Int. j. adv. multidisc. res. stud. 2025; 5(4):754-768

Received: 05-06-2025
Accepted: 15-07-2025

International Journal of Advanced Multidisciplinary Research and Studies

ISSN: 2583-049X

Assessing the Effectiveness of Business Intelligence in Business Management: A Case Study of the Banking Sector in Lusaka, Zambia

[1] Adronah Mulaziki, [2] Marvin Kabubi

[1] Department of Business and Humanities, Information Communications University, Lusaka, Zambia
[2] Department of Research and Social Sciences, Information Communications University, Lusaka, Zambia

DOI: https://doi.org/10.62225/2583049X.2025.5.4.4673
Corresponding Author: **Adronah Mulaziki**

Abstract

This study aimed at assessing the effectiveness of business intelligence in business management. A case study of the banking sector in Lusaka Zambia. The objectives of the study were to assess the effectiveness of Business intelligence in risk management, to investigate the effectiveness of business intelligence in enhancing customer insights and segmentation, to examine the effectiveness of business intelligence in promoting competitive advantage and to ascertain the effectiveness of business intelligence in market intelligence. Using case study research design, 50 respondents were purposively selected. Findings revealed that there were more female students enrolled in the programmes. The findings showed that the use of BI provided a very effective risk identification record as indicated by majority respondents (64%). Further results showed that the use of BI provided a very effective platform in mitigating the risks. Findings revealed that customer segmentation and insight was not effective as indicated by majority respondents (78%). Findings showed that operational efficiency was very effective as indicated by majority participants (66%). Similar, findings on market position revealed that it was very effective as indicated by majority participants (42%). Lastly, the findings from the study showed that market trend analysis was very effective as indicated by majority participants (58%). Similar, competitor analysis also revealed very effective position as indicated by majority participants (68%). It was recommended that since effective BI requires accurate and high-quality data and experts, Banks should establish stringent data governance policies to ensure data integrity, which includes regular audits, data cleansing processes, and a centralized data management system to support BI initiatives. Lastly, Banks must adopt advanced cybersecurity frameworks and data protection protocols to secure customer data. Compliance with data protection regulations, such as the Data Protection Act in Zambia, should be prioritized to foster trust and prevent breaches.

Keywords: Business Intelligence, Banking, Lusaka

1. Introduction

1.1 Background

Technology improvements are causing a revolution in the banking and financial sectors. These days, financial institutions have to contend with heightened competition, changing customer demands, and strict control and risk management requirements in a very volatile market. Technology has also made it possible to construct powerful business intelligence tools at the same time. The banking and financial sector can use certain technologies to tap into customer data and obtain insights that can lead to better business and management decisions. In light of this, banking and financial institutions are using business intelligence (BI) tools in a variety of ways to boost earnings, lower risk, and gain a competitive advantage. Banks can respond to shifting economic conditions in both stable and turbulent economic times thanks to business intelligence.

Business intelligence (BI) is essential to the risk management system. The intricate and ever-changing character of financial markets, in conjunction with strict legal obligations, mandates the implementation of cutting-edge technologies to efficiently manage risks. In order to assist businesses in making wise business decisions, business intelligence (BI) refers to a variety of technologies and approaches that collect, store, process, and make data accessible. BI is essential for detecting, evaluating, and controlling risks in the banking industry in order to maintain stability and compliance (Baar & Hans-George, 2018) [18]. The identification of credit risk is one of the main uses of BI in banking risk management. In order to estimate the chance of loan

defaults, banks utilize business intelligence (BI) technologies to evaluate client data, credit histories, and macroeconomic factors.

Al-aami (2013) adds that Banks can determine borrowers' creditworthiness more precisely by using predictive analytics. This enhances the loan approval procedure in addition to reducing bad debts. Banks can create complex credit scoring models with advanced business intelligence (BI) systems that integrate multiple data sources, improving the accuracy of credit risk evaluations.

In addition, BI is quite helpful when it comes to market risk, which is the danger of losses as a result of shifts in the market (Ibid). Banks handle enormous volumes of market data, such as foreign exchange rates, stock prices, and interest rates. With the use of BI technologies, this data can be monitored and analyzed in real time, enabling banks to quickly recognize and address market concerns. Making better trading and investment decisions is made possible for decision-makers by providing them with insights on market patterns and volatility through the use of dashboards and visualization tools. Furthermore, banks are able to assess the possible effects of unfavorable market moves on their portfolios thanks to scenario analysis and stress testing, which are enabled by BI (Arnott & Kerstein, 2016).

Ahmadi & Uday (2011) [1] assert that operational risk, arising from failed internal processes, systems, or external events, is another critical aspect of banking risk management that benefits from BI. Banks need to track and analyze vast amounts of transactional and operational data to detect anomalies and prevent fraud. BI tools can integrate data from various sources to provide a comprehensive view of operations, highlighting areas of potential risk. For instance, anomaly detection algorithms can identify unusual patterns in transaction data, flagging potential fraudulent activities. Additionally, BI systems support compliance monitoring by ensuring that banking operations adhere to regulatory standards, thus reducing the risk of regulatory penalties (Ibid).

The role of BI in risk management extends to liquidity risk, which pertains to a bank's ability to meet its short-term financial obligations. Effective liquidity management requires accurate forecasting of cash flows and a thorough understanding of liquidity positions. BI tools facilitate this by analyzing historical transaction data and predicting future cash flow needs. By providing real-time insights into liquidity metrics, BI enables banks to maintain optimal liquidity levels and avoid liquidity crunches. This is particularly important in times of financial uncertainty, where swift decision-making is crucial to maintain stability (Ammar, Ronald & Selden, 2017) [3].

Furthermore, the integration of BI in risk management enhances strategic decision-making at the executive level. By providing a holistic view of risk exposures across various dimensions, BI enables senior management to devise more robust risk mitigation strategies. For instance, risk dashboards that aggregate data on credit, market, operational, and liquidity risks provide a comprehensive risk profile of the bank. This empowers executives to make data-driven decisions and allocate resources effectively to areas with the highest risk exposure (Ahmadi & Uday, 2011) [1].

The advent of big data and advanced analytics has further augmented the capabilities of BI in banking risk management. The integration of artificial intelligence (AI) and machine learning (ML) with BI tools has opened new avenues for predictive risk modeling and real-time risk assessment. These technologies enable banks to process large volumes of unstructured data, such as social media feeds and news articles, to gain insights into emerging risks and trends. Consequently, banks can proactively address potential risks before they materialize, thereby enhancing their overall risk resilience (Ahmadi & Uday, 2011) [1].

Baars & Hans-George (2018) [18] emphasize that business intelligence is an indispensable tool in the risk management arsenal of banks. By leveraging advanced data analytics and visualization techniques, BI provides valuable insights into various types of risks, facilitating proactive and informed decision-making. As the banking sector continues to evolve in response to regulatory changes and market dynamics, the role of BI in risk management will only grow in significance, ensuring that banks remain resilient and compliant in an increasingly complex financial landscape.

1.2 Research Objectives

Main Objective

The main objective of this study is to assess business intelligence in risk management in the banking sector in Zambia.

Specific Objectives

1. To assess the effectiveness of Business intelligence in risk management.
2. To investigate the effectiveness of business intelligence in enhancing customer insights and segmentation.
3. To examine the effectiveness of business intelligence in promoting competitive advantage
4. To ascertain the effectiveness of business intelligence in market intelligence.

Research Questions

1. How effective are Business Intelligence tools in identifying and mitigating risks?
2. How effective is the Business Intelligence in enhancing customer insights and segmentation?
3. How does Business Intelligence promote competitive advantage?
4. How effective is Business Intelligence in market intelligence?

2. Literature Review

2.1 Effectiveness of Business Intelligence in risk management

In today's volatile business environment, risk management is a critical function that helps organizations anticipate and respond to uncertainties. Business Intelligence (BI) systems play a crucial role in this process by providing data-driven insights that can inform decision-making. The integration of BI into risk management strategies has proven to be effective in enhancing an organization's ability to foresee potential risks and implement appropriate countermeasures.

BI systems are designed to collect, process, and analyze vast amounts of data from various sources, providing organizations with valuable insights. In risk management, BI tools can identify trends, detect anomalies, and predict potential risks before they materialize. By doing so, BI helps organizations stay ahead of potential threats and take proactive measures to mitigate them (Kumar, 2023).

One of the key functions of BI in risk management is its ability to perform predictive analytics. Predictive analytics uses historical data to forecast future outcomes, allowing organizations to anticipate risks and plan accordingly. For

instance, BI can analyze market trends to predict economic downturns, enabling companies to adjust their strategies in advance (Smith, 2022). This foresight is critical in minimizing the impact of risks on an organization's operations and financial stability.

Enhancing Decision-Making with BI

BI systems also enhance decision-making by providing real-time data and reports. In the context of risk management, timely information is crucial for making informed decisions. BI tools offer dashboards and visualization features that present complex data in an easily understandable format, allowing decision-makers to quickly grasp the situation and take necessary actions (Jones, 2021).

