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Exploring the Impact of Artificial Intelligence (AI) on Business Decision-Making: A Case Study of Insurance Companies in Kitwe

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ABSTRACT

This study investigates the impact of Artificial Intelligence (AI) on business decision-making within selected insurance companies in Kitwe District, Zambia. Employing a quantitative research design, the study collected data from 50 respondents across three insurance companies.

The findings indicate that AI adoption for business decision-making is at a nascent stage, with 80% of respondents reporting either no or minimal usage. AI application is highly concentrated in core operational areas such as risk assessment (80%), claims processing (70%), and regulatory compliance (70%). Conversely, AI is entirely absent in customer-facing and strategic functions, including customer service, marketing, investment and finance, and product development. Individual AI tool usage is notably low, with 70% of respondents indicating infrequent or no personal use, highlighting a disconnect between company-level adoption and individual utilisation.

Despite limited adoption, AI has an overwhelmingly positive impact on decision quality (80% reporting improvement) and speed (70% reporting acceleration), with no respondents indicating any negative impact. While a large majority (80%) express equal confidence in AI-supported decisions compared to traditional methods, the perceived impact on error reduction is limited. The most significant implementation challenges are unclear return on investment (98%), integration issues with legacy systems (95%), data privacy and security concerns (90%), and a lack of skilled personnel (80%). Other challenges include high implementation costs (60%), employee resistance (60%), and lack of strategic direction (50%). The study recommends that insurance organisations develop comprehensive AI strategies aligned with business objectives, invest in data infrastructure and governance, address skills gaps through training and development, and adopt phased implementation approaches.

Keywords: Artificial Intelligence (AI), Business Decision-Making, AI Implementation Challenges, Insurance, Zambia

INTRODUCTION

In the rapidly evolving digital landscape, Artificial Intelligence (AI) has emerged as one of the most transformative technologies influencing modern business operations. AI refers to the simulation of human intelligence processes by machines, particularly computer systems, encompassing learning, reasoning, and self-correction (Russell & Norvig, 2020). As businesses operate in increasingly complex and data-rich environments, integrating AI into decision-making processes has become not only beneficial but essential for competitive survival in contemporary markets.

Davenport and Ronanki (2018) observed that AI has transitioned from a futuristic concept to a present-day reality, with increasing applications in data analysis, forecasting, customer relationship management, and operational optimisation. This transformation is reshaping decision-making approaches, moving from intuition-driven strategies toward data-driven, algorithm-supported frameworks. Technologies such as natural language processing, robotics, neural networks, and predictive analytics provide business leaders with real-time insights that enhance both the quality and speed of their decisions (Brynjolfsson & McAfee, 2017).

The insurance industry has been at the forefront of AI adoption due to its data-intensive nature. AI is employed in underwriting, fraud detection, claims processing, customer service, and risk assessment, fundamentally transforming how insurers operate. PwC (2019) reported that insurers leveraging AI experience reduced operational costs, improved customer satisfaction, and more accurate decision-making outcomes. Despite these documented benefits, implementation challenges persist, particularly in developing economies such as Zambia, where infrastructural limitations, inadequate technical expertise, and insufficient policy frameworks constrain adoption (ZICTA, 2021).

Scholars increasingly emphasise the importance of balancing human judgment with machine intelligence. Wilson and Daugherty (2018) assert that 'AI will not replace managers, but managers who use AI will replace those who do not.' This perspective captures the evolving nature of managerial roles in the AI era, suggesting that AI should augment rather than replace human capabilities. Given this context, there is a critical need to explore how AI influences decision-making processes in businesses within developing economies.

Despite growing global recognition of AI as a powerful tool for improving business decision-making, its adoption and practical application in developing economies like Zambia remain limited and underexplored. This study addresses this gap by providing empirical evidence from selected insurance companies in Kitwe District, Zambia, exploring the extent of AI usage, its effectiveness on decision quality and speed, and the barriers organisations face in its adoption.

Research Objectives

The general objective of this study was to explore the impact of AI on business decision-making within selected insurance companies in Kitwe District, Zambia. The specific objectives were:

(i) To investigate the extent to which AI is being used to support informed business decision-making in insurance companies.

(ii) To evaluate the effectiveness of AI in enhancing the quality and speed of business decisions within the insurance sector.

(iii) To analyse the challenges and limitations faced by insurance companies in implementing AI in business decision-making processes.

THEORETICAL FRAMEWORK

This study is guided by two key theoretical frameworks: Decision Theory and the Technology Acceptance Model (TAM). Decision Theory, drawing from economics, psychology, and management studies, focuses on how decisions are made and how different variables influence decision outcomes. The theory assumes that individuals and organisations aim to make rational choices that maximise utility based on available information (Simon, 1979). In the context of AI, Decision Theory supports the idea that AI tools enhance rationality by enabling faster and more accurate data analysis, thereby improving decision quality and effectiveness.

The Technology Acceptance Model (TAM), developed by Davis (1989), explains how users come to accept and use new technologies. TAM proposes that two main factors, perceived usefulness and perceived ease of use, determine an individual's acceptance of a technology. In this study, TAM helps explain how insurance employees perceive AI systems and whether such perceptions affect the adoption and integration of AI in decision-making processes. Together, these two frameworks offer a comprehensive lens for examining both the functional impact of AI on decision-making and the behavioural and organisational factors influencing AI adoption.

Significance of The Study

This study offers practical and theoretical value to several stakeholder groups. For business managers and organisational leaders, the findings highlight where AI investment yields the greatest returns, such as risk assessment, claims processing, and regulatory compliance, while also flagging common implementation pitfalls to anticipate.

For policymakers and regulators, the evidence on barriers such as infrastructure gaps, skills shortages, and data security concerns can inform targeted interventions, including skills development programmes and regulatory guidelines that encourage responsible AI adoption.

For researchers, the study contributes localised data to the limited body of knowledge on AI adoption in developing economies, extending theoretical understanding of AI adoption in contexts where technological infrastructure and organisational capacity differ from developed markets.

For technology developers and vendors, the findings reveal the practical needs and constraints of end-users in the Zambian insurance market, supporting the design of context-appropriate, user-friendly AI tools.

Scope of The Study

This research examines how AI influences decision-making within three selected insurance companies in Kitwe District, Zambia: Madison Insurance, Professional Insurance, and Nico Insurance. The study assesses the extent of AI usage, its impact on decision quality and speed, and the challenges encountered in implementation, drawing on a quantitative survey of 50 respondents, comprising 35 staff members and 15 beneficiaries, across the three companies.

The study is confined to managerial and operational staff and beneficiaries of the selected insurers and focuses solely on decision-making processes during the data collection period; it does not extend to other organisational functions such as product development or marketing. The geographical scope is limited to Kitwe District, which may affect the generalisability of the findings to other regions of Zambia. The findings are intended to inform similar developing-market insurers about current AI capabilities, obstacles, and opportunities for improving decision-making processes.

LITERATURE REVIEW

This section reviews the literature relevant to AI and its role in business decision-making, organised around the three research objectives: examining the extent of AI adoption, evaluating its effectiveness in improving decision quality and speed, and analysing the challenges organisations face in implementation. The review proceeds from global evidence to regional African studies and, finally, to the limited local Zambian literature. Each section synthesises findings across studies, identifying patterns, disagreements, and gaps. The section concludes by articulating the research gap that this study addresses.

Extent of AI Use in Business Decision-Making

Global Perspective

The global literature presents a consistent picture: AI adoption in business decision-making is growing but remains uneven, concentrated among large, well-resourced firms rather than distributed evenly across the corporate landscape. According to the IBM Global AI Adoption Index (2023), 42% of enterprises have actively deployed AI, while 40% are experimenting with the technology. Of those using or exploring AI, 59% have accelerated their investments and rollouts over the past two years. A global survey of 1,516 AI decision-makers found that AI has shifted from being a cost-saving lever to a revenue driver, with 69% of respondents now using AI and machine learning to create new revenue streams.

Despite these promising figures, the depth of integration remains limited. Davenport and Ronanki (2018), drawing on a survey of 250 executives and a detailed study of 152 AI projects, found that most organisations were still using AI to automate routine tasks rather than to inform core strategic decisions. The firms furthest along had invested deliberately in data infrastructure and talent well before seeing returns. This finding is echoed at much larger scale by Bughin et al. (2017), whose McKinsey Global Institute report synthesised survey responses from over 3,000 AI-aware executives across ten countries. Their research found that adoption was real and growing, but heavily concentrated among technology-sector early adopters, with traditional, risk-averse industries, insurance prominent among them, lagging noticeably behind.

Fountaine et al. (2019), reporting on a McKinsey survey of more than 1,000 executives spanning North America, Europe and Asia, sharpen this picture further. They found that only around 8% of companies reported significant financial benefit from their AI initiatives, with the remainder stuck at the pilot or proof-of-concept stage. The authors concluded that technology is not the biggest challenge; organisational culture is. This observation has direct implications for the present study, as it suggests that even where AI tools are available, organisational factors may prevent their effective use in decision-making. A 2023 survey by Workday found that 80% of business leaders agree that AI and machine learning help employees work more efficiently and make better decisions, yet 93% believe humans should remain involved in AI decision-making. This tension between recognising AI's potential and insisting on human oversight reflects the cautious approach that characterises current adoption patterns.

Sector-specific studies reinforce this pattern of concentrated, uneven adoption. Wamba et al. (2020), reviewing the supply-chain AI literature, found AI-enabled analytics increasingly embedded in inventory and logistics decisions among North American and European firms, but noted that empirical evidence for developing economies remained scarce. Chen et al. (2012), in an earlier but foundational contribution, established that the capacity to collect, process and analyse large volumes of data is what separates competitive, data-driven decision-making from its alternative; this argument underpins nearly all of the adoption literature that followed it. More recent conceptual work by Shrestha et al. (2019) builds on this foundation to argue that AI's role is best understood as augmentation rather than replacement of human decision-makers, reducing cognitive bias and accelerating information processing in complex, high-stakes environments such as those insurance firms operate in.

KPMG International (2023) found that most countries are prioritising AI and machine learning to support short-term ambitions, with leaders in their markets having already adopted the technology. However, only 40% of businesses had reached the "proactive" stage of their AI deployment strategy. Similarly, a Kearney study revealed that just over a third of executives (36%) anticipate their companies will spend $1 million or more on generative AI over the next three years, indicating that while investment is increasing, it remains concentrated among larger firms with substantial budgets.

Taken together, this body of evidence establishes that adoption is neither universal nor evenly distributed even in mature markets, and that the pattern of adoption, concentrated in efficiency-oriented, data-intensive functions, slower in customer-facing or judgement-heavy ones, recurs across the literature.

