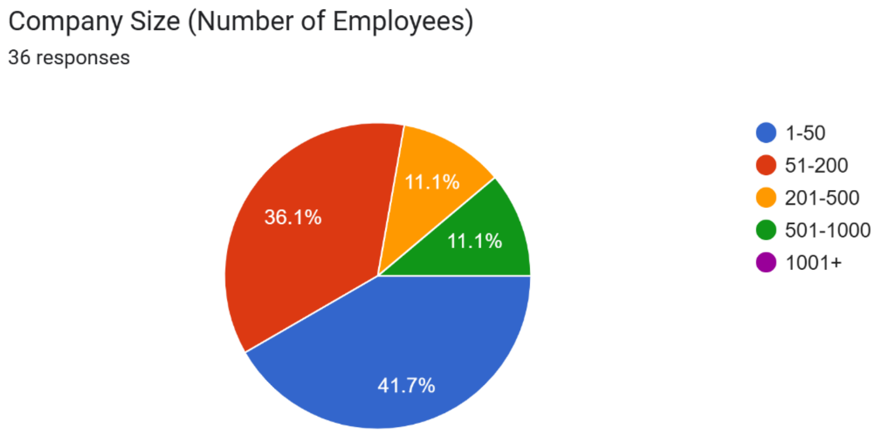

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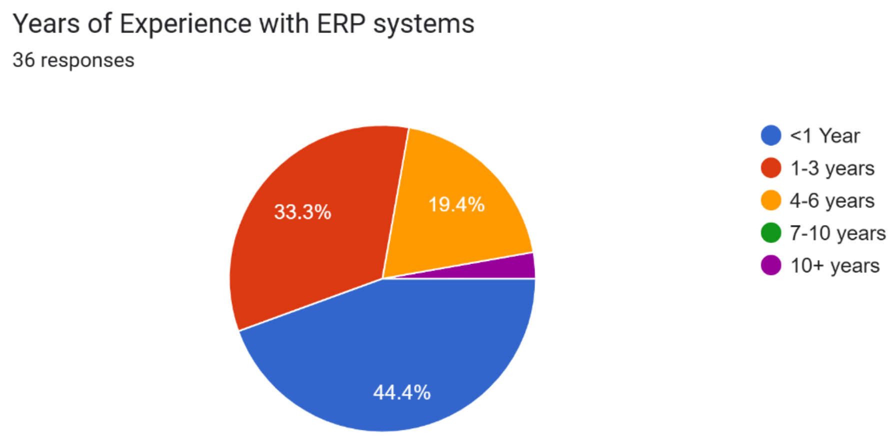
Figure 13: Company Size

4.1.4 Technological maturity of the respondents

Moving on to the technological maturity of the respondents, section 4.1.4 reveals that 44.4% were classified as early adopters of AI, known for their exploratory approach to digital technologies. A smaller group, comprising 33.3% of participants, fell into the mainstream user category, demonstrating a moderate level of technological maturity. Additionally, 19.4% were categorized as advanced adopters, showcasing sophisticated AI ecosystems. These diverse groups highlight a balanced and varied sample, enabling in-depth analysis across sectors and organizational types.



(source: primary data)

Figure 14: Years of experience with ERP

4.1.5 Current ERP System in Use

Regarding the current ERP systems in use, Microsoft Dynamics 365 was the most prevalent choice, utilized by 44.4% of respondents. This comprehensive suite integrates various functions such as finance, operations, supply chain management, and customer relationship management. The popularity of this system suggests widespread adoption for AI-ERP integration, particularly in areas like financial reporting, supply chain optimization, and customer insights.