For example, a financial institution can use BI to monitor market fluctuations and assess the risk of portfolio investments in real-time. By having access to up-to-date information, the institution can make prompt decisions to reallocate resources, thus reducing exposure to market risks (Davis, 2020).

Neural Networks Based Risk Analysis

Neural networks are artificial intelligent tools that have proven very useful in identifying patterns in complex data structures, especially involving nonlinear relationships. Schneidewind (2010) presented results of work applying neural networks to assess software reliability, where the goal was to reduce risk of project failure. Jin and Zhang (2011) gave another application demonstrating the value of artificial neural network models in projects, in this case projects involving public-private partnerships. Applications in industry include banks utilizing artificial neural network models to analyze credit card applications (Yazici, 2011), allowing banks to more efficiently control their risk post-2008 bubble. Neural network models have also been combined with test mining applications as in Groth and Muntermann (2011), where the model was applied to financial risk in day-trading. Ciampi and Gordini (2013) [27] applied artificial neural network models to manage risk of small enterprise default in Italy.

Integration of BI with Risk Management Frameworks

Integrating BI with existing risk management frameworks can significantly enhance an organization's risk mitigation capabilities. Risk management frameworks, such as the Enterprise Risk Management (ERM) model, provide a structured approach to identifying and managing risks. By integrating BI into these frameworks, organizations can leverage data-driven insights to strengthen their risk management practices (Adams, 2019).

For instance, in the ERM framework, BI can be used to identify and assess risks across various departments within an organization. This integration allows for a more comprehensive view of risks, enabling organizations to prioritize and address them more effectively. Additionally, BI can facilitate communication and collaboration among different departments by providing a unified platform for sharing risk-related information (Lee, 2018).

Several organizations have successfully implemented BI in their risk management strategies, resulting in improved risk mitigation and decision-making. One notable example is a global manufacturing company that used BI to monitor supply chain risks. By analyzing data from suppliers, logistics, and market conditions, the company was able to identify potential disruptions and take preemptive actions to ensure continuity in production (Martin, 2017).

Another example is a healthcare organization that used BI to manage patient data and assess risks related to patient safety. By analyzing data from electronic health records and other sources, the organization was able to identify trends and patterns that indicated potential risks, such as increased readmission rates or medication errors. This proactive approach enabled the organization to implement corrective measures and improve patient outcomes (Gomez, 2016).

Risk management has become a vital topic in both academia and practice during the past several decades. Most business intelligence tools have been used for enhancing risk management, and the risk management tools benefit from business intelligence approaches.

Risks exist in every aspect of our lives, and can mean different things to different people, while negatively in general they always cause a great deal of potential damage and inconvenience for the stakeholders. For example, recent disaster risks include terrorism leading to the gassing of the Japanese subway system, to 9/11/2001, to bombings of Spanish and British transportation systems, and the SARS virus disrupting public and business activities, particularly in Asia. More recently, the H1N1 virus has sharpened the awareness of the response system world-wide; the financial crisis has resulted in recession in all aspects of the economy (Wu and Olson 2009).

Risk management has become a vital topic in both academia and practice during the past several decades. Integrated approaches are required to manage risks facing an organization; sometimes effective risk-taking strategies may involve new business philosophies such as enterprise risk management. Most business intelligence tools have been used for enhancing risk management, and the risk management tools benefit from business intelligence approaches. For example, artificial intelligence models such as neural networks and support vector machines have been widely used for establishing the early warning system for monitoring a company’s financial status (e.g., Martens *et al*. 2007; Alfaro *et al*. 2008 [2]; Lin and Chen 2007). Agent-based theories are employed in supply chain risk management (e.g., Julka *et al*. 2002; Liang and Huang, 2006). Business intelligence models are also useful in hedging financial risks by incorporating market risks, credit risks, and operational risks (Wu and Olson 2009). Investigation of business intelligence tools in risk management is beneficial to both practitioners and academic researchers.

All human endeavors involve uncertainty and risk. In the food production area, science has made great strides in genetic management. But there are concerns about some of the manipulations involved, with different views prevailing across the globe. In the United States, genetic management is generally viewed as a way to obtain better and more productive sources of food more reliably. However, there are strong objections to bioengineered food in Europe and Asia. Some natural diseases, such as mad cow disease, have appeared, and these diseases are very difficult to control. The degree of control accomplished is sometimes disputed. Europe has strong controls on bioengineering, but even there a pig breeding scandal involving hazardous feed stock and prohibited medications has arisen (Suder and Gillingham, 2007). Bioengineering risks are important considerations in the food chain (Reilly and Courtenay, 2007; Fletcher, 2007).

Genetic mapping offers tremendous breakthroughs in the world of science, but involves political risks when applied to human resources management (Markel and Barclay, 2007). Even applying information technology to better manage healthcare delivery risks involves risks (Smaltz *et al*., 2007). Reliance on computer control has been applied to flying aircraft, but hasn't always worked (Dalcher, 2007) [28].

Risks can be viewed as threats, but business exists to cope with risks (Olson and Wu, 2010). Different disciplines have different ways of classifying risks. In order to explain the risk management lessons from the Credit Crisis, Jorion (2009) classified risks into: known known, known unknowns and unknown unknowns.

Risks can have four properties: uncertainty, dynamics, interconnection/dependence and complexity. The first two properties have been widely recognized in inter-temporal models from the behavioral decision and behavioral economics areas (Baucells *et al*. 2009) [13]; the last two properties are well studied in finance disciplines. Risk probability applies probability theory and various distributions to model risks. This approach can be dated back to the 1700s, leading to Bernoulli, Poisson, and Gaussian models of events and general Pareto distributions and general extreme value distributions to model extreme events. Dynamics of risks mainly uses stochastic process theory in risk management. This can be dated back to 1930s where Markov processes, Brownian motion and Levy processes were developed. Interconnection /Dependence of risks deals with correlation among risk factors. Various copula functions are built and Fourier transformations are also used. Risk complexity need be handled by use of various complexity science theory such as agent-based modeling approaches.

Risk management can be defined as the process of identification, analysis and either acceptance or mitigation of uncertainty in investment decision making. Risk management is about managing uncertainty related to a threat. Traditional risk management focuses on risks stemming from physical or legal causes such as natural disasters or fires, accidents, death and lawsuits. Financial risk management deals with risks that can be managed using traded financial instruments. The most recent concept, enterprise risk management provides a tool to enhance the value of systems, both commercial and communal, from a systematic point of view. Operations research (OR) is always useful for optimizing risk management.

On the other hand, the term intelligence was coined by researchers in artificial intelligence (AI) in the 1950s, and it has been a buzzword ever since. However, Business intelligence became a popular term in the business and IT communities in the 1990s. Business analytics was introduced to represent the critical analytical component in BI (Davenport, 2006). Competitive Intelligence is defined as "a systematic and ethical program for gathering, analyzing, and managing external information that can affect the company's plans, decisions, and operations," and is a crucial part of the emerging knowledge economy. By analyzing competition's moves, CI allows companies to anticipate market developments rather than reacting to them.

Within the particular context of Big Data, Business Intelligence and Analytics (BI&A) represents an emerging discipline that seeks to address the demands of the new business context, while presenting unique challenges and opportunities for the research community. Best practices mainly in the Anglo-Saxon educational system show that BI&A is used as a unified term to describe information-intensive concepts and methods to improve business decision-making. BI&A includes the underlying architectures, analytical tools, database management systems, data/text/Web mining techniques, business applications, and methodologies (Chiang *et al*., 2012). Curricula designed for teaching BI are therefore mostly focused on support and facilitation of interactive access to big data, enabling manipulation and transformation of these data, and providing business managers and analysts with the ability to conduct appropriate analyses and to take informed actions.

These new features of business are changing the daily life of companies: clients' evolutions, globalization, digital transformation, technology evolutions, and sustainable business requirements. In the academic environment, these topics are frequently addressed with a silo approach: strategy, marketing, Information system management, operation management, as well as many other topics. Intelligent reporting, also known as BI reporting, is defined as the process of receiving reports from a BI tool (usually a software), to translate raw data into a more decision-making-friendly deliverable. Following a BI report, there may be actionable results that translate into alterations of the short-term plan or the long-term strategy of the company.

Adoption of risk-based decisions or risk-based approach to decision-making is a practice used increasingly in the nowadays complex business environment. The use of these concepts indicates a systematic process that deals with the formulation of options under uncertainty. The subject is complex and interdisciplinary, covering all facets, dimensions, and aspects of life, in all phases of activity (planning, development, design, operation, management, etc.). The risk-based approach to decision-making focuses on the need to find alternatives to significant costs, benefits, and risks relevant to an environment with more than one objective, with no reference being made to these items. The insufficient level of knowledge of systems, processes, and phenomena cannot excuse the lack of action on the risks, but rather the imperfect understanding of the system necessarily requires a risk approach. Even without any knowledge of a risk management integrated approach, it is easily noticeable that companies, regardless of their size, need information and structured data regarding at least three types of risks (operational, financial and strategic) and in at least four of the stages of the risk management process (identification, assessment, creation of control elements and reporting and monitoring performance).