Regional African Perspective

The regional African literature on AI adoption is smaller than the global body but growing, and it tells a broadly consistent story of cautious, infrastructure-constrained uptake shaped heavily by national policy environments. Ochara and Ssewanyana (2019), reviewing AI initiatives across several African countries including Kenya, Nigeria, South Africa and Rwanda, found adoption concentrated in fintech, agriculture and healthcare, sectors where the case for AI was easiest to make against pressing local development needs. Data scarcity and skills shortages remained the binding constraint elsewhere.

This is corroborated at the SME level by Akinola and Adebayo (2021), whose study of Nigerian small and medium enterprises found cautious adoption limited mainly to customer-service automation and basic analytics, held back by cost and a lack of technical expertise. Gwagwa et al. (2020), analysing AI deployment across South Africa, Kenya, Rwanda and Nigeria for the *African Journal of Information and Communication*, found that the benefits of AI were unevenly distributed and strongly shaped by the maturity of each country's data-governance regime, a more institutional explanation for uneven adoption than firm-level cost or skill constraints alone.

Mabotuwana et al. (2017), surveying South African organisations directly, found that perceived usefulness and top-management support predicted adoption intent more strongly than infrastructure or cost considerations, suggesting that organisational culture, not just resources, shapes whether AI takes hold. Ndungi (2023), surveying Kenyan respondents on AI use across agriculture, healthcare, education and the transport sector, found chatbots and digital assistants rated far more favourably (96% and 90% success respectively) than AI applications in transport (46%), illustrating how unevenly adoption and perceived usefulness can vary even within a single country.

The PwC Africa NextGen Survey (2024) found that 77% of Africa's NextGen leaders view generative AI as a powerful tool for transformation but are concerned about their family businesses' readiness for adoption. Actual adoption levels remain low, with only 4% actively implementing generative AI in their daily tasks. KPMG International (2024) found that 54% of surveyed African CEOs are backing substantial AI investments, yet 77% highlight ethical dilemmas as some of the toughest challenges in adopting AI within their enterprises, up from 57% in 2023. According to the United Nations (2023), research has shown that AI has the potential to generate $1.2 trillion worth of economic activity in Africa, representing a 5.6% increase in the continent's GDP by 2030.

Read together, these studies suggest that African AI adoption is not simply a lagging version of the global pattern but is shaped by distinct institutional and governance factors, national data policy, organisational culture, sector-specific trust, that do not feature as prominently in the global literature. This is a reasonably populated body of evidence, though it draws almost entirely on Nigeria, Kenya and South Africa; no equivalent extent-of-adoption study exists for Southern Africa's insurance sector specifically, a gap this study begins to close.

Local Zambian Perspective

Zambian literature on the extent of AI adoption in business is markedly thinner, and what exists is mostly policy-facing rather than empirical. ZICTA (2021) sets out the intention, as part of national ICT policy, to build an enabling environment for AI, but offers no data on actual usage by Zambian businesses. This intent was formalised more concretely when the Ministry of Technology and Science (2025) launched Zambia's National Artificial Intelligence Strategy 2025-2027, developed with technical support from international partners, which identifies finance among the priority sectors for AI-driven development. The strategy outlines an ambition to become a regional leader in applying AI for sustainable development, identifying priority sectors including agriculture, healthcare, mining, education, finance, and public service delivery. What the strategy signals, however, is ambition rather than demonstrated uptake.

The one Zambian study that offers a concrete, measurable result comes from a different domain altogether. The International Growth Centre (2025), evaluating GPT-4 Turbo's use in coding open-ended responses from Zambia's 2023 Labour Force Survey, found the model significantly outperformed human enumerators in accuracy, offering potential efficiency gains of up to 130 working days annually for the Zambia Statistics Agency. This demonstrates that AI can work effectively on Zambian data, but the finding is situated in government statistics rather than private business decision-making.

A recent study by Nyirenda and Lungu (2025) investigated the role of AI in optimising logistics management at VS Cargo Limited in Ndola, Zambia. The research found that real-time tracking and warehouse automation are the primary AI technologies in use, contributing significantly to route optimisation, improved decision-making, enhanced customer satisfaction, and reduced operational costs. However, the company still faces notable challenges, including limited digital infrastructure, lack of skilled personnel, and poor interdepartmental coordination. While this study provides valuable insight into AI adoption in one Zambian logistics firm, it does not address the insurance sector.

Zambia's Ministry of Technology and Science (2025) estimates that AI could boost the national GDP by nearly 8% by 2030, despite a dominant informal economy. The administration has encouraged Zambian entrepreneurs to be proactive participants in the AI revolution. However, for many organisations in Zambia, the journey toward AI adoption is just beginning, with the potential being substantial but implementation remaining limited.

Taken together, these sources reveal a gap rather than a body of evidence: no published Zambian study has measured how extensively AI is actually used in business decision-making in the insurance sector. This absence reflects a genuine void in the literature that this study is positioned to fill.

Effectiveness of AI on The Quality and Speed of Business Decisions

Global Perspective

Where the literature on extent of adoption shows caution and unevenness, the literature on effectiveness is considerably more consistent in its optimism. Davenport and Ronanki (2018) found that the firms in their sample that had gone furthest with AI reported measurable gains in decision speed and quality, particularly in fraud detection and operational optimisation. At the macroeconomic level, Bughin et al. (2018) modelled AI's potential contribution to global output at roughly $13 trillion by 2030, attributing a substantial share of this to improved forecasting and decision-making rather than to cost savings alone.

Recent empirical research has reinforced these findings. A study by Neiroukh et al. (2024) investigated the impact of AI capabilities on decision-making processes and organisational performance, drawing on data from 230 responses from diverse organisations. The results demonstrated that AI capability significantly and positively affects decision-making speed, decision quality, and overall organisational performance. Notably, decision-making speed was found to be a critical factor contributing significantly to enhanced organisational performance, with decision-making processes partially mediating the relationship between AI capabilities and organisational performance. This study provides robust empirical evidence that AI's effectiveness operates through its influence on both the speed and quality of decisions.

Csaszar et al. (2024) explored how AI may impact strategic decision-making in firms, providing empirical evidence that current large language models can generate and evaluate strategies at a level comparable to entrepreneurs and investors. Their analysis suggests that AI has the potential to enhance the speed, quality, and scale of strategic analysis, while also enabling new approaches such as virtual strategy simulations. However, they caution that the ultimate impact on firm performance will depend on competitive dynamics as AI capabilities progress.

Shrestha et al. (2019) offer a complementary, more mechanism-focused explanation for these gains, arguing that AI improves decisions specifically by reducing the cognitive biases that affect human judgement and by processing information faster than any human team could manage. This perspective is supported by research findings showing a 66% reduction in decision turnaround time, a 16.8% improvement in forecasting accuracy, an 80% decrease in defect detection, and full traceability of managerial decisions with no compliance violations in ethical governance.

Regional and firm-level studies within the global literature add further texture. Wirtz et al. (2020), studying European, primarily German, firms, found AI supporting faster operational decisions and more informed strategic choices, though adoption was tempered by the caution that the General Data Protection Regulation (GDPR) imposes on data use. Lee and Lee (2021), using firm-level data from South Korea, China and Japan, found AI adoption associated with faster, more accurate decisions in supply chain management and market forecasting, aided by strong government backing for technology investment. Brynjolfsson and McAfee (2017), drawing on case evidence from US and European firms, reach a similar conclusion but add an important qualification: the speed and quality gains they documented were achieved only where AI adoption was paired with deliberate organisational change management, not by installing new software alone.

According to IBM's AI in Action report (2023), two-thirds of leaders say that AI has driven more than a 25% improvement in revenue growth rates, and 72% say that the C-suite is fully aligned with IT leadership about what comes next on the path to AI maturity. With confidence in AI growing, enterprises are implementing intelligent tools to improve business outcomes. However, even impressive AI performance comes with caveats; one AI concierge answered 92% of queries correctly but was still wrong 8% of the time, highlighting that AI effectiveness, while substantial, is not absolute.

The overall weight of this literature is that AI does improve decision quality and speed, but that this improvement is conditional, on data readiness, on organisational change management, and on regulatory context, rather than automatic. This conditionality matters directly for the present study, since it implies that Kitwe's insurance companies should not be expected to see effectiveness gains from AI unless the same underlying conditions are present locally.

Regional African Perspective

The regional evidence on effectiveness specifically is considerably thinner than the evidence on extent of adoption, and this thinness is itself worth noting rather than glossing over. Dagunduro et al. (2023) surveyed 125 Nigerian accounting and audit firms and found that AI tools, expert systems, machine learning and intelligent agents, significantly improved audit decision quality and the reliability of auditors' judgement. Ndungi (2023), discussed above in the context of adoption, also speaks to effectiveness: Kenyan respondents rated AI-supported tools as highly effective in some domains (chatbots, digital assistants) but markedly less so in others (transport), suggesting that effectiveness in the African context may be more sector-dependent than the global literature implies.

A study on generative AI's impact on SME productivity in South Africa found that the overall impact was predominantly positive, paving the way for further technological advancements and adoption in the sector (PwC, 2024). African business and technology leaders have noted that as organisations continue to build out their AI strategies, immense productivity and innovation gains are expected to be realised by the effective integration of data and AI into core business processes. Business AI is seen as a tool for accelerated decision-making, with enterprises that leverage business AI to enhance decision-making gaining greater competitiveness and increased operational efficiency.

Beyond these studies, however, rigorous regional evidence on whether AI actually improves decision quality or speed is difficult to find, and none exists for the insurance sector specifically. This is a genuine gap in the regional literature: while African researchers have documented adoption patterns and implementation barriers in reasonable depth, comparatively little empirical work has tested whether the AI that has been adopted is actually delivering the quality and speed benefits the global literature promises. The present study, in asking this question directly of Kitwe's insurance companies, addresses a question the regional literature has largely left untested.

Local Zambian Perspective

At the Zambian level, effectiveness evidence narrows to a single source. The International Growth Centre (2025) study of GPT-4 Turbo's performance on Zambia's Labour Force Survey data offers the only concrete Zambian evidence that AI can outperform human effort on a defined task, but again, this is a government statistical exercise rather than a private-sector business decision. No Zambian study, in insurance, banking, or any other business context, has yet examined whether AI use improves the quality or speed of business decisions. This is the starkest gap identified anywhere in this review, and it is precisely the question this study's second objective is designed to answer.