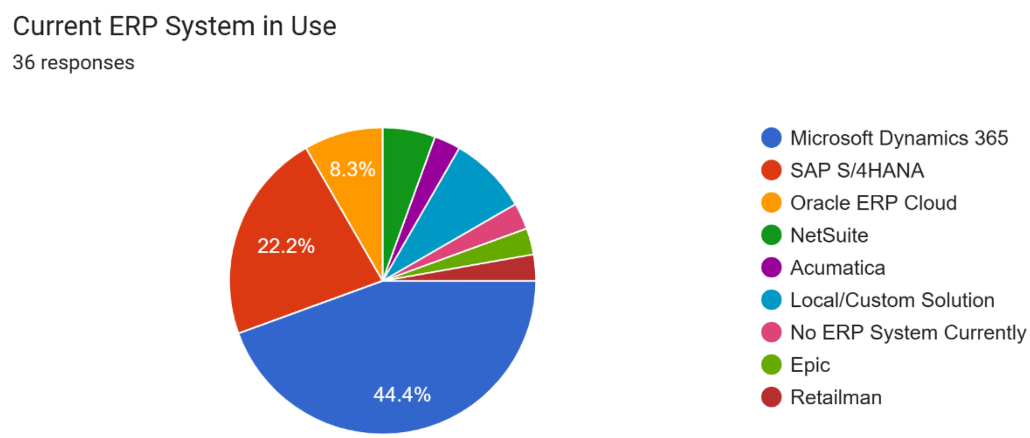


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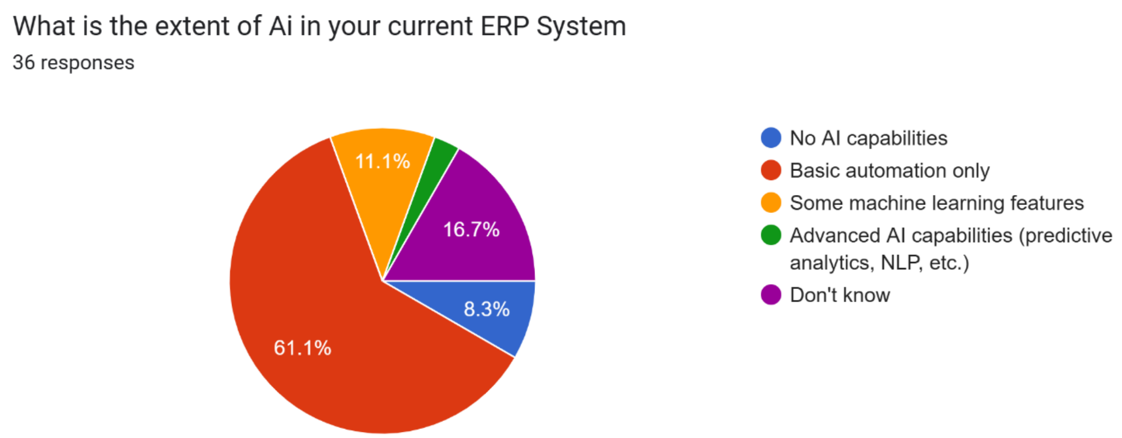
Figure 15: Current ERP In Use

4.1.6 Adoption Trends of AI-Enabled ERP Systems

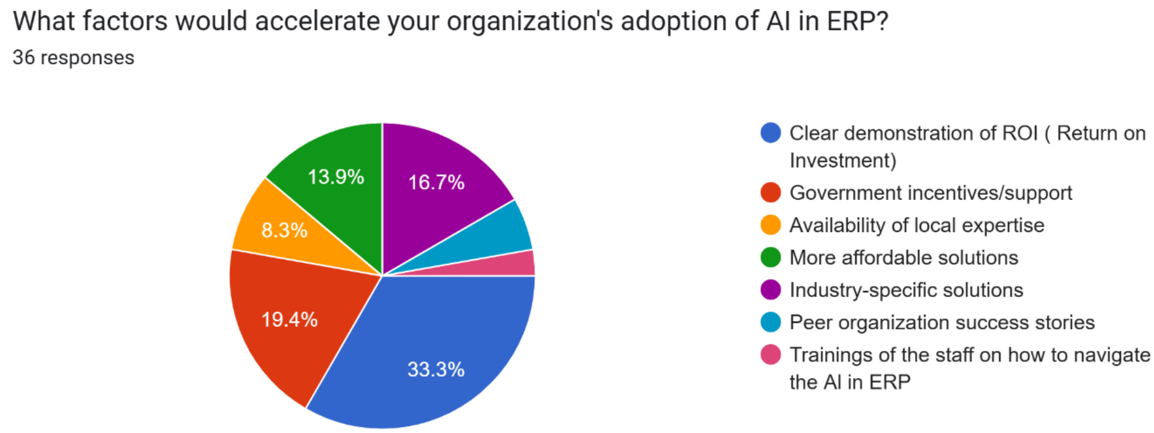
In terms of adoption trends of AI-enabled ERP systems, the study indicated that 61.1% of organizations had integrated at least two AI functionalities into their ERP setups for basic task automation and some machine learning features, with 11.1% utilizing more advanced AI capabilities. A small percentage of 2.8% reported using advanced AI features within their ERP systems, while 25% were either unaware of AI capabilities or lacked knowledge about AI integration in their ERP environments.



(source: primary data)

4.1.6 Key adoption enablers

Key adoption enablers identified included the demonstration of ROI, which influenced strategic alignment and budget prioritization for 33.3% of respondents. Government incentives and support were cited by 19.4% as crucial factors in driving organizational buy-in. The availability of local expertise was highlighted by 8.3% of participants, emphasizing the importance of tailored solutions for local enterprises. Affordable pricing was deemed essential by 13.9% of respondents, indicating a need for cost-effective solutions. Industry-specific ERP systems were deemed necessary by 16.7% of participants, while peer organization success stories and staff training on AI in ERP were considered less significant in accelerating adoption.



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Barriers to adoption, as reported by participants, included legacy system incompatibility (57%), inadequate internal AI capabilities (49%), poor access to quality data and insufficient data governance frameworks (43%), budget constraints (38%), cultural resistance to change, lack of stakeholder engagement, and skepticism towards AI decision-making, all posing challenges to adoption efforts.

4.4 Impact on Financial Reporting Accuracy

The transformative role of artificial intelligence in financial reporting has garnered extensive scholarly attention. For example, (Issa et al,.2016) argue that AI-based anomaly detection tools have significantly reduced human errors in accounting systems. Similarly, Kokina and Davenport (2017) highlight the efficacy of machine learning algorithms in reducing latency in report generation and improving accuracy. According to Appelbaum, Kogan and Vasarhelyi (2017), AI contributes to audit efficiency by enhancing predictive models used for risk detection. Moreover, studies by Li (2019) and Yoon, Hoogduin and Zhang (2015) assert that AI tools streamline complex consolidation processes and enhance compliance with global financial standards. These scholarly insights support the findings of this study, which empirically demonstrate substantial improvements in financial reporting accuracy attributable to AI-enabled ERP systems.