Rasmussen's Risk Management Framework (1997) is a tool best suited for BI practices. It hinges on the core belief that there are various levels of action in each system and these levels communicate, interact, and shape each other's behavior. Rasmussen (1997) lists six degrees: a Government level – for rules, laws, and regulations; a Regulatory level – for industry standards; a Company level – for company policies and procedures; a Management level – for work processes; a Staff level; and a Work level. The resilience of the system is highly dependent on the way these levels interact in a feedback loop, with decisions made at stage 1 (Government) propagating down to the stage 6 (Work) and receiving feedback consequently. BI becomes thus critical not solely at the corporate level, but also for higher decision makers of a business ecosystem.

The last several decades have also witnessed a tremendous progress in computational intelligence including fuzzy logic, neural networks and genetic algorithms/evolutionary computation and optimization approaches such as linear programming, nonlinear programming, game theory, multicriteria decision analysis. Optimization approaches have been widely applied in industry in many areas of forecasting, performance evaluation, automatic control, and function approximation.

Early-Warning Systems

Many papers have addressed the value of early warning as a means to control risk. Krstevska (2012) cited their use in macroeconomic models, with specifics to the economy of Macedonia. A number of models implemented through computer systems. Flores (2009) [29] dealt with early warning in insurance using stochastic optimization. Castell and Dacuycuy (2009) [24] discussed macroeconomic and financial surveillance mechanisms. Hua (2011) reviewed methods used for early warning in real estate. Within industrial applications, Xie *et al*. (2009) described a procedure to identify logistics risks for small-to-median enterprises.

Risk-based decision making

Using computer tools for risk-based decision making has been widely studied in the information systems field as decision support systems since the 1970s (Keen and Scott Morton, 1978; Sprague and Carlson, 1982). Warenski (2012) employ artificial intelligence to provide another application of loan-risk analysis, in this case demonstrating financial modeling in the paper and pulp industry. Otim *et al*. (2012) provide a recent analysis specifically addressing the evaluation of value and risk in information technology investments. Such investments involve complex sets of stakeholders, leading to the need to consider organizational politics. Kozhikode and Li (2012) studied to role of political pluralism in the expansion of commercial banks in India, including consideration of risk management. Industrial decision making not only involves multiple stakeholders, but also multiple criteria (Olson, 1996), driven in part by the very existence of these multiple stakeholders. Silvestri *et al*. (2012) provided a multiple criteria risk assessment technique for risk analysis in manufacturing safety. Lakemond *et al*. (2013) gave a method for consideration of risk in product development, enabling early assessment of risk and other challenges.

Game Based Risk Analysis

John Nash provided one of the most popular works in game theory (1950), studying the role of competitive strategy. This well-studied field is active in industrial risk management. Zhao and Jiang (2009) considered a non-cooperative complete information game model considering multiple emerging risks in a project management environment. Merrick and Parnell (2011) etended game theoretic models to include probabilistic risk analysis in the context of counterterrorism. Their application involved container screening for radiological materials. Lin *et al*. (2012) used game theory to model vertical differentiation in online advertising, finding that a higher ad revenue rate may lead to lower service prices. Game theory has also been applied to small and medium-sized enterprise risk management by Gnyawali and Park (2009).

Credit Risk Decisions

The financial industry's primary tasks in risk management is to assess probability of default. Gurnÿ and Tichÿ (2009) presented a scoring model for US banks using linear discriminant analysis. Chen *et al*. (2012) [26] offered another study, in this case using the Six Sigma DMAIC methodology to reduce financial risk. Wu and Olson (2010) demonstrated how predictive scorecards have been used for large bank risk management of credit worthiness. Caracota *et al*. (2010) [23] gave a scoring model for small and medium enterprises seeking a bank loan. Poon (2009) reviewed the effectiveness of government sponsored enterprise (Freddie Mac and Fannie Mae) credit scoring, showing how credit bureau scoring led to support of opposing strategies of risk averse and risk avaricious investment.

Data Mining in Enterprise Risk Management

Data mining has become a very popular means to apply statistical and artificial intelligence tools to analysis of large data sets. Among the many applications to risk management, Shiri *et al*. (2012) applied data mining tools to corporate finance, to include management fraud detection, credit risk estimation, and corporate performance prediction. Jans *et al*. (2010) focused their data mining study to address the risk of internal fraud, finding that data mining tools provided better results than univariate analysis. Holton also addressed occupational fraud, applying text mining to support fraud audits. In other industries, Nateghi *et al*. (2011) applied data mining techniques to better predict power outages, especially those related to hurricanes. Ghadge *et al*. (2012) reviewed text mining applications to support risk management in supply chains. Two studies specifically addressed use of data mining to reduce the risk of occupational injury (Bevilacqua *et al*., 2010 [14]; Murayama *et al*, 2011).

Agent-based Risk Management

Artificial intelligence is often implemented through use of agent-based systems, having computers emulate human decision makers. This approach has been applied to risk management in supply chains by Smeureanu *et al*. (2012) with specific examination of peer partner company risk of bankruptcy. Giannakis and Louis (2011) also addressed supply chain risk management through agent models, in this case examining the inherent risks in both demand and supply of resources in economic downturns. Agents have also specifically been applied to simulation models, enabling the use of simulation models for analysis of more complex problems. Caporale *et al*. (2009) [17] presented an optimal model for financial market under conditions of crisis, combining simulation and game theory through agents. A related approach is particle swarm optimization, which was applied by Chang Lee *et al*. (2009) [25] to project risk management and by Kumar *et al*. (2010) to design more robust supply chain designs. This approach was found to allow modeling of more complicated situations Mizgier *et al*. (2012) applied agent-based modeling of supply chains, modeling risk of bankruptcies of participating firms in self-emerging networks.

Engineering Risk Analysis based on Optimization Tools

Optimization tools are fundamental to engineering efforts to design better systems (Ben-Haim, 2012). The existence of uncertainty violates many of the required assumptions for

many optimization models. The presence of risk implies the presence of uncertainty, making development of optimization models more difficult. However, there have been models presented to optimize engineering systems. Ahmadi and Kumar (2011) [1] gave a model considering the increased probability of failure in mechanical systems due to aging. Buurman *et al*. (2009) [15] gave a framework for dynamic strategic planning of engineering systems using real options analytsis, finding that this approach had considerable advantages over static design. Popovic *et al*. (2012) applied complex optimization to maintenance systems involving risk.

Knowledge Management and Data Mining for Natural Disasters Risk Management in Industry

Knowledge management is a very broad area of study, evolving from decision support systems, expert systems and artificial intelligence, to include data mining and business analytics. Knowledge management also includes consideration of how tacit knowledge within organizations can be captured in computer systems such as case-based reasoning. A few articles are found in application of knowledge management to industrial risk management. Folino *et al*. (2010) employed grid technologies in geoscience through data mining to analyze and manage natural disasters such as landslides, earthquakes, floods, and wildfires. Their system was intended to aid disaster prevention and response. Li *et al*. (2010) focused on prediction of natural disasters using domain knowledge and spatial data to develop a Bayesian network.

Krstevska (2012) studies the risks in Enterprise Resource Planning (ERP) projects. Particularly, they have built Fuzzy Cognitive Maps (FCM) of ERP maintenance risks. The main advantage of FCM lies in them being capable of modelling complex phenomena based on the experts' perceptions. This tool models uncertainty and related events, imitating human reasoning. The tool proposed specifically models ERP maintenance project outcomes and risks perceptions, as well as their hidden interactions. Authors show that FCMs enable the developing of forecasting exercises through simulations. Practitioners would thus assess the joint influence of ERP maintenance risks on project outcomes. The tool proposed would help practitioners to manage ERP maintenance projects risks in a more effective and proactive way.

Silvestri, Felice and Petrillo (2012) present a new stock trading method using Kansei evaluation integrated with a Self-Organizing Map model for improvement of a stock trading system. The proposed approach aims to aggregate multiple expert decisions, achieve the greatest investment returns, and reduce losses by dealing with complex situations in dynamic market environments. Kansei evaluation and Fuzzy Evaluation models are applied to quantify trader sensibilities about stock trading, market conditions, and stock market factors with uncertain risks. In Kansei evaluation, group psychology and sensibility of traders are quantified that represent in fuzzy weights. Kansei and stock-market data sets are visualized by SOM, together with aggregate expert preferences in order to find potential companies, matching with trading strategies at the right time and eliminating risky stocks. Authors test the proposed approach in daily stock trading on the HOSE, HNX (Vietnam), NYSE and NASDAQ (US) stock markets. Authors show that the new approach, applying Kansei evaluation enhances the capability of investment returns and reduce losses. Authors also show that the proposed approach performs better than other current methods to deal with various market conditions.