Challenges and Limitations in Implementing AI in Business Decision-Making

Global Perspective

The global literature is comparatively unified on what makes AI implementation difficult. Fountaine et al. (2019), drawing on their large McKinsey survey, found that fragmented strategy, weak data foundations and unclear governance were the most common reasons AI initiatives failed to scale beyond pilot projects. Davenport and Ronanki (2018) reached a similar conclusion from their interview data, identifying data quality, talent scarcity and ethical concerns as the barriers executives raised most frequently. Between them, these two studies establish cost, data infrastructure, governance and talent as the four recurring pillars of implementation difficulty in the global literature.

The IDC Financial Insights 2023 Survey (IDC, 2024), which examined responses from 223 insurance providers across multiple regions including the US, Canada, the UK, Germany, France, South Africa, Singapore, India and Australia, found that insurers face a clash between traditional corporate culture and digital expectations, compounded by the struggle to acquire and retain digital talent. Data governance and model oversight were identified as imperative, with insurers described as standing at "stage zero" of their AI governance journeys, navigating through the complexities of accountability and technological advancement. The survey identified cost, data fragmentation, and regulatory compliance as key challenges.

A 2023 Swiss Re report (Swiss Re, 2023) highlighted that a critical lack of quality data and data engineering is preventing the insurance industry from harnessing rapid advances in machine intelligence. The report noted that data is often not available when most needed and sometimes lost in organisational silos. Another Swiss Re analysis identified five major pitfalls in enterprise machine intelligence transformation: costs (with 93% of respondents at US insurers expressing concern around costs), absence of a firm-wide data strategy, too few data engineers, lack of clear governance, and insufficient executive commitment.

The McKinsey analysis of InsureTech Connect 2023 (McKinsey & Company, 2023) found that one major challenge of adopting generative AI is training staff, because using the technology typically still requires human involvement. Companies are also weighing which AI tools to build in-house and which to source from technology vendors. Privacy threats and regulatory concerns about ethics and bias were identified as significant risks. A 2023 Deloitte study (Deloitte, 2023) found that only 1.33% of insurance companies had invested in AI, though data from 2024 indicates a shift is underway, with 77% of respondents indicating they are in some stage of adopting AI somewhere within their value chain.

Concerns about job losses and regulatory uncertainty also impede swift implementation. Some regulators fear that increased use of AI will open loopholes in established systems that could make them vulnerable to hackers and other malicious actors. Questions about data security, cost implications, and consumer protection remain critical. The high cost of changing data management systems and processes, combined with poor quality of data, are currently the main challenges facing insurers.

A 2023 Workday global survey (Workday, 2023) found that 77% of respondents are concerned about the timeliness or reliability of underlying data, and nearly three-quarters (73%) of business leaders feel pressure to implement AI at their organisations but remain wary. This tension between pressure to adopt and caution about implementation reflects the complex environment in which AI decisions are made.

Regional African Perspective

The regional literature on implementation challenges is the most developed of the three themes at the African level, and it includes the single most directly comparable study to the present research found anywhere in this review. Moyo et al. (2022) conducted a census of twenty Zimbabwean insurance companies, administering questionnaires to operations managers and following up with interviews with twelve of them, analysed thematically using NVivo. They found that AI and machine-learning adoption was hindered above all by a shortage of resources, a lack of in-house expertise, and the high cost of AI-compliant systems. This study, because it comes from the same industry and a neighbouring country, provides the closest available comparator for what might be expected in Kitwe.

Mabotuwana et al. (2017), returning to their South African organisational survey discussed earlier, found that organisational readiness and internal skills gaps constrained adoption more than the raw cost of technology itself, a nuance that complicates any simple 'AI is too expensive' narrative. Akinola and Adebayo (2021) identified cost, technical expertise and data-privacy concern as the leading barriers facing Nigerian SMEs specifically, while Gwagwa et al. (2020) locate the deeper structural problem one level up, in weak data-governance capacity and inconsistent regulation across African markets more broadly.

In West Africa, the insurance sector faces unique challenges including a largely informal economy, small-scale insurance companies, and a heavy reliance on agriculture, which present both hurdles and opportunities for AI innovation (Moyo et al., 2022). In East Africa, while there is a clear argument for implementing data analytics in insurance companies, wholesale adoption comes with challenges, primarily poor quality of data and the high cost of changing data management systems and processes.

The Zimbabwean insurance sector, according to a 2024 analysis (Moyo et al., 2022), faces challenges including low penetration rates, operational inefficiencies and widespread mistrust, with the country's insurance penetration rate around 1.6%. These contextual factors shape the environment in which AI adoption decisions are made.

These studies, read together, suggest that implementation barriers in Africa mirror the global pattern, cost, talent, data, governance, but are compounded by weaker institutional and regulatory foundations than exist in the markets the global literature is mostly drawn from. This is a reasonably strong regional base, and Moyo et al. (2022) remains the only sector-matched comparator available in the entire literature reviewed for this study.

Local Zambian Perspective

Two Zambian studies speak to implementation challenges, and neither is set in insurance. Mweemba and Kalusa (2026), collecting primary data from employees and management at Zambia National Commercial Bank Plc, found that limited digital infrastructure, implementation costs, security concerns and a shortage of skilled personnel were the dominant barriers to AI integration in Zambian commercial banking. This finding closely mirrors both the global pillars identified in Section 2.3.1 and the regional Zimbabwean insurance findings of Moyo et al. (2022), suggesting these barriers may be fairly generalisable across Zambian financial services even though no insurance-specific data yet exists.

Mutelo (2025), studying Zambian higher education rather than a commercial sector, found that limited digital infrastructure, unreliable internet access and the absence of clear institutional policy prevented awareness of AI tools from translating into sustained use. This distinction between awareness and actual use may well apply to insurance employees in Kitwe as much as to university researchers.

Nyirenda and Lungu (2025), in their study of VS Cargo Limited in Ndola, found that the logistics firm faced notable challenges including limited digital infrastructure, lack of skilled personnel, and poor interdepartmental coordination. Their correlation analysis indicated strong relationships between AI adoption and logistics performance indicators, with route optimisation showing the highest positive correlation ($r = 0.877$). The study recommended continuous training for staff, leadership sensitisation, infrastructure upgrades, and stronger data management practices.

A 2025 study on factors influencing user adoption of AI in Zambia's telecommunications industry identified challenges and strategic approaches to adoption (ZICTA, 2025). The Zambia Enterprise AI Market report highlights increasing demand for personalised user experiences and government initiatives promoting AI technologies across various sectors as drivers of adoption.

While these studies are not perfectly matched to the present research context, their findings are strikingly consistent with both the global and regional literature reviewed above, which lends some confidence that the barriers identified elsewhere are likely to recur in Zambian insurance as well. What is missing, and what this study supplies, is direct evidence from the sector itself.

Research Gap

The literature reviewed in this chapter reveals a clear pattern of uneven knowledge across geographic levels. The global body of evidence is extensive and methodologically diverse across all three themes, extent of adoption, effectiveness, and implementation challenges. The regional African literature is moderately developed for extent of adoption and implementation challenges but noticeably thinner for effectiveness. The Zambian literature is sparse throughout and does not address the insurance sector at all.

Several specific gaps emerge from this review. First, no study identified examines the extent, effectiveness and challenges of AI use together within a single business-decision-making context in Zambia. Second, while the global literature has established that AI can improve decision quality and speed, these findings have not been tested in the Zambian insurance context. Third, the closest available comparator study, Moyo et al.'s (2022) census of Zimbabwe's insurance industry, does not examine whether AI actually improves decision quality or speed. Fourth, the Zambian literature on AI adoption is predominantly policy-focused or situated in non-commercial contexts such as government statistics and higher education, with no empirical studies examining AI in insurance decision-making.

The present study is positioned to close these gaps directly, using insurance companies in Kitwe District as its empirical setting and addressing all three research objectives within a single, coherent framework.

Research Methodology

This section outlines the research methodology used to examine the impact of AI on business decision-making in selected insurance companies in Kitwe District, Zambia, covering the research design, sampling design, target population, data collection methods and instruments, data analysis procedures, limitations of the study, and ethical considerations.

Research Design

This study employed a quantitative research design, chosen because it allows for the systematic collection of numerical data that can be statistically analysed to identify patterns, relationships, and trends (Creswell & Creswell, 2018). This approach was well suited to measuring the extent of AI usage, testing perceived relationships between AI adoption and decision quality and speed, and generalising findings across the surveyed companies through structured questionnaires. The research was cross-sectional in nature, with data collected at a single point in time to capture the current state of AI adoption and its perceived impact rather than changes over time.

Sampling Design

The study used purposive sampling to select insurance companies in Kitwe District that had implemented AI. Within these companies, convenience sampling was employed to select respondents from managerial and operational staff who were readily accessible, while snowball sampling was used to reach beneficiaries, with initial respondents referring other customers who had interacted with the companies. This combination of techniques ensured the selection of knowledgeable participants and balanced representation across roles, enhancing the relevance and accuracy of the data collected on AI adoption and its impact on business decisions.

Target Population

The target population consisted of employees, managers, and beneficiaries from three insurance companies operating in Kitwe District: Madison Insurance, Professional Insurance, and Nico Insurance. These companies were selected because they represent a cross-section of the local insurance industry and had indicated some level of AI adoption in their operations.

The population included 35 staff members drawn from management, underwriting, claims processing, and customer service departments, together with 15 beneficiaries (customers), bringing the total target population to 50 respondents. This composition was intended to capture both internal organisational experiences and the effects of AI-influenced decisions on those who experience their outcomes.

Data Collection Methods

The study used quantitative methods to collect data, with structured questionnaires administered as the primary instrument. Questionnaires were chosen because they allow standardised data to be gathered systematically from a relatively large number of respondents, facilitating statistical analysis and ensuring consistency across the sample (Saunders, Lewis & Thornhill, 2019).

Staff questionnaires were distributed in person at respective workplaces, while beneficiary questionnaires were distributed through the insurance companies' customer service channels with the assistance of company staff, over a data collection period of approximately four weeks.

Data Collection Instruments

The questionnaire was divided into four sections. Section A collected demographic information, including gender, education level, and position within the company. Section B measured the extent of AI use in business decision-making, including specific areas of application and frequency of personal use. Section C assessed the effectiveness of AI in improving decision quality and speed, confidence in AI-supported decisions, and error reduction. Section D identified the major challenges faced in implementing AI, including cost, skills shortages, data concerns, resistance, and integration issues. The questionnaire combined closed-ended questions with predefined response options and Likert-scale items to measure attitudes and perceptions, and was reviewed for clarity prior to administration.

Data Analysis

Data from the structured questionnaires were analysed using descriptive statistics, including frequencies and percentages, calculated using the Statistical Package for the Social Sciences (SPSS). Descriptive statistics were used to summarise respondent demographics, the extent of AI adoption, the perceived effectiveness of AI on decision quality and speed, and the challenges encountered in implementation. Findings were organised according to the study's three research objectives and are presented in the following section using figures with accompanying interpretation.