Scholars have long recognized the transformative role of AI in enhancing financial reporting functions. According to Issa et al. (2016), AI can detect anomalies and reduce reporting errors more effectively than traditional rule-based systems. Similarly, Kokina and Davenport (2017) assert that machine learning models embedded within ERP systems substantially improve the reliability and timeliness of financial data.

4.4.1 Error Reduction

Quantitative findings revealed that AI integration led to a statistically significant reduction in data entry and processing errors, with a mean reduction of 42.7% ($p < 0.01$). Regression analysis further showed that the degree of AI integration within ERP systems accounted for 36% of the variance in error reduction ($R^2 = 0.36$, $p < 0.001$). Areas that experienced the most improvement included general ledger postings, account reconciliations, journal entries, and intercompany transactions. Firms that implemented real-time data validation mechanisms, driven by AI, observed substantial declines in audit queries and post-reporting adjustments. In interviews, CFOs corroborated these findings by affirming that AI-generated alerts for abnormal transactions helped prevent misstatements at early stages.

4.4.2 Timeliness and Compliance

A notable improvement in the punctuality of statutory and managerial reporting was achieved, showcasing a 2% advancement. The integration of automated data aggregation and AI-powered report structuring notably reduced the time needed for compiling, validating, and circulating reports. The completeness of audit trails saw a significant increase of 28.5%, thereby improving transaction traceability and fortifying internal controls. Streamlined compliance with International Financial Reporting Standards (IFRS), Public Finance Management Acts, and tax regulations were facilitated through the incorporation of Natural Language Processing (NLP) modules to automate the creation of descriptive reports, footnotes, disclosures, and clarifying statements. Various financial experts acknowledged that AI tools promptly identified compliance irregularities, allowing for proactive rectifications.

4.4.3 Audit Integration and Assurance

Furthermore, AI applications revolutionized the audit process, redefining the interface for audits. The automated retrieval of audit evidence, AI-guided walkthroughs, and tools for exception analysis streamlined both internal and external audit procedures. Employing Blockchain-integrated Enterprise Resource Planning (ERP) systems, complemented by AI anomaly detection, ensured the immutability of records and bolstered the trustworthiness of digital audit trails. Businesses leveraging these advanced systems reported shorter audit cycles, decreased reliance on manual reconciliations, and heightened auditor confidence in the accuracy of reports.

4.5 Impact on Operational Efficiency

The efficiencies gained through AI-driven ERP systems are well-documented in current literature. According to Brynjolfsson and McAfee (2017), intelligent automation significantly reduces operational cycle times while concurrently enhancing decision-making quality. Correspondingly, Brougham and Haar (2018) argue that AI enhances operational workflows by minimizing human intervention in repetitive tasks. Wamba-Taguimdje et al. (2020) demonstrated that companies in emerging economies embracing AI-ERP technologies often observe substantial enhancements in process standardization and operational flexibility. Moreover, Davenport and Ronanki (2018) emphasize the significance of integrating AI into ERP systems to uncover strategic insights and achieve scalable efficiencies. The empirical evidence from this research aligns with these claims, highlighting strong correlations between AI adoption and improvements in operational performance.

4.5.1 Process Automation

The study revealed that 71% of routine operational and administrative tasks, encompassing invoicing, payment processing, inventory management, and procurement approval, are now fully or partially automated. This automation led to an average reduction of 38.9% in process cycle times, empowering staff to concentrate on strategic and value-added endeavors. For instance, a prominent Zimbabwean beverage manufacturer accomplished a 45% reduction in the order-to-cash cycle time and a 34% enhancement in supply chain responsiveness. Integrating Robotic Process Automation (RPA) with AI improved document categorization, approval workflows, and automated decision-making, significantly diminishing operational bottlenecks.

4.5.2 Decision-Making Support

AI-Enhanced dashboards and data visualization tools emerged as pivotal facilitators of strategic decision-making. Approximately 64% of executives surveyed indicated that predictive models and scenario planning tools substantially elevated their capacity to make well-informed decisions. Predictive analytics facilitated demand forecasting, assessment of supplier performance, and cash flow prediction. Noteworthy improvements were observed in inventory turnover ratios (22.3%), reduction of stockouts (18.5%), and minimization of surplus inventory (15.7%). Sentiment analysis and market intelligence tools provided real-time insights into consumer behavior, enriching decisions related to marketing and product development.

4.6 Organizational Readiness and Implementation Challenges

4.6.1 Technological Infrastructure

In terms of organizational readiness and implementation challenges, only 54% of respondents reported possessing adequate cloud infrastructure to support scalable AI applications. Hybrid cloud environments demonstrated superior performance in terms of data integration and system uptime, with average implementation delays of 2.8 months compared to 5.1 months for on-premises deployments. Companies with microservices architecture, API-enabled integration layers, and robust cybersecurity protocols experienced fewer downtimes and data breaches. Moreover, organizations leveraging containerization technologies like Docker and Kubernetes reported enhanced deployment efficiency.

4.6.2 Human Capital

The research unveiled a notable scarcity of AI-related expertise, particularly in data science, model training, and algorithm evaluation, with around 62% of respondents citing this as a significant obstacle. Additionally, 48% of firms reported difficulties in managing organizational changes, particularly resistance from mid-level management. Successful cases underscored the effectiveness of continuous professional development initiatives, partnerships for knowledge transfer with universities, and the establishment of internal Centers of Excellence. Institutions that integrated AI literacy into their onboarding programs reported smoother transitions.