Yazici (2011) aims at developing Case-based Reasoning hybrid models for predicting business failure. The work is motivated by the fact that accuracy and effectiveness tend to get reduced when CBR alone is applied to handle many attributes. The hybrid models developed by the study to enhance the accuracy of bankruptcy prediction include: RST-CBR (combining Rough Set Theory with CBR), RST-GRA-CBR (integrating RST, Grey Relational Analysis, and CBR), and CART-CBR (combining Classification and Regression Tree with CBR). In order to verify the ability of the proposed models to achieve optimal accuracy rate, the work further compares the predictive ability of CBR with those of other comparative models.

Warenski (2012) present an integrated frame including an extensive risk factor system and a hybrid assessment approach combining machine learning methods a rule-based reasoning. In particular, authors explore the effectiveness of machine learning methods for fraud risk assessment. A number of experiments are conducted on a data set from Chinese listed companies. Authors indicate that the proposed Ensemble of classifier outperforms all the individual classifiers—Logistic Regression (LR), Back-Propagation Neural Network (BPNN), C5.0 Decision Tree (DT), and Support Vector Machine (SVM) in terms of accuracy and composite error rate. Among individual classifiers, SVM and BPNN are found to provide better results. C5.0 DT is proved to have unique advantage in providing lower type error rate and rule-based knowledge.

Li *et al*. (2010) develop a security risk analysis model to identify the causal relationships among risk factors and analyze the complexity and uncertainty of vulnerability propagation. In the proposed model, a Bayesian network (BN) is developed to simultaneously define the risk factors and their causal relationships based on the knowledge from observed cases and domain experts. Authors perform the security vulnerability propagation analysis to determine the propagation path with highest probability and largest path risk exposure. The ant colony optimization is used in SRAM to establish the BN structure and determine vulnerability propagation paths and their occurrence probabilities. SRAM enables organizations to establish proactive security risk management plans for information systems.

Wu and Olson (2010) propose one calibration method for the agent-based continuous double auction (CDA) stock market by scaling analysis based on the work by Pasquini and Serva (1999). Authors design and build an agent-based CDA stock market, which use the same trading mechanism as the Chinese stock market. Authors also perform a scaling analysis of the absolute returns in both the artificial and real stock markets, and show volatility correlations as power laws in all the markets, where the power-law exponent is not unique, and all such exponents follow a multi-scale behavior.

2.2 The Effectiveness of Business Intelligence in Enhancing Customer Insights and Segmentation

Business intelligence (BI) has become a cornerstone of modern business strategy, particularly in enhancing customer insights and segmentation. This technology-driven process involves the collection, integration, analysis, and presentation of business information, allowing organizations

to make more informed decisions. The effectiveness of BI in customer insights and segmentation is profound, offering deep analytical capabilities that help businesses understand their customers better and tailor their strategies accordingly.

2.2.1 The Role of Business Intelligence in Customer Insights

Business intelligence tools and systems are essential for extracting actionable insights from vast amounts of data. These tools can analyze customer behavior, preferences, and purchasing patterns to reveal hidden trends and insights that are not immediately apparent through traditional analysis methods. For example, BI can help businesses understand which products or services are most popular among specific demographic groups, identify seasonal trends in purchasing, and track the effectiveness of marketing campaigns.

One of the key advantages of BI is its ability to process and analyze large datasets quickly and accurately. This capability is crucial in today's data-driven environment, where businesses are inundated with information from various sources, including social media, customer feedback, sales data, and more. By utilizing BI, companies can consolidate this data into a coherent structure, enabling them to identify patterns and trends that would otherwise go unnoticed.

2.2.2 Enhancing Customer Segmentation with Business Intelligence

Customer segmentation is a critical aspect of marketing and business strategy. It involves dividing a customer base into distinct groups that share similar characteristics, such as demographics, purchasing behavior, or preferences. Effective segmentation allows businesses to tailor their products, services, and marketing efforts to meet the specific needs of each segment, thereby improving customer satisfaction and loyalty.

BI enhances customer segmentation by providing detailed insights into customer data. Advanced analytics tools within BI systems can perform complex segmentation tasks that go beyond traditional methods. For instance, machine learning algorithms can analyze customer data to identify segments based on a combination of factors, such as buying behavior, customer lifetime value, and engagement levels. This granularity in segmentation enables businesses to create highly targeted marketing campaigns that resonate with specific customer groups, ultimately leading to higher conversion rates and customer retention.

Moreover, BI can continuously monitor and update customer segments in real time, allowing businesses to adapt to changing market conditions and customer behaviors. This dynamic approach to segmentation ensures that businesses remain agile and responsive to their customers' needs, which is particularly important in highly competitive markets.

2.2.3 Predictive Analytics and Customer Insights

One of the most powerful aspects of BI in enhancing customer insights and segmentation is predictive analytics. Predictive analytics involves using historical data, machine learning, and statistical algorithms to predict future outcomes. In the context of customer insights, predictive analytics can forecast customer behavior, identify potential churn risks, and predict future sales trends.

By leveraging predictive analytics, businesses can proactively address customer needs and prevent issues before they arise. For example, if predictive models indicate that a particular customer segment is likely to experience a decline in engagement, the company can intervene with targeted offers or communications to re-engage those customers. This proactive approach not only improves customer retention but also enhances the overall customer experience.

Furthermore, predictive analytics can help businesses identify cross-selling and up-selling opportunities by analyzing customer purchase history and preferences. By understanding which products or services are likely to appeal to specific customer segments, companies can create personalized offers that increase the likelihood of additional sales.

2.2.4 Integration of BI with Customer Relationship Management (CRM) Systems

The integration of BI with Customer Relationship Management (CRM) systems is another key factor in enhancing customer insights and segmentation. CRM systems store vast amounts of customer data, including contact information, purchase history, and interaction records. When combined with BI tools, this data can be analyzed to generate deeper insights into customer behavior and preferences.

For example, BI tools can analyze CRM data to identify patterns in customer interactions, such as the frequency of purchases, response to marketing campaigns, and customer service inquiries. These insights can then be used to segment customers more effectively and to tailor marketing strategies to meet the specific needs of each segment.

Moreover, the integration of BI with CRM allows for real-time data analysis, enabling businesses to make informed decisions quickly. This real-time capability is particularly valuable in dynamic markets where customer preferences can change rapidly. By having up-to-date insights at their fingertips, businesses can respond to changes in customer behavior promptly, ensuring that their marketing efforts remain relevant and effective.

2.2.5 The Impact of BI on Customer Experience

Enhancing customer insights and segmentation through BI has a direct impact on the overall customer experience. By understanding customers' needs and preferences more deeply, businesses can create more personalized and engaging experiences that resonate with their target audience.

Personalization is a key driver of customer satisfaction and loyalty. According to a study by Accenture, 91% of consumers are more likely to shop with brands that provide personalized offers and recommendations (Accenture, 2018). BI enables this level of personalization by providing the data and insights needed to tailor products, services, and communications to individual customers.

Additionally, BI can help businesses identify and address pain points in the customer journey. By analyzing customer feedback, service interactions, and purchasing behavior, companies can pinpoint areas where the customer experience may be falling short and take corrective action. This continuous improvement process not only enhances customer satisfaction but also strengthens the relationship between the business and its customers. While the effectiveness of BI in enhancing customer insights and

segmentation is well-established, there are challenges and considerations that businesses must address to fully realize its benefits. One of the primary challenges is data quality. BI is only as effective as the data it analyzes, so it is crucial for businesses to ensure that their data is accurate, complete, and up-to-date.

Another consideration is the complexity of BI tools. While these tools offer powerful analytical capabilities, they can be complex to implement and use effectively. Businesses need to invest in training and support to ensure that their teams can fully leverage the capabilities of BI systems.

Privacy and data security are also critical considerations. As businesses collect and analyze more customer data, they must ensure that they are compliant with data protection regulations and that customer data is stored and processed securely.

Business Intelligence (BI) has become an indispensable technological partner for any organization intending to survive in its competitiveness within the market in today's era of data-driven decision-making (Soumaya *et al*, 2019). BI is that category of tools, applications, and methodologies through which an organization can obtain, store, analyze, and make available to a set of decision-makers huge volumes of data. At the core of modern BI lies the power to boost customer experience and engagement by not just meeting but anticipating the needs of customers in order to breed loyalty and business growth.

Customer experience (CX) is what customers perceive in their interactions with an organization during all points from prospect to repeat buyer. It's an all-embracing term that encapsulates all points of customer contact with the brand—from navigation on the website to customer service to personalized marketing communications. In a modern business environment, great CX is critical to delivery within a customer-centric operation, as it greatly influences brand loyalty and customer retention.

BI tools help synthesize data from a multichannel environment: social media, customer databases, online interactions, and others. This integration helps firms use the actionable insights for powering strategic decisions, elevating customer interactions, and bringing out the best efficiency and effectiveness in operations. The current evolution of BI technologies has further extended the analytical capabilities of businesses by infusing them with artificial intelligence (AI) and machine learning. More precisely, BI is now currently offering to its businesses the capability for more accurate predictions and to supply deep insights into the patterns of consumer behavior.