LIMITATIONS OF THE STUDY

Geographical scope: The study was confined to selected insurance companies in Kitwe District, which may limit the applicability of the findings to other regions of Zambia where AI adoption levels may differ.

Sample size: The total sample size was relatively small (50 respondents), which may not fully capture the diversity of experiences and perceptions across the broader insurance sector, despite efforts to ensure representation across organisational levels.

Confidentiality concerns: Some respondents, particularly at managerial level, were reluctant to disclose detailed information regarding AI strategies due to confidentiality concerns, limiting the depth of insight into certain aspects of AI implementation.

Early stage of adoption: Because AI adoption in Zambia's insurance sector remains at an early stage, some responses reflected limited experience or exposure, which may have affected the richness and consistency of the data.

Cross-sectional design: The cross-sectional design, conducted within a specific timeframe, limited the ability to assess the long-term impact of AI on business decision-making.

Ethical Considerations

Ethical integrity was a key priority throughout the study. All participants were provided with clear information about the purpose of the study and their rights, and informed consent was obtained from each respondent prior to data collection. The confidentiality and anonymity of participants were strictly maintained, with data anonymised and stored securely. Participants were treated with dignity and without coercion, retaining the right to decline participation or withdraw at any point without consequence. Institutional approval was obtained from the management of the selected insurance companies, and the researcher maintained objectivity and honesty throughout data collection, analysis, and reporting.

RESEARCH FINDINGS AND DISCUSSIONS

This chapter presents and discusses the findings from data collected in selected insurance companies in Kitwe District on AI's impact on business decision-making. It covers the demographic characteristics of respondents, the extent of AI usage, the effectiveness of AI on decision quality and speed, and implementation challenges.

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The findings are presented using descriptive statistics including frequencies, percentages, and means, with results linked to existing literature and theoretical frameworks to provide a thorough understanding of AI's role in the local insurance sector.

Demographic Characteristics of Respondents

This section presents the demographic characteristics of the respondents who participated in the study. The demographic variables provide background context necessary to understand how organisational features influence the adoption and effectiveness of AI in business decision-making.

The researcher conducted the survey with 50 respondents from three insurance companies in Kitwe. The insurance companies surveyed were Madison Insurance, Professional Insurance, and Nico Insurance. The distribution of respondents was as follows: Madison Insurance (20), Professional Insurance (15), and Nico Insurance (15). While the insurance companies indicated they are using some form of AI, they were not ready to disclose which specific AI tools or technologies they are using.

Gender Distribution of Respondents

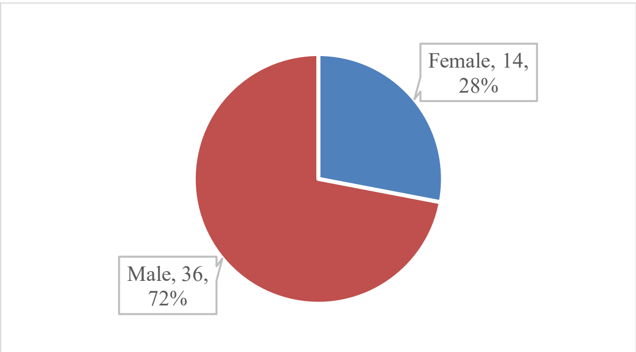

Figure 4.1.1: Gender Distribution of Respondents (n=50)

Figure 4.1.1 presents the gender distribution of the respondents. Out of the 50 total respondents, 36 were male, representing 72% of the sample, while 14 were female, accounting for 28%. This shows that the majority of the respondents were male, indicating a gender imbalance in the composition of the sample. This distribution may influence the overall analysis depending on the role gender plays in the study context.

Educational Level of Respondents

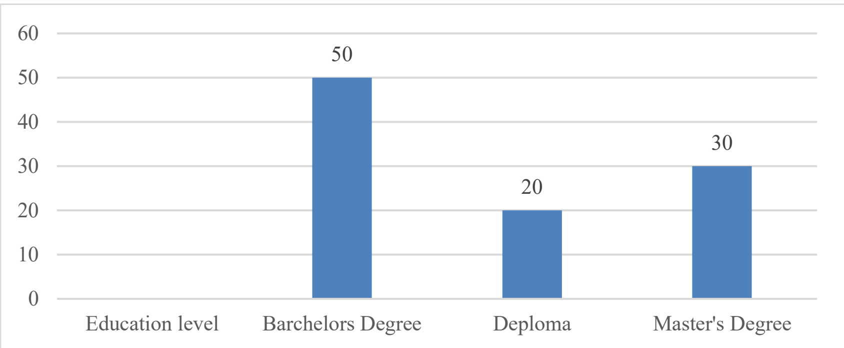

Figure 4.1.2: Educational Level of Respondents (n=50)

Figure 4.1.2 shows the educational qualifications of the 50 respondents. Half of the respondents (50%) hold a Bachelor's Degree, 30% have a Master's Degree, and 20% possess a Diploma. This indicates that the majority of respondents are highly educated, with 80% holding at least a bachelor's degree. The distribution reflects a well-educated sample, which could positively influence the quality of insights provided in the study.

Employment Position of Respondents

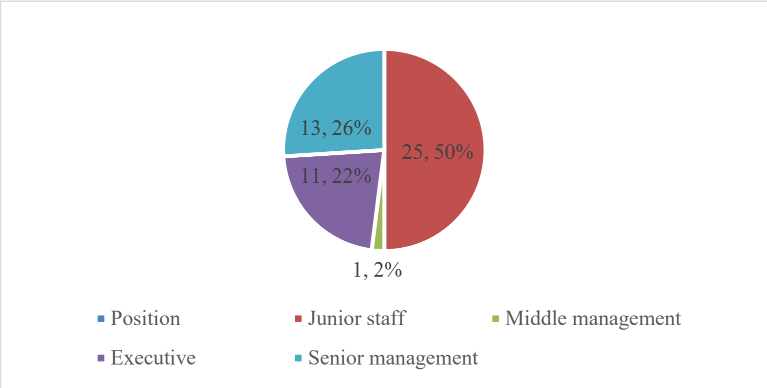

Figure 4.1.3: Employment Position of Respondents (n=50)

Figure 4.1.3 displays the employment positions of the 50 respondents. The majority (50%) were junior staff, followed by senior management at 26%, and executives at 22%. Only 2% of respondents were from middle management. This suggests that most of the feedback was gathered from employees in lower-level positions, with a notable proportion also representing senior roles. The underrepresentation of middle management may influence the balance of perspectives in the data collected.

Extent of AI Usage in Business Decision-Making

This section addresses the first research objective: to investigate the extent to which AI is being used to make informed business decisions.

Extent of AI Usage in Companies

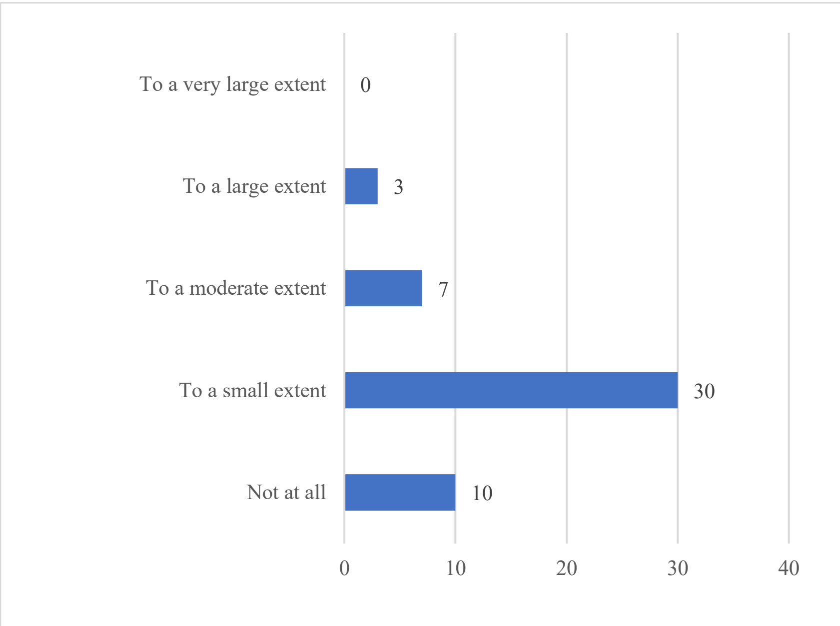

Figure 4.2.4: Extent of AI Usage in Companies (n=50)

The respondents were asked to indicate the extent to which AI is currently used in their company to support business decision-making. The results indicate that 10 (20%) reported it is not used at all, 30 (60%) indicated AI is used to a small extent, 7 (14%) reported to a moderate extent, and (3) 6% indicated to a large extent. No respondents reported usage to a very large extent. This data indicates that AI has not been widely adopted in most of the insurance companies in Kitwe, with the majority of companies using AI only minimally.

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Areas of AI Application in Companies

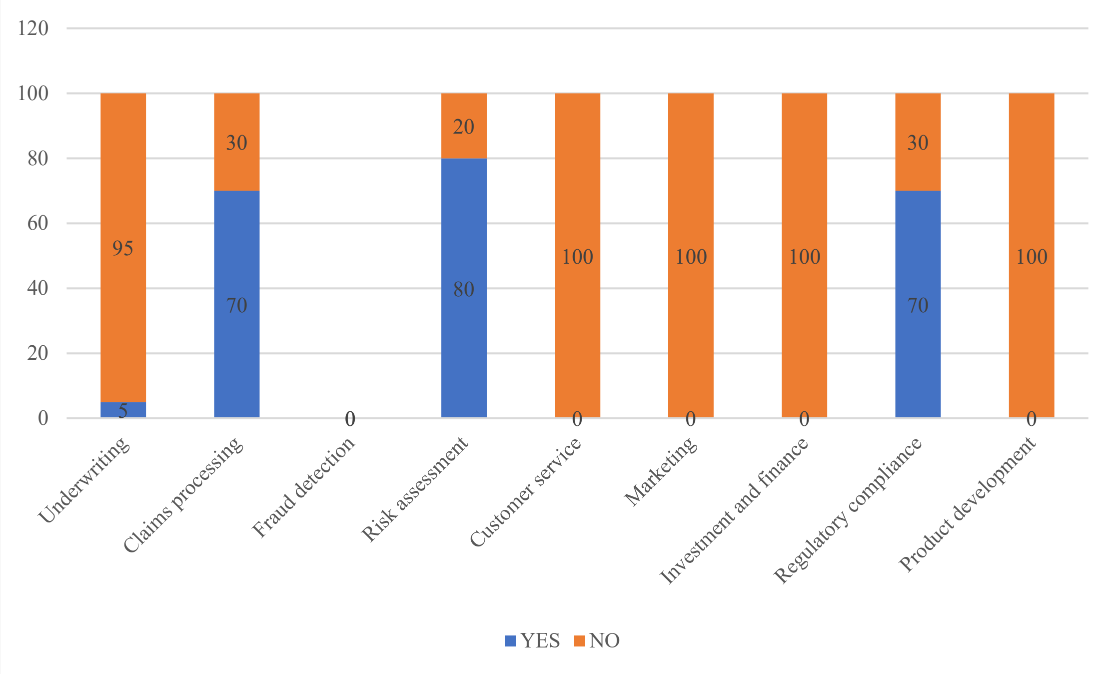

Figure 4.2.5: Areas of AI Application (Select all that apply, n=50)

The respondents were asked to select areas in their company where AI is used for decision-making. The data shows that 5% have adopted AI in underwriting, 70% in claims processing, 80% in risk assessment, and 70% in regulatory compliance. Conversely, 0% are using AI for customer service, marketing, investment and finance, and product development. This concentration of AI in core operational areas suggests that companies are primarily leveraging AI for efficiency and compliance within established processes rather than for innovation or customer engagement.