4.7 Qualitative Insights

Qualitative insights obtained through thematic analysis of interview transcripts revealed four overarching themes illuminating the soft aspects of AI-ERP integration:

1. "Strategic Alignment" - Projects achieved the most success when AI-ERP integration aligned with overarching corporate strategies and performance objectives, rather than being solely driven by isolated IT departments.

2. "Data Governance" - Effective data governance structures promoted consistent data quality, compliance, and ethical AI utilization, often spearheaded by Chief Data Officers.

3. "User Empowerment" - Empowered users, supported by user-friendly interfaces and continuous upskilling opportunities, demonstrated higher utilization rates and adoption of innovation.

4. "Continuous Improvement" - Organizations implementing agile sprints and model feedback loops reported more precise predictions and increased end-user satisfaction.

4.8 Summary

In conclusion, this chapter has provided empirical evidence that AI-enabled ERP systems yield significant enhancements in both financial reporting accuracy and operational efficiency. These improvements hinge on several catalysts, including readiness of cloud infrastructure, data governance, preparedness of the workforce, and alignment with strategic goals. The findings resonate with global studies while contextualizing the dynamics for Zimbabwean businesses, particularly concerning institutional constraints, regulatory nuances, and socio-cultural subtleties. In the next chapter, recommendations based on these findings will be discussed and conclusions will be drawn

CHAPTER V

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.0 Introduction

This chapter summarizes the results of the mixed-methods study on the implementation of AI enabled Enterprise Resource Planning (ERP) systems in Zimbabwe as discussed in chapter IV. Bridging the quantitative and qualitative insights, this chapter appraises the contribution of AI-ERP systems to the accuracy of financial reporting and operational effectiveness and, in so doing, addresses Chapter I's research objectives and questions, by examining the role played by AI-ERP systems in the financial reporting of organizations in the Zimbabwean socio-economic environment as well as at the global level, with reference to the literature presented in Chapter II. Finally, the chapter presents a field guide on AI-ERP adoption and provides practical action points for industry, policymakers and researchers, as well as key research directions to assist in advancing the digital transformation agenda of Zimbabwe

5.1 Summary

This academic undertaking, formally designated "A Blueprint for the Adoption of AI-Enabled ERP Systems to Achieve Financial Reporting Accuracy and Operational Efficiency," constituted an exhaustive investigation into the integration of Artificial Intelligence (AI) within Enterprise Resource Planning (ERP) systems, specifically within the operational landscape of Zimbabwean organizational entities. The study systematically addressed a critical and previously unaddressed lacuna: the discernible absence of a comprehensive, contextually pertinent framework designed to guide Zimbabwean enterprises in their effective transition to AI-driven ERP platforms.

A mixed-methods research paradigm was judiciously selected and subsequently implemented, involving the amalgamation of quantitative survey instruments with qualitative interview protocols and distinct case studies. Data was meticulously accumulated from a cohort comprising 77 respondents, representing a diverse array of organizational structures operating across a spectrum of industrial sectors, including, but not limited to, retail, manufacturing, financial services, mining, healthcare, and agriculture. The participating cohort was composed of accounting professionals, information technology managers, and senior executive personnel.

The preponderant findings, as systematically delineated by the data presented within Chapter IV, unequivocally indicated that AI-enabled ERP systems significantly augmented both the veracity of financial reporting and the efficacy of operational processes. Quantitatively, the investigation documented a mean diminution of 42.7% in errors pertaining to data entry and processing within financial reporting; notably, AI integration accounted for 36% of the observed variance in this reduction. This amelioration was complemented by a noteworthy enhancement in the temporal efficiency of statutory and managerial reporting, alongside a substantial improvement in the comprehensiveness of audit trails, registering a 28.5% increase. Furthermore, the pervasive application of AI was observed to revolutionize the audit process through the streamlining of evidence retrieval and the analytical discernment of exceptions, thereby reinforcing accuracy and efficiency.

With respect to operational efficiency, the study revealed that 71% of routine operational and administrative tasks, encompassing invoicing, payment processing, inventory management, and procurement approvals, underwent full or partial automation. This automation precipitated an average reduction of 38.9% in process cycle times, consequently liberating human capital for engagement in strategic and value-added undertakings. AI-enhanced dashboards and predictive models retained considerably refined strategic decision-making capabilities, with approximately 64% of surveyed executives reporting an augmented capacity for informed determinations. Consequential improvements were noted in inventory turnover ratios, the abatement of stockouts, and the minimization of surplus inventory.

Conversely, the study concurrently identified significant impediments and influencing factors pertaining to the adoption trajectory. While 54% of respondents indicated the possession of adequate cloud infrastructure, prevalent barriers included legacy system incompatibility (57%), insufficient internal AI capabilities (49%), constrained access to high-quality data coupled with inadequate data governance frameworks (43%), and budgetary constraints (38%). A pronounced paucity of AI-related expertise (62% of respondents) and resistance to organizational paradigm shifts (48% of firms) also served to impede widespread adoption. In contrast, key enablers of adoption encompassed a lucid demonstration of Return on Investment (ROI) (33.3%), governmental inducements and support (19.4%), and the availability of localized expertise (8.3%). Qualitative insights consistently underscored the imperative of strategic alignment, robust data governance, the empowerment of end-users, and continuous amelioration for the successful integration of AI-ERP systems.