The aim of this review would be to establish just how BI tools are put to use in improving CX and engagement. This includes the nature of the BI technologies, strategic applications of these tools in various industries, and case studies to this effect. This study will also address challenges companies have during the deployment of business intelligence solutions and future changes that are likely to reshape the way businesses use data in enhancing customer experiences (Soumaya *et al*, 2019).

Business Intelligence (BI) is a complex framework of technology, applications, and practices that are very critical to the collection, integration, analysis, and presentation of business information. In general, BI supports the main goal of achieving better business decision-making. In other words, BI systems assist companies in making raw data useful for the conduction of business analysis. This category includes reporting and OLAP, analytics, data mining, process mining, complex event processing, business performance management, benchmarking, text mining, predictive analytics, and prescriptive analytics.

Customer experience (CX), on the other hand, is all about the customers' internal and subjective response resulting from any direct or indirect contact with a company. Direct contact usually occurs in the process of purchase, use, and service, and is generally instigated by the customer. Indirect contact most frequently occurs through unplanned encounters with representations of a company's products, services or brands in the form of word-of-mouth recommendations or criticisms, advertising, news reports, reviews and so on.

The integration of BI with CX is based on the analytical information that serves to enhance the perception and administration of customer experience. With BI, organizations will be able to acquire knowledge about consumer preferences, their behaviors, and their expectations. That may help in customizing the experience, easing the service, and being able to provide a more adequate answer to the needs of the customers through more data-driven approaches. This eventually leads to a more personalized, satisfying customer journey—the main factor in building loyalty and increasing overall satisfaction (Business Intelligence, 2023).

And along with the constant evolution of BI tools, changes in artificial intelligence and machine learning allow the capability to analyze complex datasets much deeper, larger, and faster. This results in sharp insights into customer behavior and agile responses to changing market dynamics.

An understanding of the theoretical underpinnings of BI and its nexus with CX is crucial for any business seeking to exploit data for a competitive advantage. This background explains how some BI strategies and tools are used in the enhancement of customer engagement and experience in different industries.

Business intelligence tools and technologies that companies can use in improving CX will involve how the company can acquire, serve, and retain customers through proper collection, processing, and analysis of customers' relevant data. This ensures that such companies glean more insight into their customers' behaviors and preferences in the development of personalized marketing strategies and the enhancement of customer service. The sections below describe some of the major business intelligence tools and technologies that transform customer data into actionable insights.

- **CRM Systems**: The entire front edge of analyzing customer data, these systems aggregate data from all touchpoints in order to get a 360-degree view of the customer journey (Somayah & Alikhani, 2014). They track interactions, sales, and service data to effectively segment and target marketing efforts.
- **Data Warehousing and Data Lakes**: These are technologies that act as a central store for integrated data from different sources. Data Warehousing avails highly structured and filtered data that is ideal for query and reporting with speed, while Data Lakes avail a much more flexible environment well-suited for unstructured data and performance of complex analysis. Both are pivotal in supporting the other BI tools.
- **Advanced Analytics Platforms**: Platforms like SAS, IBM Watson, and Tableau further enhance the already

strong capabilities of BI with even more powerful statistical tools and predictive analytics algorithms. These platforms use past behavior patterns of customers to predict future customer actions and, hence, enable businesses to be proactive in satisfying customer demands (Muhammad *et al*, 2020).

- **Data Visualization Tools**: Tools that help in transforming complicated sets of data into easy graphical representation through the likes of Microsoft Power BI, Tableau or QlikView, which in turn enable easy understanding of patterns, trends, and anomalies by the decision-makers. Effective visualization makes it easier to communicate insights across an organization to facilitate faster, more informed decisions.
- **AI and Machine Learning**: Working their way into BI tools at an increasing rate, these technologies further the depth of insights and predictive abilities. For instance, AI algorithms deducing customer sentiment and trends from social media, surveys, and other text sources, while machine learning can continue to improve the models with new data, enhancing the accuracy of prediction of customer behavior with time.

These BI tools and technologies support organizations to understand their customers better, deliver experiences in a more personalized manner, and react quickly to changes in markets—all leading to much higher levels of customer satisfaction and customer loyalty (Business Intelligence, 2023).

Business Intelligence itself is not about the analysis of data. It is principally the formulation of action strategies which could make a huge difference in customer engagement and experience. In other words, an effective BI strategy helps a business understand its customers and then act on that insight in ways that create increased customer satisfaction and loyalty (Business Intelligence, 2023). Let us delve here into some key strategies of how businesses can make use of BI to enhance customer engagement (Amir *et al*, 2020).

Personalization at Scale: The application of one of the most potent BI potentials in customer engagement is mass personalization. Enterprises are able to manage highly personalized marketing messages, product recommendations, and service offers using customer data and their behavioral patterns. This will include the use of data from different sources such as purchase history, browsing behavior, and even customer feedback for personalized interactions based on individual preferences. Advanced analytics and machine learning models can predict what offers or products a customer would be interested in, even before the customer explicitly conveys them. Such proactive personalization leads to far more improved engagement and experience fulfillment.

Customer Segmentation for Targeted Marketing: Segmenting Yet another important strategy that can be used with BI is the effective segmentation of customers. Based on shared characteristics such as demographic, purchasing behaviors, or engagement levels, businesses can divide their customers into distinct groups to whom they can make targeted marketing efforts that match their needs and preferences. It not only makes the marketing communications highly relevant but also raises the efficiency in marketing spend through this targeted approach.

BI tools facilitate dynamic segmentation of customers and on-the-fly updating of these segments to ensure that the marketing will always be in line with the current behavior of the customers.

Optimizing Customer Experience: BI tools provide the organization with the ability to map and analyze the customer journey from all contact points. Such a holistic view enables companies to zero in on any choke points in the customer experience. Insights enable a business to streamline the process, eliminate friction points, and create the easiest journey for the customer (Amir *et al*, 2020).

For example, BI analytics identify that customers are dropping off at some stage during the online checkout process: designed interventions to solve that may include simplifying checkout or new payment options.

Interactions with the use of BI in real-time data analysis: This can transform customer interaction. Real-time BI tools can give immediate insight into customer behavior and feedback during interaction, enabling the customer service representative to make an informed decision and react better to customer needs. This is very useful in dynamic environments like e-commerce, where an immediate response can turn browsing into purchases, or in customer service, where a quick solution to complaints may improve satisfaction and thus retention.

3. Research Methodology

3.1 Research Design

The case study design is chosen for this study to facilitate the acquisition of detailed information from research participants and gather insight for obtaining answers to the research question. The case study design will allow for an extensive and thorough understanding of the issues from a broader perspective with data from various sources, and it will be based on the premise associated with the purpose of the study and data collection method (Wachowicz, 2015) [16]. The research problem identified in my study is best addressed by a mixed method research technique. In light of the fact that doing so will strengthen the research by adding more meat to the findings as well as make up for any shortcomings in one approach.

3.2 Target Population.

A specific group of people that a researcher or organization wants to study, reach, or serve is referred to as the "target population." Specific traits pertinent to the goals of a research study, marketing campaign, public health initiative, or any other activity are used to define this group. (Creswell and Creswell, 2018) [22]. The Bank of Zambia has registered a total number 19 banks both local and international. Under its guidelines on risk management, the Bank of Zambia instructed all registered banks to put in place risk management system which will comprise of operational, credit, strategic, liquidity, market, reputational and legal risk (Risk Management Guidelines, 2008). Therefore, following this instruction from the Bank of Zambia, the target population for this study is 55.

3.3 Sample Size

The process of choosing a group of people from a population in order to estimate characteristics of the entire population is known as sampling design. Target population, sampling frame, sample size, and sampling strategy (random, stratified, cluster sampling, etc.) are all defined in this process (Shah, 2011). Representative, objective samples are guaranteed by good design. This study will therefore

utilize purposive sampling. A sort of non-probability sampling known as "purposeful sampling" involves the researcher purposefully choosing participants based on predetermined characteristics. In order to best help the researcher, address the study questions, the goal is to concentrate on certain, interesting features of a population (Palinkas *et al*, 2015) [35].

3.4 Sampling Procedure

Purposive sampling was used for all respondents as they can easily be identified. For data collection, questionnaires and interview schedules for primary data were used. Secondary data was also obtained from literature. Qualitative data analysis was mainly used. However, in certain circumstances, quantitative methods were employed, where numerical data was available.

4. Research Results/Findings

4.1 Background characteristics of the respondents

4.1.1 Gender: The researcher collected the demographic information relating to gender from respondents. The study found that majority participants (64%) were males while 36% accounted for females who took part.