Frequency of Personal use of AI Tools

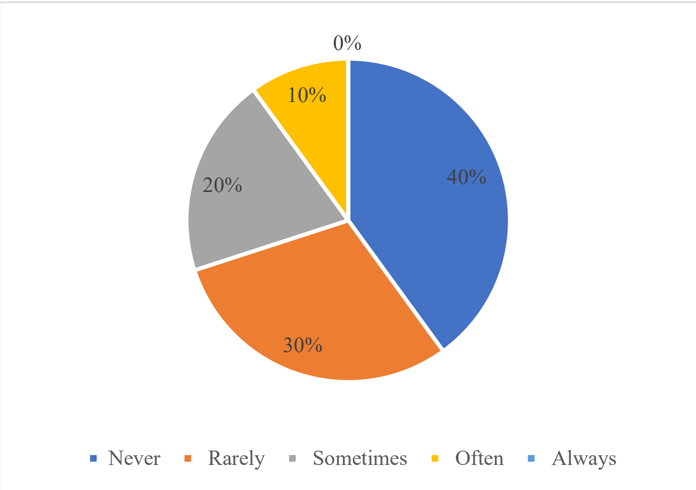

Figure 4.2.6: Frequency of Personal Use of AI Tools (n=50)

The respondents were asked to indicate how frequently they personally use AI tools to assist in making business decisions. The data indicates that 40% have never used AI for decision-making, 30% rarely use AI, 20% use AI sometimes, and only 10% often use AI for decision-making. No respondents reported always using AI tools. This finding highlights a critical disconnect between company-level AI adoption and individual utilisation of AI tools by employees.

Effectiveness of AI on Quality and Speed of Business Decisions

This section addresses the second research objective: to investigate the effectiveness of AI on the quality and speed of business decisions.

Effect of AI on Decision Quality

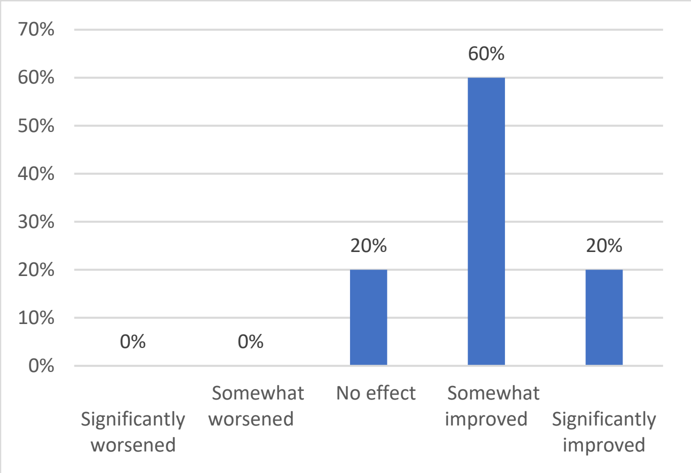

Figure 4.1.7: Effect of AI on Decision Quality (n=50)

The data indicate that none of the respondents indicated that decision-making quality had worsened or somewhat worsened. It shows that 20% of respondents indicated they have not seen any effect in the quality of decision-making made by AI, while 60% had seen somewhat improvement and 20% had seen significant improvement in the quality of decision-making by AI. This suggests that AI has an overwhelmingly positive impact on decision quality, with 80% of respondents reporting improvement.

Effect of AI on Decision Speed

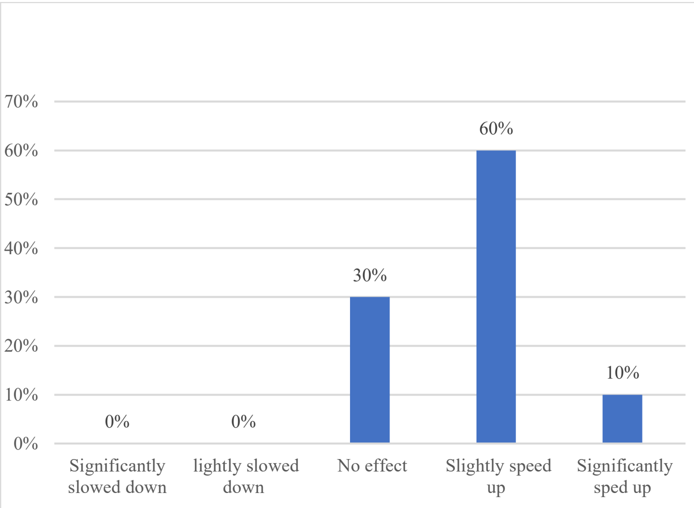

Figure 4.2.8: Effect of AI on Decision Speed (n=50)

The respondents were asked to indicate how AI has affected the speed of decision-making in their company. The results indicate that 0% of respondents indicated that decision-making has significantly slowed down or slightly slowed down. Then 30% of respondents indicated there is no effect on speed of decision-making, 60% indicated decision-making has slightly sped up, while 10% indicated the speed of decision-making has improved significantly. This indicates that AI accelerates decision-making processes in the majority of cases, with 70% of respondents reporting some level of speed improvement.

Confidence in AI-Supported Decisions

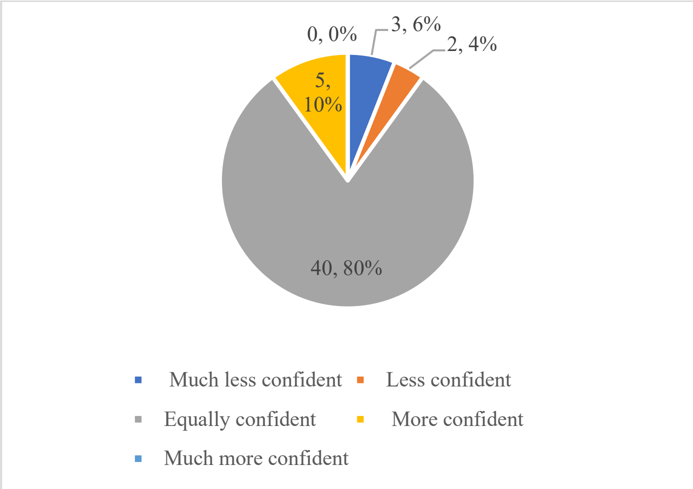

Figure 4.2.9: Confidence in AI-Supported Decisions (n=50)

The respondents were asked to indicate how confident they are in decisions made with AI support compared to traditional methods. The data indicate that 80% of respondents are equally confident in decisions made with support of AI, 10% are more confident, 6% are much less confident, and 4% are less confident. This suggests that while AI does not significantly increase confidence for most respondents, it also does not decrease it, with the majority viewing AI-supported decisions as comparable to traditional approaches.

Extent of Error Reduction by AI

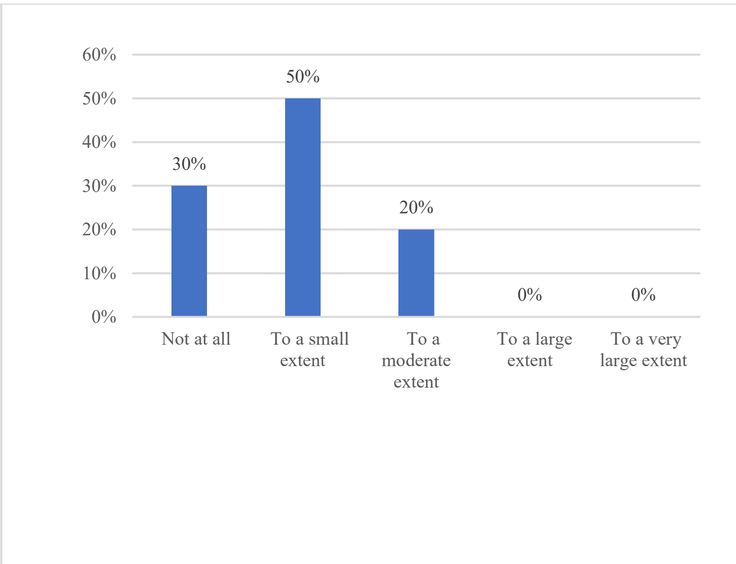

Figure 4.3.10: Extent of Error Reduction by AI (n=50)

The respondents were asked to indicate the extent to which AI has contributed to reducing errors in decision-making. The data show that 30% of respondents indicated that AI has not contributed to reducing errors at all, 50% indicated to a small extent, and 20% indicated to a moderate extent. None indicated to a large extent or very large extent. This finding suggests that while AI is perceived to contribute somewhat to error reduction, its impact is limited, with 80% reporting either no or only small extent of error reduction.

Challenges and Limitations in Implementing AI

This section addresses the third research objective: to analyze the challenges and limitations faced by insurance companies in implementing AI in business decision-making processes.