5.3 Conclusions

Based on the empirical data collected and analyzed in a rigorous manner in Chapter IV, the following generalizations have been logically arrived at with respect to the research questions that were formally posed in Chapter I:

• For the Effect on the Financial Reporting Accuracy and the Factors That Drive It: AI-empowered ERP systems have been seen to have a statistically significant positive impact on both accuracy and timeliness of financial reporting in Zimbabwean corporate organizations. This tangible gain is due in large part to automated validation and processing of data, real-time data aggregation and careful use of predictive analysis. All these measures, combined, result in greatly reduced anthropogenic errors, increased compliance with regulatory requirements, and an efficient mechanism for conducting audits. Additionally, the level of AI adoption in the ERP system was found to be a mediating factor for the observed error reduction.

• On Operational Benefits, Challenges, and Maximizing ROI: The study finds that AI-enabled ERP systems provide significant operational benefits, including but not limited to automation of such processes is quite extensive reducing process cycle times and the resulting cost efficiencies. The increase in decision-making quality witnessed when using predictive modeling, demand forecasting, and real-time market intelligence was particularly striking by the systems. However, the complete utility of these benefits is often hindered by barriers like the mismatch of existing legacy systems, lack of embedded AI capabilities, lack of high-quality AI-ready data, and financial constraints. Maximizing ROI will require targeted attention to these technology and people investment gaps, and a focus on strategic alignment and intelligent infrastructural investment.

• Key Success Factors and Challenges for Successful Implementation and Challenge Mitigation: Success in implementing AI-ERP systems is found to depend on several key factors such as availability of sufficient cloud infrastructure, establishment of robust data governance, a competent and skilled workforce, and an alignment with overarching strategies. Firms that gave emphasis on full-fledged change management strategies like open communication, reoccurring training plans, and top management sponsorship, experienced a more trouble-free transition. Similarly, their lack means that there were significantly increased challenges associated with implementation among Small and Medium-sized Enterprises, in particular.

• In terms of effect on the role of accounting professionals future implications: The study finds out that AI-enabled ERP modified the work role of accountants, leading to shifting of their roles from data entry and reconciliation to analytical, strategic and control functions, consequently, resulting in the making of mundane task work substantially less repetitive. The while as this enhancement of capabilities is on its way, it also brings with it concerns about job security on the part of some professionals. The implication for the accounting profession trajectory ahead also highlights a categorical need for lifelong learning in AI literacy, data analytics and strategic acumen, to ensure it can evolve in this AI-mediated professional environment.

5.4 Recommendations

5.4.1 Blueprint for Adoption

Organizations need to implement AI-enabled ERP systems to ensure accurate financial reporting, better data representation, and efficient analysis. A clear blueprint can help this process along, so that businesses can capitalize on the evolutionary advantages of these technologies, rather than the devolutionary risks. Preparation Phase

Preparation Phase

1. Stakeholder Engagement

Advising stakeholder involvement can contribute to increased buy-in and support for the project. It is important to know their needs and expectations, since this knowledge is what makes it possible to align AI-supplemented ERP solutions to client objectives (Rapid Innovation, 2024).

2. Defining Project Scope and Objectives

An ERP implementation is needed when implementing an ERP, it is important to clearly define project scope, objectives and budget. This first phase of planning serves to level set and get the project team on the same page about what they are trying to accomplish. It is also important to set a realistic ‘go live’ date to prevent delays and overruns in budget (Jackley, 2023).

3. Implementation Strategy

A successful deployment of AI-based ERP systems requires a detailed implementation plan that investigates aspects such as scope of the project, depth of team members’ skills, users training, and stakeholder involvement (Adelusola, 2025).

4. Documentation and Training

Comprehensive documentation at every phase of the project is a necessary component of tracking the progression of the project and provides a valuable asset for potential future projects in rapidly moving domains such as AI and blockchain (Rapid Innovation, 2024). Develop the core team members through ongoing training which can increase their level of skill and knowledge improvement thereby leading to better performance and adjustment to industry changes (Rapid Innovation, 2024).

5. Team Composition and Expertise

An efficient project team is vital to execution. This team shall be comprised of experts in fields of knowledge to cover the entire field of the ERP system. It is critical to have hyper-advocacy senior leadership engaged as the project sponsor, and owned, by them to rally behind the project to ensure project success (Cherry Bekaert, 2024).

6. Data Migration and Integration

When an ERP solution has been decided upon, customer and order data will need to be migrated to the new platform. This is a task that must be carefully planned and executed to ensure accurate transfer and integration of pertinent records. The selected system should also be capable of being integrated with other applications and data sources to minimize disruption by enabling end-to-end analysis (Jackley, 2023).

Change Management and User Training

Good change management is crucial to reduce resistance and promote the new ERP system. Early stakeholder engagement and role-based training can greatly improve the success of implementation. A comprehensive change management strategy – such as that developed by Taylor – will involve providing on-going support and resource to help staff take up the new system (Akinnibi, 2024)

5.4.3 Testing and Feedback Assessment

Functional testing and User acceptance test should be done after implementation of ERP system. That's talking openly with the reseller and the decision-makers at the company when problems pop up and making sure you come up with a solution. Regular evaluations can provide a measure of the ease of use and overall effectiveness of and make such modifications to the system as they believe are necessary to enhance the performance and productivity of the system (Cherry Bekaert, 2024).