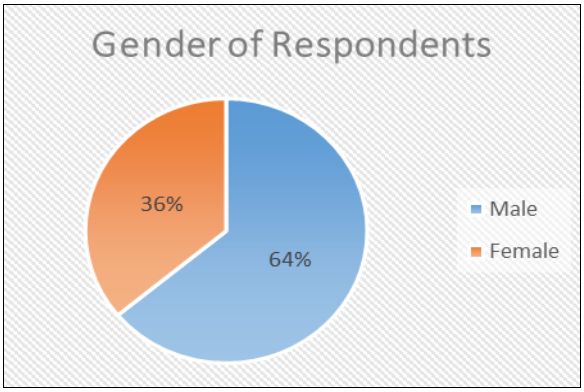


Fig 1: Graphic presentation of gender chararectristics of respondents

4.1.2 The age range showed that majority participants (42%) were aged between 28 and 32 years. Followed by 38% representing those aged above 33 years. 18% accounted for those between 23 and 27 years while 2% represented those aged between 18 and 22 years respectively.

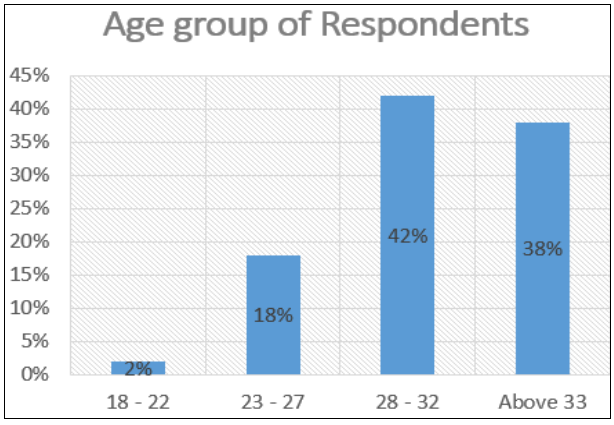


Fig 2: Age range of respondents.

4.1.3 In relation to the role/position, majority respondents (48%) had roles relating to customer services, followed by Information Technology staff who accounted for 36%. Analysts represented 14% while managers accounted for 2% respectively.

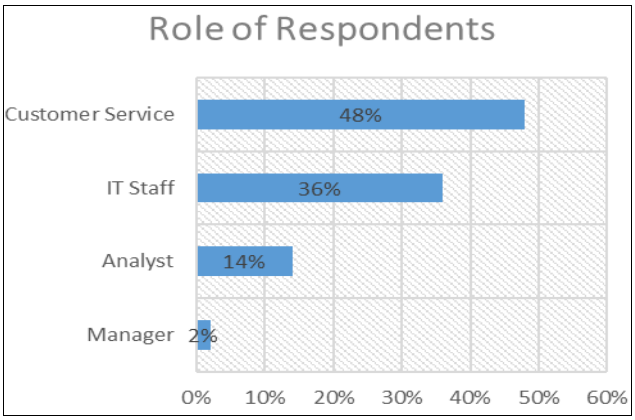


Fig 3: Presentation of Roles/positions

4.1.4 Years of work experience presented varying practices within participants. Majority (44%) were found to have been working between 8 and 10 years. 30% represented those who has been offering their service to the company for between 1 and 3 years. This was followed by 24% representing those who had been working between 4 and 7 years. 0.50% was recorded for those who are beginners, thus having been working for less than 1 year as indicated on the figure below.

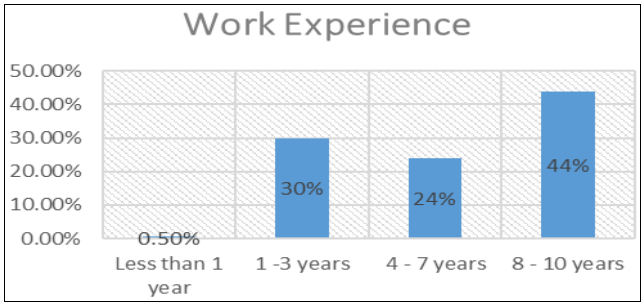


Fig 4: Work experience

4.1.5 The effectiveness of Business Intelligence in risk management

The researcher further inquired from participants to indicate usage of Business Intelligence system using the scale from 1 to 5 (i.e 1 representing Very Effective while 5 representing Not Effective). Risk identification recorded very effective as indicated by 64% of participants from the overall respondents. Risk monitoring and reporting recorded that it was not effective as indicated by 62% from the overall participants. Risk assessment recorded that it was effective as indicated by 60% from the overall participants. Risk mitigation on the other hand recorded a very effective as indicated by 46% of respondents from the overall total of participants.

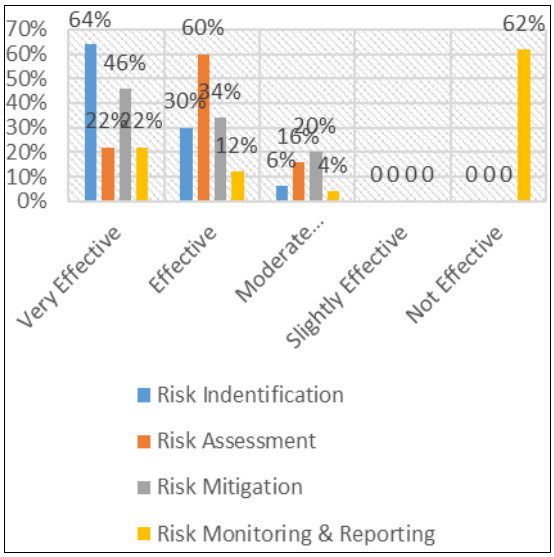


Fig 5: Business intelligence in risk management

The researcher further inquired from participants to indicate usage of Business Intelligence effectiveness in risk management using the scale from 1 to 5 (i.e 1 representing Very Effective while 5 representing Not Effective). Respondents were asked to indicate how effective the Business Intelligence system is in assisting with developing and implementing risk mitigation strategies. Respondents indicated that the system was effective as shown from majority (54%) responses from the overall participants. The study inquired further on how accurate and timely the Business Intelligence system is in monitoring and reporting. Majority respondents (44%) indicated moderately effective. This was derived from the overall total of participants.

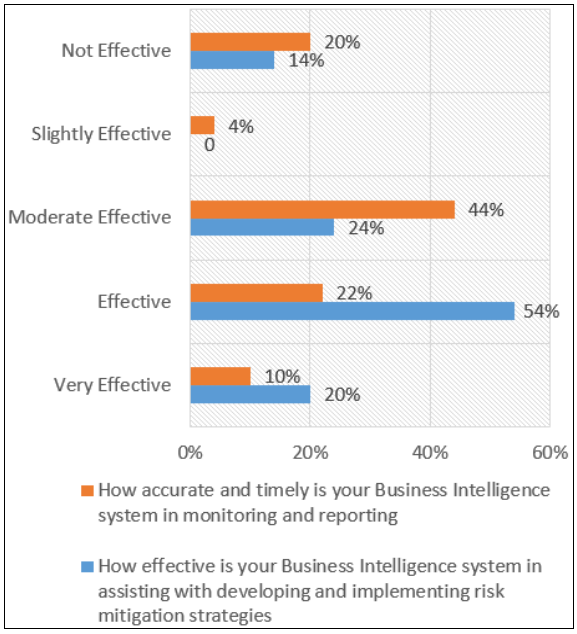
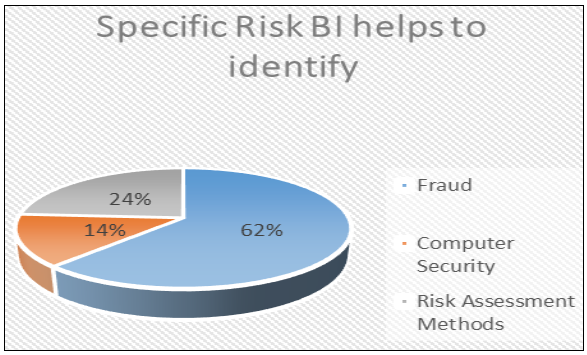


Fig 6: Use of BI in risk management

The researcher inquired further from the participants to find out the specific risks that Business Intelligence system has helped them to identify and assess. Majority participants (62%) Indicated that the system helped them to detect fraud. This was seconded by respondents who indicated risk assessment methods accounting for 24%. Computer security was recorded for those who accounted for 14%.



The effectiveness of Business Intelligence in enhancing customer insights and segmentation

The researcher further inquired from participants to indicate usage of Business Intelligence system using the scale from 1 to 5 (i.e 1 representing Very Effective while 5 representing Not Effective). Customer data collection recorded very effective as indicated by 66% of participants from the overall respondents. Customer segmentation and insight recorded that it was not effective as indicated by 78% from the overall participants. Customer personalization recorded that it was slightly effective as indicated by 38% from the overall participants. Customer data analysis on the other hand recorded an effective as indicated by 22% of respondents from the overall total of participants.