Major Challenges in AI Implementation

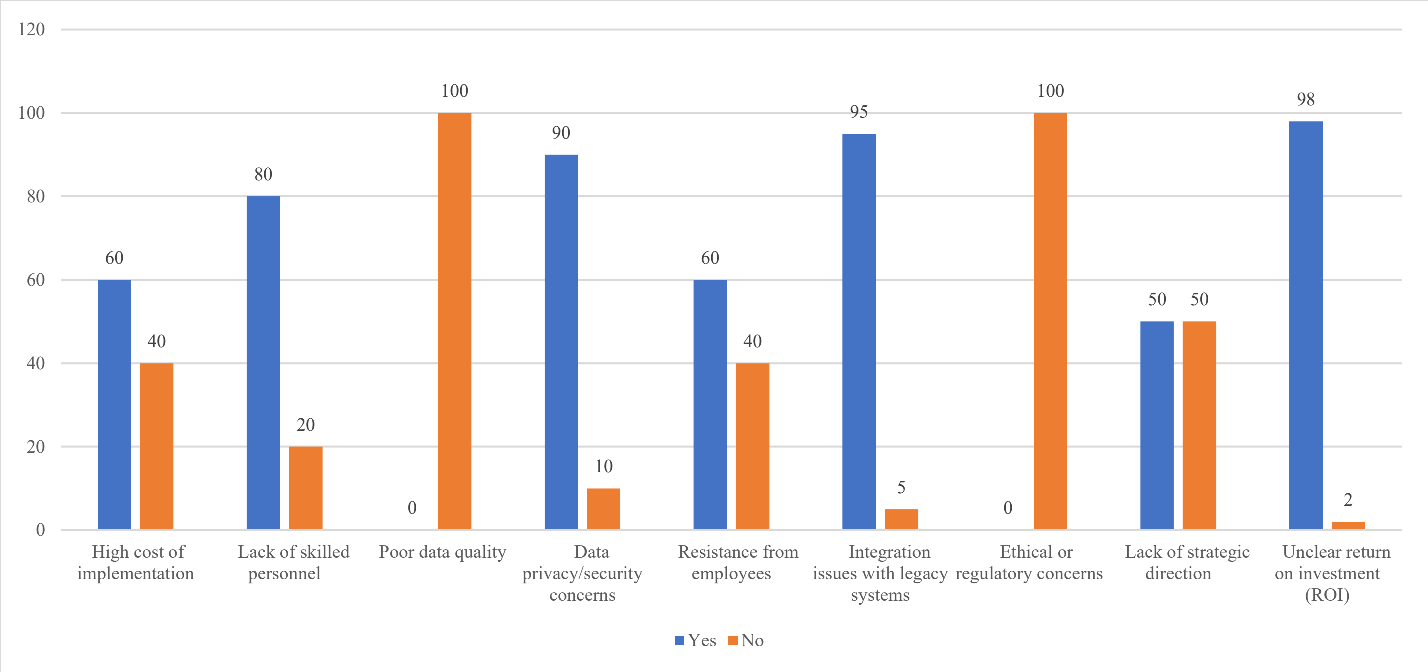

Figure 4.4.11: Major Challenges in AI Implementation (Select all that apply, n=50)

The respondents were asked to indicate the major challenges their company has faced in implementing AI in decision-making. The data indicate that the following contribute to challenges in implementing AI:

- **Unclear return on investment (ROI):** 98% of respondents cited this as a challenge, making it the most significant barrier. This reflects the difficulty in quantifying the financial benefits of AI initiatives, which makes it challenging to justify investments.

- **Integration issues with legacy systems:** 95% of respondents identified this as a major technical impediment. Many organisations operate with outdated IT infrastructures that were not designed to accommodate modern AI applications, making integration complex and costly.

- **Data privacy and security concerns:** 90% of respondents raised this as a critical consideration. AI systems often rely on vast amounts of sensitive data, and ensuring privacy and security is paramount, especially with increasing regulatory scrutiny.

- **Lack of skilled personnel:** 80% of respondents cited this as a major bottleneck. The development, deployment, and maintenance of AI systems demand specialised expertise in areas such as machine learning, data science, and AI ethics.

- **High cost of implementation:** 60% of respondents identified this as a substantial financial barrier. Implementing AI solutions requires significant upfront investment in hardware, software, and specialised talent.

- **Resistance from employees:** 60% of respondents reported this as a notable human capital concern. The introduction of AI can evoke fear of job displacement and changes in work processes, leading to hesitancy among employees.

- **Lack of strategic direction:** 50% of respondents indicated this as a challenge. Many companies embark on AI initiatives without a clear vision or defined objectives, leading to fragmented efforts and inefficient resource allocation.

DISCUSSION OF FINDINGS

This section discusses the findings in relation to the research objectives, existing literature, and theoretical frameworks that guided the study.

Extent of AI Usage in Business Decision-Making

The findings indicate that AI adoption in Kitwe's insurance companies is at a nascent stage, with 80% of respondents reporting either no AI usage or usage to only a small extent. This limited adoption aligns with the global literature, which suggests that many organisations are still in the early stages of AI integration, often focusing on automating routine tasks rather than leveraging AI for complex strategic decision-making (Davenport & Ronanki, 2018). Bughin et al. (2017) found that adoption was heavily concentrated among technology-sector early adopters, with traditional, risk-averse industries like insurance lagging noticeably behind. The Kitwe findings mirror this pattern, indicating that the Zambian insurance sector is following a similar cautious approach.

The finding that AI application is highly concentrated in core operational areas such as risk assessment (80%), claims processing (70%), and regulatory compliance (70%) is consistent with the global literature. Research by Wamba et al. (2020) found that AI-enabled analytics are increasingly embedded in data-intensive functions where efficiency gains are most readily achievable. The complete absence of AI in customer-facing and strategic functions (customer service, marketing, investment and finance, and product development) suggests that companies are prioritising efficiency and compliance over innovation and customer engagement. This pattern reflects a strategic choice to leverage AI where the business case is most apparent, while remaining cautious in areas that require more sophisticated AI capabilities or where the return on investment is less certain.

The low individual usage of AI tools (70% reporting infrequent or no personal use) highlights a critical disconnect between company-level adoption and individual utilisation. This finding can be interpreted through the Technology Acceptance Model (TAM), which proposes that perceived usefulness and perceived ease of use determine an individual's acceptance of a technology (Davis, 1989). The low personal usage suggests that employees may not perceive AI tools as sufficiently useful or easy to use, or they may lack the training and support needed to integrate AI into their workflows. This aligns with findings from Fountaine et al. (2019), who noted that organisational culture and employee readiness are often more significant barriers than technology itself.

Effectiveness of AI on Decision Quality and Speed

The findings demonstrate that AI has an overwhelmingly positive impact on both decision quality and speed. A significant majority (80%) of respondents reported improvement in decision quality due to AI, with no respondents indicating a decline. Similarly, 70% of respondents observed an acceleration in decision processes with AI support, with no one reporting any slowing down. This finding is consistent with the global literature, which consistently reports that AI enhances decision-making by reducing cognitive biases, improving forecasting accuracy, and streamlining routine processes (Shrestha et al., 2019; Davenport & Ronanki, 2018).

The absence of any negative impacts on either decision quality or speed is particularly noteworthy. This suggests that AI, at least in the areas where it has been implemented, is functioning as intended and delivering tangible benefits. The research by Neiroukh et al. (2024) found that AI capability significantly and positively affects decision-making speed, decision quality, and overall organisational performance. The Kitwe findings support this conclusion, indicating that even in a developing economy context with nascent AI adoption, the technology is delivering measurable improvements.

However, the finding that 80% of respondents report either no contribution or only a small extent of error reduction due to AI is concerning. This suggests that while AI is improving decision quality and speed, it is not yet perceived as significantly reducing errors. This may reflect the early stage of AI adoption, where systems are not yet fully optimised or integrated to achieve significant error reduction. It may also indicate that the 'garbage in, garbage out' principle applies, where flawed input data leads to imperfect outputs (O'Neil, 2016). This finding underscores the need for organisations to invest in data quality and governance alongside AI implementation.

The finding that 80% of respondents express equal confidence in AI-supported decisions compared to traditional methods, with an additional 10% feeling more confident, indicates a general acceptance of AI as a decision-support tool. This confidence is likely built on demonstrated improvements in decision quality and speed, even if the impact on error reduction is limited. The Technology Acceptance Model (TAM) would suggest that this confidence reflects a positive perception of AI's usefulness, which is a key determinant of technology adoption (Davis, 1989).

Challenges in AI Implementation

The findings reveal that the challenges faced by insurance companies in Kitwe are multifaceted, encompassing technical, human-centric, and financial issues. The most significant challenge identified was unclear return on investment (98%), followed by integration issues with legacy systems (95%), data privacy and security concerns (90%), and lack of skilled personnel (80%). These findings are highly consistent with both the global and regional literature on AI implementation challenges.

The dominance of unclear ROI as the primary challenge aligns with findings from PwC (2020), which noted that demonstrating a clear return on investment remains a top challenge for organisations investing in AI. The difficulty in quantifying the precise financial benefits of AI, especially in areas like decision-making where benefits may be realised through improved efficiency, better risk management, or enhanced customer satisfaction, makes it challenging to justify and sustain AI initiatives.

The high prevalence of integration issues with legacy systems (95%) reflects the practical complexities of AI deployment in established organisations. This finding is consistent with research by LaValle et al. (2011), who found that integrating new AI systems with existing IT infrastructure is a major technical hurdle. Many organisations operate with outdated or disparate systems that were not designed to accommodate modern AI applications, making integration technically challenging, time-consuming, and costly.

The concern over data privacy and security (90%) reflects growing apprehension surrounding the ethical and legal implications of AI. This finding is consistent with research by IBM (2023), which consistently highlights data governance, privacy, and security as critical considerations that can significantly impact the success of AI initiatives. Concerns about data breaches, algorithmic bias, and the misuse of personal information can erode trust and lead to public backlash.

The lack of skilled personnel (80%) is a critical bottleneck that has been widely documented in the literature (Manyika et al., 2017; Russell & Norvig, 2020). The development, deployment, and maintenance of AI systems demand specialised expertise in areas such as machine learning, data science, AI ethics, and software engineering. Many organisations struggle to find and retain individuals with these highly sought-after skills, leading to a talent gap that impedes progress.

The other challenges identified, high cost of implementation (60%), resistance from employees (60%), and lack of strategic direction (50%), are also well-documented in the literature. These findings collectively suggest that addressing the challenges of AI implementation requires a holistic approach that combines technological solutions with robust change management, strategic planning, and a commitment to ethical considerations.

THEORETICAL IMPLICATIONS

The findings of this study have implications for both Decision Theory and the Technology Acceptance Model (TAM), which guided the research.

Decision Theory: Simon (1979) argued that individuals and organisations aim to make rational choices that maximise utility based on available information. The finding that AI improves decision quality and speed supports the idea that AI enhances rationality by enabling faster and more accurate data analysis. By reducing cognitive biases and providing predictive capabilities, AI allows managers to make more informed, evidence-based decisions. However, the limited impact on error reduction suggests that AI's rationality-enhancing potential is not yet fully realised, possibly due to data quality issues or the early stage of implementation.