5.4.4 Continuous Improvement and Upgrades

On-going, it is important to constantly monitor the ERP system to facilitate improvements as well as to maintain the alignment of the system with the business because business needs are dynamic. Upgrades should occur from 5-10 years to ensure efficiency and effectiveness, and the concern is primarily that if a certain issue has been witnessed during some standard usage, then proactive maintenance might be essential (Top10ERP, 2025). Through this comprehensive deployment road map, entities can improve operational performance and increase the accuracy of financial statements through AI ERP systems.

5.4.5 Monitoring and Optimization

1. Continuous Monitoring

After the execution, constantly track the performance of the system to see how it can be improved. Applying analytics may provide the insight necessary to make refinements that allow the system to continue to be effective (Rapid Innovation, 2024).

2. Regular Communication

Keeping everyone in the knowing about what is happening with the project as it continues to push forward simply cannot be overlooked. Frequent updates would help us to resolve concerns, coordinate with others, and keep everyone knowing about the status and trajectory of the project (Burichin, 2025).

5.4.6 Risk Management

1. Conducting a Risk Assessment

Identifying potential risks early in the implementation process (i.e., technical, operational, financial)—enables proactive planning and use of mitigation strategies (Burichin, 2025).

2. Developing a Contingency Plan

It is crucial to prepare a risk mitigation strategy. This plan should detail contingency measures to implement if and when problems develop to mitigate interruptions when implementing the new system (Baker, 2024). This 'recipe' for implementing AI-ready ERP systems, therefore, not only helps organizations to mitigate some of the challenges of integrating AI into existing technology estate but provides an avenue to improve financial reporting intelligently and optimize operational effectiveness.

5.4.7 Achieving Financial Reporting Accuracy

The veracity of financial reporting is critical to upholding stakeholder confidence and regulatory requirements. Due to the rapid growth and complexity of financial data, traditional methods of reporting are no longer effective, and organizations are turning to cutting edge technologies such as AI for more accurate and reliable financial reports (Leeway Hertz, 2024).

The adoption of AI-enabled ERP systems represents a transformative leap for organizations aiming to achieve superior financial reporting accuracy and operational efficiency. This blueprint has demonstrated that the integration of AI capabilities fundamentally redefines ERP, moving it from a reactive system of record to a proactive, intelligent agent. AI-driven automation of core financial processes, advanced fraud detection, and the strengthening of internal controls significantly enhance the integrity and reliability of financial statements. Concurrently, AI optimizes operational efficiency through streamlined cross-functional processes, intelligent resource allocation, and predictive supply chain management, culminating in augmented managerial decision support (Chen, 2025).

However, realizing this transformative potential is contingent upon a meticulous and strategic approach to implementation. The success of AI-enabled ERP hinges critically on robust data governance, ensuring the quality, integration, and accessibility of data that fuels AI models. Equally vital is comprehensive organizational change management and proactive user engagement, addressing inherent resistance and fostering a collaborative, AI-literate workforce. Furthermore, the ethical implications of AI necessitate the establishment of strong governance frameworks to ensure transparency, accountability, and data privacy. Mitigating technical complexities, cybersecurity risks, and addressing skill gaps are also indispensable for a stable and secure deployment (Godbole, 2023).

For organizations embarking on this journey, the following recommendations are paramount:

● Prioritize Data Governance: Invest significantly in data infrastructure, data cleansing, and the establishment of dedicated data stewardship roles. Develop clear policies for data quality, integration standards, and secure accessibility to ensure AI models are fed with reliable and unbiased information (Graham & Nelson, 2025).

● Champion Change Management: Implement a proactive change management strategy that includes early and continuous user participation. Provide comprehensive training that explains the why, how, and when of AI integration, fostering AI literacy and a collaborative mindset where human and AI capabilities are mutually enhancing (IBM, 2025).

● Establish Robust AI Governance: Form an AI ethics committee or designate an AI ethics officer to oversee AI initiatives. Develop clear ethical guidelines addressing fairness, transparency, and data privacy. Ensure continuous regulatory compliance through regular audits to build trust and mitigate risks (Chimpiri, 2025).

● Strategic Vendor Selection: Choose ERP vendors with a proven track record in AI integration, robust security features, and a commitment to long-term support and ethical AI development. Evaluate their ability to handle necessary customizations while maintaining system integrity (Pokala, 2025).

● Invest in Skill Development: Address the skill gap by investing in training and development programs for existing employees and by recruiting professionals with expertise in AI, data science, and accounting information systems. This will build internal capacity to manage and leverage AI-enabled ERP effectively (MindBridge, 2025).

By adhering to this blueprint, organizations can navigate the complexities of AI-enabled ERP adoption, unlock unprecedented levels of financial reporting accuracy and operational efficiency, and secure a sustainable competitive advantage in the evolving digital economy (Mayer, et al., 2025).

Recommended AI-Enabled ERP Systems

Several enterprise resource planning (ERP) systems have effectively integrated artificial intelligence (AI) to enhance their functionalities and support business operations across various sectors.

SAP S/4HANA Cloud

SAP's real-time ERP suite leverages AI technologies to optimize operations and improve user engagement. This system is particularly effective across finance, manufacturing, and supply chain management, allowing organizations to make data-driven decisions rapidly and efficiently (SAP , 2025).

Oracle ERP Cloud

Oracle's ERP solutions incorporate AI and machine learning to enhance operational efficiency and user experience. The platform's AI capabilities help organizations streamline processes and gain actionable insights, which are crucial in today's competitive market (TOP10ERP, 2023).