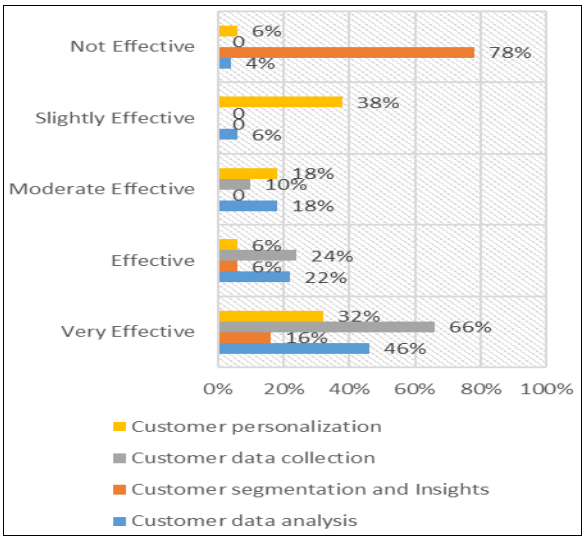


Fig 8: Use of BI system

The researcher further inquired from participants to indicate usage of Business Intelligence system in customer insights and segmentation using the scale from 1 to 5 (i.e 1 representing Very Effective while 5 representing Not Effective). Respondents were asked to indicate how effective the Business Intelligence system is in collecting and analyzing relevant customer data. Respondents indicated that the system was very effective as shown from majority (62%) responses from the overall participants. The study inquired further on how Business Intelligence assist in creating accurate and effective customer segments. Majority respondents (52%) indicated very effective from the overall participants. Lastly, the respondents were asked to indicate the effectiveness of Business Intelligence in helping their target marketing efforts to specific customers. Majority (42%) indicated that the system was effective. This was derived from the overall total of participants.

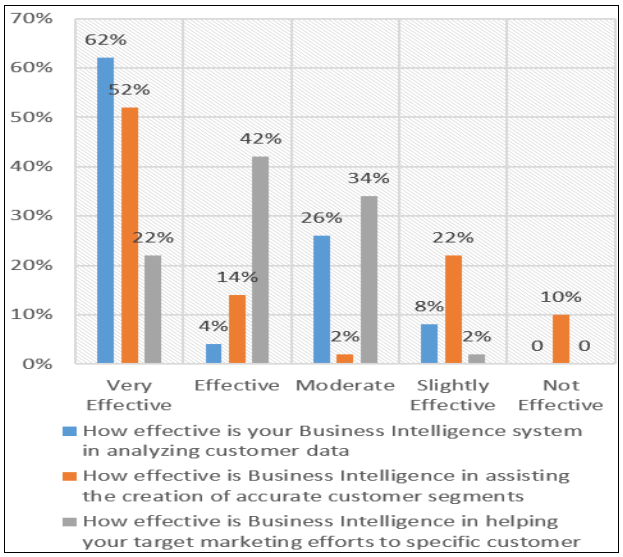


Fig 9: BI system usage in customer insights and segmentation

Participants were further inquired to elaborate on any successful marketing campaign that were formed by their use of Business Intelligence driven customer segmentation. Majority participants highlighted their success through a platform that ensures updated Taxpayer Identification Number (TPIN). One participants narrated,

> *'One of the success story of using BI is the automated update of TPIN. We are able to easily track down customers who don't have TPIN and we launch a campaign to sensitize them via direct messages or emails.'*

The effectiveness of Business Intelligence in promoting competitive advantage

The researcher further inquired from participants to indicate the competitive advantages of Business Intelligence system using the scale from 1 to 5 (i.e 1 representing Very Effective while 5 representing Not Effective). Data driven decision making recorded very effective as indicated by 58% of participants from the overall respondents. Operational efficiency recorded that it was very effective as indicated by 66% from the overall participants. Innovation recorded that it was very effective as indicated by 42% from the overall participants. Market position on the other hand recorded effective as indicated by 42% of respondents from the overall total of participants.

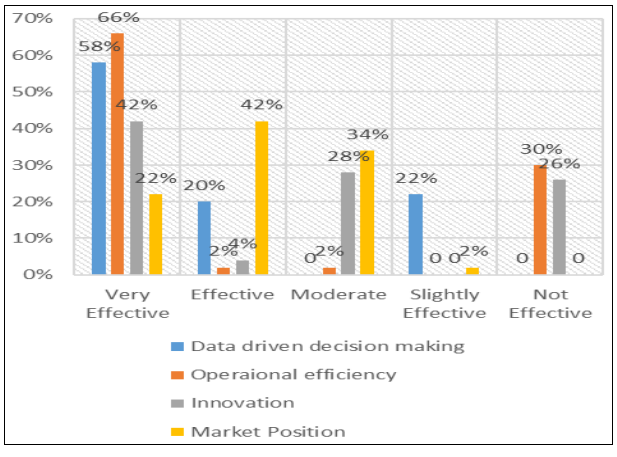
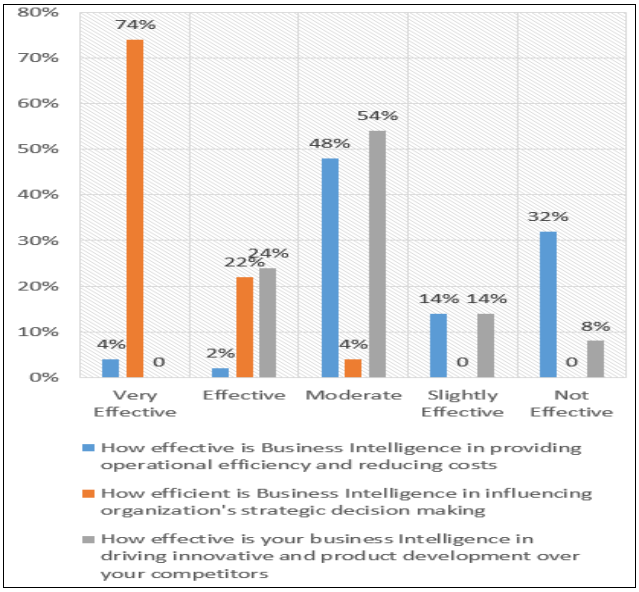


Fig 10: Competitive advantage of BI system

The researcher further inquired from participants to indicate usage of Business Intelligence system in competitive advantage using the scale from 1 to 5 (i.e 1 representing Very Effective while 5 representing Not Effective). Respondents were asked to indicate how Business Intelligence contribute to providing operational efficiency and reducing costs. Respondents indicated that the system was moderate as shown from majority (48%) responses from the overall participants. The study inquired further on how Business Intelligence influence organization's strategic decision making. Majority respondents (74%) indicated very effective from the overall participants. Lastly, the respondents were asked to indicate the effectiveness of Business Intelligence in driving innovative and product development over competitors. Majority (54%) indicated that the system was moderate. This was derived from the overall total of participants.

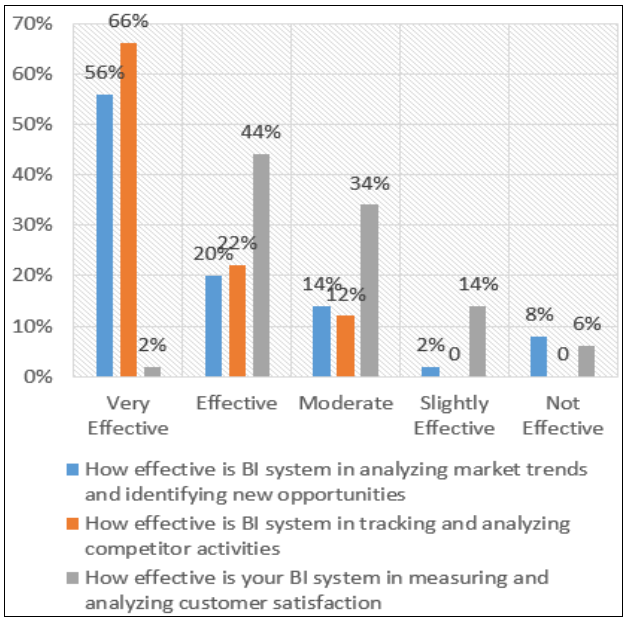


To ascertain the effectiveness of Business Intelligence in market intelligence

The researcher further inquired from participants to indicate the marketing intelligence of Business Intelligence system using the scale from 1 to 5 (i.e 1 representing Very Effective while 5 representing Not Effective). Market trend analysis recorded very effective as indicated by 58% of participants from the overall respondents. Customer satisfaction analysis recorded that it was effective as indicated by 42% from the overall participants. Return on investment analysis recorded that it was moderate as indicated by 62% from the overall participants. Competitor analysis on the other hand recorded very effective as indicated by 68% of respondents from the overall total of participants.

The researcher further inquired from participants to indicte usage of Business Intelligence system in marketing intelligence using the scale from 1 to 5 (i.e 1 representing Very Effective while 5 representing Not Effective). Respondents were asked to indicate how effective Business Intelligence is in analyzing market trends and identifying new opportunities. Respondents indicated that the system was very effective as shown from majority (56%) responses from the overall participants. The study inquired further on how Business Intelligence system assist in tracking and analyzing competitor activities. Majority respondents (66%) indicated very effective from the overall participants. Lastly,

the respondents were asked to indicate the effectiveness of Business Intelligence in measuring and analyzing customer satisfaction. Majority (44%) indicated that the system was effective. This was derived from the overall total of participants.