Technology Acceptance Model (TAM): Davis (1989) proposed that perceived usefulness and perceived ease of use determine an individual's acceptance of a technology. The low personal usage of AI tools (70% infrequent or no use) suggests that employees may not perceive AI tools as sufficiently useful or easy to use. The finding that 80% of respondents express equal confidence in AI-supported decisions compared to traditional methods indicates that perceived usefulness is moderate, but may not be strong enough to drive widespread adoption. The challenges identified, particularly lack of skilled personnel and resistance from employees, further support the TAM framework, as they reflect barriers to perceived ease of use and usefulness.

SUMMARY OF FINDINGS

The key findings of this study are summarised as follows:

1. **Limited AI Adoption:** AI adoption in Kitwe's insurance companies is at a nascent stage, with 80% reporting either no or minimal usage. AI is concentrated in core operational areas (risk assessment, claims processing, regulatory compliance) and absent in customer-facing and strategic functions.

2. **Positive Impact on Decision Quality and Speed:** AI has an overwhelmingly positive impact on decision quality (80% reporting improvement) and speed (70% reporting acceleration). No respondents reported negative impacts on either measure.

3. **Limited Impact on Error Reduction:** While AI improves decision quality and speed, its impact on error reduction is limited, with 80% reporting either no or small extent of error reduction.

4. **Moderate Confidence in AI:** 80% of respondents express equal confidence in AI-supported decisions compared to traditional methods, with only 10% feeling more confident.

5. **Low Personal Usage:** 70% of respondents report infrequent or no personal use of AI tools, highlighting a disconnect between company-level adoption and individual utilisation.

6. **Multifaceted Implementation Challenges:** The most significant challenges are unclear ROI (98%), legacy system integration (95%), data privacy concerns (90%), and lack of skilled personnel (80%). Other challenges include high cost (60%), employee resistance (60%), and lack of strategic direction (50%).

CONCLUSION AND RECOMMENDATIONS

This chapter presents the conclusion and recommendations of the study on the impact of AI on business decision-making within selected insurance companies in Kitwe District, Zambia. The conclusion synthesises the key findings in relation to the three research objectives: the extent of AI usage in business decision-making, the effectiveness of AI on decision quality and speed, and the challenges faced in AI implementation. The recommendations are organised by stakeholder group and provide practical, measurable actions for insurance companies, policymakers, and future researchers.

Conclusion

This study set out to explore the impact of AI on business decision-making within selected insurance companies in Kitwe District, Zambia. The research was guided by three specific objectives: to investigate the extent of AI usage in business decision-making, to evaluate the effectiveness of AI on decision quality and speed, and to analyse the challenges faced in AI implementation. The study employed a quantitative research design, collecting data from 50 respondents across three insurance companies using structured questionnaires. The findings provide valuable insights into the current state of AI adoption and its perceived impact in the Zambian insurance sector.

Extent of AI Usage

The findings reveal that AI adoption in Kitwe's insurance companies is at a nascent stage, with 80% of respondents reporting either no AI usage or usage to only a small extent. This limited adoption aligns with the global literature, which suggests that many organisations are still in the early stages of AI integration, often focusing on automating routine tasks rather than leveraging AI for complex strategic decision-making (Davenport & Ronanki, 2018). Bughin et al. (2017) found that adoption was heavily concentrated among technology-sector early adopters, with traditional, risk-averse industries like insurance lagging noticeably behind. The Kitwe findings mirror this pattern, indicating that the Zambian insurance sector is following a similar cautious approach.

AI application is highly concentrated in core operational areas such as risk assessment (80%), claims processing (70%), and regulatory compliance (70%). This concentration is consistent with the global literature, which shows that AI-enabled analytics are increasingly embedded in data-intensive functions where efficiency gains are most readily achievable (Wamba et al., 2020). The complete absence of AI in customer-facing and strategic functions, including customer service, marketing, investment and finance, and product development, suggests a primary focus on leveraging AI for efficiency and compliance within established processes rather than for innovation or customer engagement. This pattern reflects a strategic choice to leverage AI where the business case is most apparent, while remaining cautious in areas that require more sophisticated AI capabilities or where the return on investment is less certain.

Individual AI tool usage for business decision-making is notably low, with 70% of respondents indicating infrequent or no personal use. Only 10% of respondents reported using AI often, highlighting a critical disconnect between company-level adoption in specific departments and the actual utilisation of AI tools by individual employees for their decision-making processes. This gap suggests that while organisations may have invested in AI technologies, they have not yet successfully integrated these tools into the daily workflows of their employees. This finding can be interpreted through the Technology Acceptance Model (TAM), which proposes that perceived usefulness and perceived ease of use determine an individual's acceptance of a technology (Davis, 1989). The low personal usage suggests that employees may not perceive AI tools as sufficiently useful or easy to use, or they may lack the training and support needed to integrate AI into their workflows.

Effectiveness of AI on Decision Quality and Speed

The findings demonstrate that AI has an overwhelmingly positive impact on business decision-making within the surveyed companies. A significant majority (80%) of respondents reported an improvement in decision quality due to AI, with no one indicating a decline. This finding is consistent with the global literature, which consistently reports that AI enhances decision-making by reducing cognitive biases, improving forecasting accuracy, and streamlining routine processes (Shrestha et al., 2019; Davenport & Ronanki, 2018). The research by Neiroukh et al. (2024) found that AI capability significantly and positively affects decision-making speed, decision quality, and overall organisational performance. The Kitwe findings support this conclusion, indicating that even in a developing economy context with nascent AI adoption, the technology is delivering measurable improvements.

Similarly, 70% of respondents observed an acceleration in decision processes with AI support, and no one reported any slowing down. This finding aligns with research by Csaszar et al. (2024), who found that AI has the potential to enhance the speed, quality, and scale of strategic analysis. The absence of any negative impacts on either decision quality or speed is particularly noteworthy, suggesting that AI is functioning as intended in the areas where it has been implemented.

Despite general confidence in AI-supported decisions, with 80% of respondents expressing equal confidence compared to traditional methods, the perceived impact of AI on error reduction is limited. A substantial 80% of respondents reported either no contribution or only a small extent of error reduction due to AI, with no respondents perceiving a large or very large extent of reduction. This finding may reflect the early stage of AI adoption, where systems are not yet fully optimised or integrated to achieve significant error reduction. It may also indicate that the 'garbage in, garbage out' principle applies, where flawed input data leads to imperfect outputs (O'Neil, 2016). This finding underscores the need for organisations to invest in data quality and governance alongside AI implementation.

Challenges in AI Implementation

The findings reveal that the challenges faced by insurance companies in Kitwe are multifaceted, encompassing technical, human-centric, and financial issues. The most significant challenge identified was unclear return on investment, cited by 98% of respondents. This reflects the difficulty in quantifying the precise financial benefits of AI initiatives, making it challenging to justify and sustain AI investments. This finding aligns with research by PwC (2020), which noted that demonstrating a clear return on investment remains a top challenge for organisations investing in AI.

Integration issues with legacy systems (95%) represent a major technical impediment, as many organisations operate with outdated IT infrastructures that were not designed to accommodate modern AI applications. This finding is consistent with research by LaValle et al. (2011), who found that integrating new AI systems with existing IT infrastructure is a major technical hurdle. Data privacy and security concerns (90%) are critical considerations for AI adoption, reflecting growing apprehension surrounding the ethical and legal implications of AI. This finding is consistent with research by IBM (2023), which consistently highlights data governance, privacy, and security as critical considerations that can significantly impact the success of AI initiatives.

A significant lack of skilled personnel (80%) acts as a major bottleneck, as the development, deployment, and maintenance of AI systems demand specialised expertise that is scarce in the Zambian context. This finding is consistent with research by Manyika et al. (2017) and Russell and Norvig (2020), who identified the scarcity of AI talent as a top challenge for companies attempting to scale AI. The challenges of high cost of implementation (60%), resistance from employees (60%), and a lack of strategic direction (50%) are also well-documented in the literature.

Theoretical Implications

The findings of this study have implications for both Decision Theory and the Technology Acceptance Model (TAM), which guided the research.

In relation to Decision Theory (Simon, 1979), the finding that AI improves decision quality and speed supports the idea that AI enhances rationality by enabling faster and more accurate data analysis, reducing cognitive biases, and providing predictive capabilities. By automating data processing and analysis, AI allows for faster decisions that are also more informed and accurate, breaking the traditional trade-off between speed and quality (Brynjolfsson & McAfee, 2017). However, the limited impact on error reduction suggests that AI's rationality-enhancing potential is not yet fully realised, possibly due to data quality issues or the early stage of implementation. This suggests that organisations must address foundational data issues before they can fully realise the rationality-enhancing benefits of AI.

In relation to TAM (Davis, 1989), the low personal usage of AI tools (70% infrequent or no use) suggests that employees may not perceive AI tools as sufficiently useful or easy to use. The finding that 80% of respondents express equal confidence in AI-supported decisions compared to traditional methods indicates that perceived usefulness is moderate, but may not be strong enough to drive widespread adoption. The challenges identified, particularly lack of skilled personnel and resistance from employees, further support the TAM framework as they reflect barriers to perceived ease of use and usefulness. This suggests that organisations must address both technical and human factors to drive successful AI adoption.

Contribution To Knowledge

This study makes several contributions to the existing body of knowledge. First, it provides empirical evidence on AI adoption and its impact on business decision-making in the Zambian insurance sector, an area that has been largely unexplored in the literature. The findings extend the understanding of AI adoption beyond developed economies to a developing economy context, providing insights into the unique challenges and opportunities that exist in such settings.

Second, it extends the application of Decision Theory and TAM to the Zambian context, demonstrating their relevance in understanding AI adoption in developing economies. The study shows that these theoretical frameworks, which were developed primarily in Western contexts, have explanatory power in understanding AI adoption dynamics in Zambia.

Third, it identifies the specific challenges faced by insurance companies in Zambia, providing a foundation for future research and policy development. The identification of unclear ROI, legacy system integration, data privacy concerns, and skills shortages as the primary challenges provides a clear agenda for both practitioners and policymakers.

Fourth, it offers practical recommendations for insurance companies, policymakers, and researchers seeking to promote responsible AI integration. These recommendations are grounded in empirical evidence and are tailored to the specific context of the Zambian insurance sector.

RECOMMENDATIONS

Based on the findings and conclusions of this study, the following recommendations are made for various stakeholders.

Recommendations For Insurance Companies

Develop a Comprehensive AI Strategy: Insurance organisations should develop a clear AI strategy that aligns with business objectives and includes well-defined metrics to measure return on investment. This strategy should address the specific areas where AI can deliver the greatest value, such as risk assessment, claims processing, and regulatory compliance, while also exploring opportunities for innovation in customer-facing functions. The strategy should include short-term, medium-term, and long-term goals with measurable KPIs. For example, companies could set specific targets such as reducing claims processing time by 30% within 12 months or improving risk assessment accuracy by 15% within 18 months.