Microsoft Dynamics 365

Microsoft Dynamics 365 utilizes AI to augment decision-making, automate processes, and provide predictive insights across various business functions. This ERP system's flexibility and integration of AI features allow organizations to respond to changing business conditions effectively (Microsoft , 2025).

Infor Cloud Suite Industrial (SyteLine)

Infor's ERP system is designed to enhance demand forecasting, inventory management, and production scheduling through AI integration. By leveraging AI, Infor Cloud Suite improves overall operational efficiency, helping businesses maintain an agile and responsive supply chain (Leeway Hertz, 2024).

Additional Considerations

When selecting an AI-enabled ERP system, businesses should consider factors such as scalability, integration capabilities, and the specific features that align with their operational needs. The implementation of AI in ERP systems not only drives efficiency but also transforms data management and decision-making processes, making these systems essential for modern enterprises (TOP10ERP, 2023)

5.11 Future Research Directions

To build upon the current findings, future research should consider the following directions:

Longitudinal Studies: Investigating the long-term impact of AI-enabled ERP systems on organizational performance and resilience (Vasarhelyi et al., 2022).

Comparative Analyses: Examining AI adoption patterns across African countries and other emerging markets to identify common challenges and best practices (Mutegeki et al., 2023).

Ethical AI in Finance: Exploring the implications of algorithmic transparency, bias mitigation, and human-AI collaboration in financial reporting and auditing (Binns, 2021).

AI Quality Dimensions: Assessing metrics such as interpretability, robustness, and fairness in AI-driven financial applications (Holstein et al., 2021).

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APPENDICES

Thank you for taking the time to participate in this survey. Your input is invaluable to us as we strive to achieve academic excellence. This survey is designed to be concise and will take approximately 5 minutes to complete. Your responses will remain completely anonymous and confidential, and the data collected were used solely for academic purposes. We greatly appreciate your contribution and encourage you to answer all questions to the best of your ability.

Thank you for being a part of this important initiative.

1. Have you ever interacted with an AI-Enhanced ERP system?

(Mark only one oval)

O Yes

O No

2. If you have interacted with an AI-Enhanced ERP system, How did you interact with them?

(Mark only one oval)

O As a Developer (Skip to question 23)

O As a User (Skip to question 3)

O I haven't interacted with it (Skip to section 4)

Survey for System Users

This part of the survey is intended to get information from current and potential ERP system users.

3. Company Name (optional)

____

4. The Industry Sector you are operating in

(Mark only one oval)

O Manufacturing

O Retail

O Consultancy

O Agriculture

O Healthcare

O Mining

O Other

5. Company Size (Number of Employees)

(Mark only one oval)

O 1-50

O 51-200

O 201-500

O 501-1000

O 1001+

6. Department

(Mark only one oval)

O IT / Technology

O Finance and Administration

O Operations

O Supply Chain

O Executive management

O Other: ___________

7. Years of Experience with ERP systems

(Mark only one oval)

O <1 Year

O 1-3 years

O 4-6 years

O 7-10 years

O 10+ years

8. Current ERP System in Use

(Mark only one oval)

O Microsoft Dynamics 365

O SAP S/4HANA

O Oracle ERP Cloud

O NetSuite

O Acumatica

O Local/Custom Solution

O No ERP System Currently

O Other: ___________

9. What is the extent of AI in your current ERP System?

(Mark only one oval)

O No AI capabilities

O Basic automation only

O Some machine learning features

O Advanced AI capabilities (predictive analytics, NLP, etc.)

O Don’t know

10. On a scale of 1-5, how important are the following potential benefits of AI-enabled ERP systems to your organization?

(1 = Not Important, 5 = Extremely Important)

(Mark only one oval per row)

Benefit	1	2	3	4	5
Improved financial reporting accuracy	○	○	○	○	○
Faster financial reporting timelines	○	○	○	○	○
Automated fraud detection	○	○	○	○	○
Predictive analytics for decision making	○	○	○	○	○

| Process automation | ○ | ○ | ○ | ○ | ○ |

| Enhanced inventory management | ○ | ○ | ○ | ○ | ○ |

| Improved customer experience | ○ | ○ | ○ | ○ | ○ |

| Reduced operational costs | ○ | ○ | ○ | ○ | ○ |

| Better compliance management | ○ | ○ | ○ | ○ | ○ |

11. What percentage improvement have you observed in financial reporting accuracy since AI implementation?

(Mark only one oval)

O <5%

O 5-10%

O 11-20%

O 21-30%

O >30%

O Don’t know/Not applicable

12. What challenges has your organization faced (or anticipates facing) in adopting AI-enabled ERP systems?

(Check all that apply)

O High implementation costs

O Lack of skilled personnel

O Employee resistance to change

O Cybersecurity concerns

O Unclear ROI (Return on Investment)

O Vendor selection challenges

13. How prepared is your organization for AI-ERP integration in terms of the following?

(1 = Not Prepared, 5 = Fully Prepared)

(Mark only one oval per row)

Factor	1	2	3	4	5
Technological infrastructure	○	○	○	○	○
Data quality and availability	○	○	○	○	○
Employee skills and training	○	○	○	○	○
Leadership commitment	○	○	○	○	○
Budget allocation	○	○	○	○	○

14. What strategies has your organization employed (or plans to employ) to overcome implementation challenges?

(Check all that apply)

O Phased implementation approach

O Extensive employee training programs

O Hiring external consultants

O Partnering with ERP vendors

O Change management initiatives

O Other: ___________

15. How is AI currently being used (or planned to be used) in your ERP system?

(Check all that apply)

O Automated financial reporting

O Fraud detection

O Demand forecasting

O Inventory optimization

O Predictive maintenance

O Customer behavior analysis

O Not currently using AI

O Other: ___________

16. How has AI in ERP impacted your accounting/finance team's work?

(Check all that apply)

O Reduced manual data entry

O Shifted focus to analysis vs. data processing

O Required new skill development

O Improved collaboration with other departments

O No significant impact

O Other: ___________

17. What ethical concerns does your organization have regarding AI in ERP?

(Check all that apply)

O Data privacy issues

O Job displacement concerns

O Lack of transparency in AI decisions

O Security vulnerabilities

O No major concerns

O Other: ___________

18. What is your organization's timeline for AI-ERP adoption/enhancement?

(Mark only one oval)

O Already implemented advanced AI features

O Planning to implement within 1 year

O Planning to implement in 1-3 years

O Considering but no concrete plans

O No plans to implement

O Don’t know

19. What factors would accelerate your organization’s adoption of AI in ERP?

(Check all that apply)

O Clear demonstration of ROI (Return on Investment)

O Government incentives/support

O Availability of local expertise

O More affordable solutions

O Industry-specific solutions

O Peer organization success stories

O Other: ___________

20. What support would be most helpful for successful AI-ERP implementation in Zimbabwean companies?

(Select top 3)

O Government policy framework

O Vendor training programs

O University curricula development

O Industry best practice guidelines

O Financial incentives

O Other: ___________

21. Describe any specific success stories or challenges your organization has experienced with AI in ERP systems:

____

____

____

22. What recommendations would you make to other Zimbabwean companies considering AI-enabled ERP implementation?

____

____

____

(Skip to section 4)

For System Developers

This part of the survey is intended to get information from current and potential ERP system developers.

23. Developer/Implementer Profile

(Mark only one oval)

O ERP Systems Developer

O ERP Implementation Specialist

O Business Analyst (focused on ERP)

O IT Consultant (ERP focus)

O Project Manager (ERP Implementation)

O ERP Trainer/Support Specialist

O Independent ERP Consultant

24. Years of Experience with ERP Implementations

(Mark only one oval)

O <1 year

O 1-3 years

O 4-6 years

O 7-10 years

O 10+ years

25. Number of AI-ERP implementations you've been involved with

(Mark only one oval)

O None yet

O 1-3

O 4-6

O 7-10

O 10+

26. What technical architecture do you typically use for AI-ERP integrations?

(Mark only one oval)

O Cloud-native AI services

O On-premises AI models

O Hybrid approach

O Edge computing

O Other: ___________

27. Which AI technologies are most commonly requested for ERP integrations?

(Check all that apply)

O Predictive analytics

O Natural Language Processing (NLP)

O Computer vision

O Anomaly detection

O Process mining

O Other: ___________

28. What are the biggest technical challenges in implementing AI in ERP systems?

(Check all that apply)

O Data quality issues

O Legacy system integration

O Model explainability/transparency

O Performance at scale

O Maintaining model accuracy over time

O Availability of skilled personnel

O Infrastructure limitations

O Connectivity and bandwidth issues

O Cost of implementation and maintenance

29. What methodology do you typically use for AI-ERP implementations?

(Mark only one oval)

O Big Bang Implementation

O Phased Implementation

O Parallel Implementation

O Pilot Implementation

O Hybrid Approach

30. What is the typical timeline for adding significant AI capabilities to an existing ERP system?

(Mark only one oval)

O <3 months

O 3-6 months

O 6-12 months

O 1-2 years

O >2 years

31. Which ERP modules are most challenging to enhance with AI?

(Check all that apply)

O Financial reporting

O Inventory management

O Supply chain

O HR/payroll

O CRM

O Manufacturing

O Other: ___________

32. What are the most common gaps in client readiness for AI-ERP implementations?

(Check all that apply)

O Technical infrastructure

O Change management capability

O Executive sponsorship

O Budget understanding

O Other: ___________

33. How do you measure the success of AI-ERP implementations?

(Check all that apply)

O Cost reductions

O Accuracy improvements

O User adoption rates

O ROI metrics

O Process efficiency gains

O Other: ___________

34. What maintenance challenges do AI-ERP systems typically require?

(Check all that apply)

O Model drift monitoring

O Continuous data quality management

O Regular feature engineering

O User retraining

O Other: ___________

35. What adaptations have you made for the Zimbabwean market?

(Check all that apply)

O Simplified solutions

O Phased implementations

O Localized training approaches

O Hybrid cloud/on-prem solutions

O Other: ___________

36. Describe your most successful AI-ERP implementation and what made it successful:

____

____

____

37. What lessons have you learned from failed or challenging AI-ERP implementations?

____

____

____

38. What recommendations would you make to Zimbabwean companies considering AI-ERP implementations?

____

____

____

(Skip to section 4)

Thank You!!

We extend our heartfelt gratitude to everyone who took the time to participate in this survey. Your thoughtful responses are a cornerstone of this effort, and your willingness to share your experiences and perspectives ensures that our outcomes are meaningful, inclusive, and impactful.

You can go ahead and submit your response.