Invest in Data Infrastructure and Governance: Companies should prioritise investment in robust data collection, storage, and analysis infrastructure. Strong data governance frameworks should be established to ensure data quality, privacy, and security, addressing the 90% of respondents who cited data privacy and security concerns. This includes implementing data protection policies, ensuring compliance with relevant regulations such as the Zambian Data Protection Act, and establishing clear protocols for data access and usage. Companies should also invest in data cleaning and standardisation to address the 'garbage in, garbage out' problem that limits AI effectiveness.

Address Skills Gaps Through Training and Development: Organisations should invest in workforce development to bridge the AI skills gap identified by 80% of respondents. This includes providing tailored training programmes to enhance employee understanding of AI tools and their applications, developing partnerships with educational institutions for talent pipelines, and creating career development pathways that incentivise AI skill acquisition. Training should be designed to address the low personal usage of AI tools (70% infrequent or no use) by building confidence and competence among employees. Companies could implement a structured training programme starting with basic AI literacy for all staff, followed by advanced training for specific roles such as underwriters and claims processors, and leadership training on AI strategy and governance.

Foster a Culture of Innovation and Adaptability: Companies should cultivate an organisational culture that embraces technological change and innovation. This includes addressing resistance from employees (60% of respondents) through effective change management strategies, clear communication about the benefits of AI, and involving employees in the AI implementation process. Leadership should demonstrate commitment to AI adoption and create an environment where experimentation and learning are encouraged. Companies could establish innovation committees, celebrate AI successes, and create forums for employees to share their experiences with AI tools.

Adopt a Phased Implementation Approach: Rather than attempting large-scale, comprehensive AI adoption, companies should consider a phased and iterative implementation approach. This includes starting with small-scale pilot projects with clear objectives, learning from these experiences, and gradually scaling successful initiatives. This approach addresses the challenges of unclear ROI and integration with legacy systems by allowing companies to demonstrate value incrementally and manage technical complexity. A suggested phased approach could include: Phase 1 (0-6 months) piloting AI in risk assessment where adoption is already at 80%; Phase 2 (6-12 months) expanding to claims processing automation; Phase 3 (12-18 months) beginning customer service AI integration; and Phase 4 (18-24 months) exploring marketing and product development AI.

Address Legacy System Integration: Given that 95% of respondents cited integration issues with legacy systems as a major challenge, organisations should develop a clear roadmap for modernising their IT infrastructure. This may include adopting API-based integration approaches, investing in middleware solutions, or gradually migrating to cloud-based platforms that are more compatible with AI applications. Companies should prioritise investments in system integration and consider engaging specialised vendors with experience in legacy system modernisation.

Establish Clear Governance and Ethical Frameworks: Companies should develop clear policies and ethical guidelines for AI usage to address concerns about data privacy, security, and algorithmic bias. This includes establishing oversight mechanisms, ensuring transparency in AI decision-making, and regularly auditing AI systems for fairness and accuracy. Companies should also establish clear accountability structures for AI-related decisions and ensure compliance with emerging AI regulations.

Measure and Communicate ROI: To address the 98% of respondents who cited unclear ROI as a challenge, companies should develop robust measurement frameworks for AI initiatives. This includes establishing baseline metrics before AI implementation, tracking key performance indicators throughout the implementation process, and regularly reporting on progress to stakeholders. Companies should also develop clear business cases for AI investments that articulate both quantitative and qualitative benefits.

Recommendations For Policymakers

Develop Supportive Policy Frameworks: Policymakers should create an enabling environment for AI adoption through the development of comprehensive AI policies and regulations. This includes addressing data privacy and security concerns, establishing standards for AI governance, and providing guidance on ethical AI use. The National Artificial Intelligence Strategy 2025-2027 provides a foundation that should be operationalised with concrete implementation plans. Policymakers should also consider developing sector-specific AI guidelines for the insurance and financial services industries.

Invest in Digital Infrastructure: Government should prioritise investment in digital infrastructure, including reliable internet connectivity, data centres, and technology parks, to address the infrastructural limitations identified in the study. This investment should extend beyond urban areas to ensure equitable access to AI technologies across the country. Policymakers should consider public-private partnerships to accelerate infrastructure development and ensure that infrastructure investments are aligned with AI adoption needs.

Support Skills Development: Given the critical shortage of skilled AI personnel (80% of respondents), policymakers should invest in education and training programmes to develop AI capabilities. This includes integrating AI and data science into university curricula, establishing specialised training centres, and creating incentives for private sector investment in workforce development. Policymakers should also consider scholarship programmes for AI-related studies and partnerships with international institutions for knowledge transfer.

Promote Public-Private Partnerships: Government should facilitate partnerships between public institutions, private sector organisations, and international partners to accelerate AI adoption. This includes supporting collaborative research, knowledge sharing, and technology transfer initiatives that can help Zambian organisations overcome implementation challenges. Policymakers could establish innovation hubs, AI centres of excellence, and industry-academia collaboration platforms.

Provide Financial Incentives: To address the high cost of implementation (60% of respondents) and unclear ROI (98%), policymakers should consider providing financial incentives for AI adoption, such as tax breaks, grants, or subsidised loans for technology investment. These incentives should be targeted at sectors with high potential for AI-driven productivity gains, including insurance and financial services. Policymakers should also consider establishing an AI innovation fund to support early-stage AI projects.

Support Research and Development: Policymakers should invest in AI research and development to build local capacity and generate knowledge that is relevant to the Zambian context. This includes funding for academic research, establishing research centres focused on AI applications in key sectors, and supporting collaborative research between Zambian and international institutions.

Recommendations For Future Research

Conduct Sector-Wide Studies: Future research should expand the scope of this study to include a larger sample of insurance companies across Zambia, as well as other sectors of the economy such as banking, mining, agriculture, and telecommunications. This would provide a more comprehensive understanding of AI adoption patterns and their impact on business decision-making across the Zambian economy. Comparative studies across sectors would identify sector-specific challenges and opportunities for AI adoption.

Longitudinal Studies: Longitudinal research should be conducted to assess the long-term impact of AI on decision quality, speed, and organisational performance. This would address the limitation of the current cross-sectional design and provide insights into how AI benefits evolve over time. Longitudinal studies could track AI adoption across multiple time points, measuring changes in decision quality, speed, and error reduction as AI systems mature and organisations gain experience.

Qualitative Research: In-depth qualitative studies using interviews and case studies should be conducted to complement the quantitative findings of this research. This would provide richer insights into the decision-making processes, organisational dynamics, and contextual factors that influence AI adoption. Qualitative research could explore the experiences of employees, managers, and beneficiaries in greater depth, uncovering the nuances of AI adoption that quantitative methods may miss.

Comparative Studies: Comparative research should be conducted across different African countries to identify regional patterns and best practices in AI adoption. This would help Zambian organisations learn from the experiences of their counterparts in other developing economy contexts. Comparative studies could examine how different policy environments, infrastructure conditions, and cultural factors influence AI adoption outcomes.

AI Tool-Specific Studies: Future research should examine the specific AI tools and technologies being used in Zambian organisations, addressing the limitation of companies' reluctance to disclose this information. This would provide more detailed insights into the types of AI that are most effective in the local context. Research could examine the effectiveness of different AI applications such as machine learning, natural language processing, predictive analytics, and chatbots in the Zambian context.

Customer Perspectives: Research should investigate customer perceptions of AI-influenced decisions and services, providing a more complete picture of AI's impact on business decision-making. This would address the limited representation of beneficiary perspectives in the current study. Research could explore how customers perceive AI-driven services, their trust in AI-influenced decisions, and their willingness to engage with AI-enabled organisations.

Barriers to AI Adoption: Future research should investigate the barriers to AI adoption in greater depth, exploring why organisations that have recognised the potential of AI have not yet fully adopted it. This could include research on organisational readiness, change management challenges, and the role of leadership in driving AI adoption.

AI and Employment: Research should examine the relationship between AI adoption and employment in the Zambian context, addressing concerns about job displacement and the need for workforce transitions. This could include research on the skills that are most at risk of automation and the skills that will be most in demand in an AI-enabled economy.

AI Ethics and Governance: Research should investigate the ethical and governance challenges of AI adoption in the Zambian context, including issues of algorithmic bias, transparency, and accountability. This could contribute to the development of ethical frameworks and governance mechanisms that are appropriate for the Zambian context.

Sector-Specific Studies: Research should be conducted on AI adoption in specific sectors beyond insurance, including banking, agriculture, healthcare, mining, and education. This would provide insights into the unique opportunities and challenges in each sector and inform sector-specific policies and strategies.

SUMMARY

This study has provided empirical evidence on the impact of AI on business decision-making within selected insurance companies in Kitwe District, Zambia. The findings reveal that AI adoption is at a nascent stage, concentrated in core operational areas such as risk assessment, claims processing, and regulatory compliance, with limited integration into customer-facing and strategic functions.

The study found that AI has demonstrated positive impacts on decision quality and speed, with 80% of respondents reporting improvement in decision quality and 70% reporting acceleration in decision processes. However, the impact on error reduction is limited, with 80% of respondents reporting either no or small extent of error reduction. This suggests that AI is generally seen as a valuable asset for enhancing decision-making, but its role is primarily as a supportive tool rather than a transformative one.

Implementation challenges are multifaceted, encompassing unclear ROI (98%), legacy system integration issues (95%), data privacy concerns (90%), skills shortages (80%), high cost (60%), employee resistance (60%), and lack of strategic direction (50%). These challenges reflect both global patterns and context-specific factors that must be addressed to accelerate AI adoption.

The study makes several contributions to knowledge, including empirical evidence on AI adoption in the Zambian insurance sector, extension of theoretical frameworks (Decision Theory and TAM) to the Zambian context, identification of specific challenges faced by insurance companies, and practical recommendations for stakeholders.

The recommendations provided are intended to guide insurance companies in developing effective AI strategies, assist policymakers in creating supportive environments for AI adoption, and inform future research directions. Key recommendations for insurance companies include developing comprehensive AI strategies, investing in data infrastructure and governance, addressing skills gaps, fostering a culture of innovation, adopting phased implementation approaches, addressing legacy system integration, establishing governance frameworks, and measuring ROI. Recommendations for policymakers include developing supportive policy frameworks, investing in digital infrastructure, supporting skills development, promoting public-private partnerships, providing financial incentives, and supporting research and development.

As the Zambian economy continues to digitise and global competition intensifies, the strategic adoption of AI will become increasingly important for organisational success. This study provides a foundation for understanding the current state of AI adoption and its impact on business decision-making, offering insights that can inform both practice and policy in the evolving digital landscape of Zambia.

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