5. Discussion of Findings

5.1 Overview

This chapter will highlight and explain thoroughly the findings of this study. The results will be discussed under each objective to clearly show response and their contribution to the generation of new knowledge.

5.2 Effectiveness of Business Intelligence in identifying and mitigating risks

The findings showed that the use of BI provided a very effective risk identification record as indicated by majority respondents (64%). Further results showed that the use of BI provided a very effective platform in mitigating the risks. Findings clearly shows that the through use of BI, majority participants effectively dealt with risks that were identified and put up measures to mitigate it. A similar study by Negash (2014) found that BI systems help detect early indicators of risk by providing a comprehensive view of the business landscape, allowing managers to act preemptively. The findings from Negash (2014) clearly support the findings from this study as they both acknowledge that BI enables organizations to make data-driven decisions by offering insights through data aggregation, trend analysis, and real-time data visualization. This supports the identification of potential risks and assists in timely risk mitigation.

The adoption of BI for risk management can reduce costs associated with potential failures. Chae, Olson, and Sheu (2014) noted that organizations implementing BI solutions experienced a reduction in risk-related costs, as early risk detection through BI minimized the impact and severity of adverse events.

5.3 Effectiveness of Business Intelligence in enhancing customer insights and segmentation

Findings of the study under this objective revealed that customer segmentation and insight was not effective as indicated by majority respondents (78%). Two noticeable factors could have influenced the findings namely data quality issues and limited resources to hire experts. The first factor refers to the fact that banks have customers who been their client for many years. This therefore may affect data quality if those clients are not providing updated information or if there are inconsistencies in the data they provided, this directly affect analyses of segmentation. The second factor emphasize the need for experts that are able to identify the inaccurate, outdated or inconsistency information provided by clients. Such skills call for experts such as data analysts or data scientists with advanced skills in data management.

A study by Chen and Nath (2020) showed that predictive analytics and data mining techniques fixed within BI systems allow companies to predict future customer behavior accurately. This ability to anticipate customer needs not only aids in more precise segmentation but also provides a competitive advantage, as organizations can proactively design services to meet anticipated demands. Another study adds that when BI is integrated with CRM systems, it merges customer data, including purchase history, preferences, and behavior patterns, into a single view. This integration enables businesses to create more personalized customer experiences and targeted marketing strategies, directly leading to improved customer segmentation and increased revenue (Davenport and Harris, 2022).

5.4 Promotion of competitive advantage by using Business Intelligence

Competitive advantage was measured using two factors namely, operational efficiency and market position. Findings showed that operational efficiency was very effective as indicated by majority participants (66%). Similar, findings on market position revealed that it was very effective as indicated by majority participants (42%). The results reveal two factors which are cardinal to this study. The first factor provide evidence that banks in Lusaka are effective in their operations. However, the second factors provide further information that indicate that operational efficiency is not a guarantee of a favorable market position. This clearly shows that there is more that banks can do in Lusaka to be both operation efficient as well as be listed under a favourable market position. A study by Davenport and Harris (2022) points out that market strategies, proper customer segmentations that come as a result of accurate, updated and consistence data availability and presence of experts is key in determining market positions in the banking sector.

5.5 Effectiveness of Business Intelligence in Market Intelligence

The effectiveness of Business Intelligent on market intelligence was measured using two factors namely, market trend analysis and competitor analysis. The findings from the study showed that market trend analysis was very effective as indicated by majority participants (58%). Similar, competitor analysis also revealed very effective position as indicated by majority participants (68%). A similar study by Preko and Kester (2015) which focused on the impact of business intelligence in the banking industry of Ghana showed that banks that had adopted BI in market trend analysis had competitive advantage over banks that did not. Another has shown that companies employing BI tools in market trend experience improved customer retention rates and revenue growth due to more targeted marketing and product development strategies (Wixom &

Watson, 2021).

In today's competitive landscape, achieving a competitive advantage requires not only knowing the current market but also predicting future trends. BI contributes significantly by enabling deep insights into customer behaviors and preferences, helping businesses personalize offerings and meet specific market demands (Lönnqvist & Pirttimäki, 2018).

6. Conclusion and Recommendations

6.1 Conclusion

In conclusion, according to the study evaluating the use of business intelligence (BI) in corporate management, which focuses on the banking industry in Lusaka, Zambia, BI systems greatly improve competitive advantage, operational efficiency, and decision-making procedures. Banks can now gather, examine, and comprehend enormous volumes of data as a result of BI technologies, which helps them make better, data-driven decisions that improve customer service and strategic planning. According to the report, challenges such as lack of experts or data analyst in banks, data privacy issues, and a lack of awareness on the complexity of the system limit the usefulness of BI in Lusaka, despite the fact that BI is essential for resource optimization and service customization to match consumer expectations. Clearly, banks in Lusaka are benefiting greatly from BI, which aids them in navigating aggressive and quickly changing market. Notwithstanding its potential, the report emphasizes that effective implementation and full use of BI necessitate a supported infrastructure, sufficient training, and ongoing enhancements to take into account new developments in technology and regulations.

6.2 Recommendations

1. Effective BI requires accurate and high-quality data and experts. Banks should establish stringent data governance policies to ensure data integrity, which includes regular audits, data cleansing processes, and a centralized data management system to support BI initiatives.
2. Banks must adopt advanced cybersecurity frameworks and data protection protocols to secure customer data. Compliance with data protection regulations, such as the Data Protection Act in Zambia, should be prioritized to foster trust and prevent breaches.

7. References

1. Ahmadi A, Uday K. Cost based risk analysis to identify inspection and restoration intervals of hidden failures subject to aging. IEEE Transactions on Reliability. 2011; 60(1):197-209.
2. Al-Azmi AR. Data, text and web mining for business intelligence: A survey. arXiv preprint arXiv: 1304.3563, 2013.
3. Ammar S, Ronald W, Selden S. Ranking State Financial Management: A Multilevel Fuzzy Rule ‐ based System. Decision Sciences. 2017; 31(2):449-481.
4. Arneson H, Kerstin E. Measuring empowerment in working life: A review. Work. 2016; 26(1):37-46.
5. Arnott D, Graham P. Eight key issues for the decision support systems discipline. Decision Support Systems. 2008; 44(3):657-672.
6. Ansoff I, McDonnell. Implanting strategic management (2nded). New York: Prentice Hall, 1990.
7. Ansoff HI. Corporate strategy. New York: McGraw-Hill, 1987.
8. Bharadwaj Sundar G, Varadarajan PR, Fahy J. Sustainable competitive advantage in service industries: A conceptual model and research propositions. Journal of Marketing, Oct 1993; 57(4):83-99.
9. Barney JB, Hersterly WS.Strategic management and Competitive advantage: Concepts and cases (2nd ed). London: Prentice Hall, 2008.
10. Boro AN. Extent to which Competitive Intelligence Practices Influence Achievement of Competitive Advantage: A case study of Kcb Bank Kenya Limited, Unpublished MBA project, University of Nairobi, 2014.
11. Calof JL, Wright S. Competitive Intelligence: A Practitioner, Academic and inter-disciplinary Perspective. European Journal of Marketing. 2008; 42(7/8):717-730.
12. Alfaro E, García N, Gámez M, Elizondo D. Bankruptcy forecasting: An empirical comparison of AdaBoost and neural networks. Decision Support Systems. 2008; 45(1):110-122.
13. Baucells M, Heukamp FH. Probability and time tradeoff. SSRN working paper, 2009. Available at http://ssrn.com/abstract=970570
14. Bevilacqua M, Ciarapica FE, Giacchetta G. Data mining for occupational injury risk: A case study. International Journal of Reliability, Quality & Safety Engineering. 2010; 17(4):351-380.
15. Buurman J, Zhang S, Babovic V. Reducing risk through real options in systems design: The case of architecting a maritime domain protection system. Risk Analysis. An International Journal. 2009; 29(3):366-379.
16. Wachowicz J. Fundamentals of Financial Management. 13 ed. London: Pearson Education Limited, 2015.
17. Caporale GM, Serguieva A, Hao Wu. Financial contagion: Evolutionary optimization of a multinational agent-based model. Intelligent Systems in Accounting, Finance & Management. 2009; 16(1-2):111-1125.
18. Baars H, Hans-George K. Management support with structured and unstructured data-an integrated business intelligence framework. Information Systems Management. 2018; 25(2):132-148.
19. Bai B, Jerome Y, Xiaoguang, Y. False financial statements: Characteristics of China's listed companies and CART detecting approach. International Journal of Information Technology & Decision Making. 2008; 7(2):339-359.
20. Banda M. Impact of Customer Relationship Management Systems on Customer Satisfaction in Zambian Banks. Journal of Banking & Finance. 2019; 34(3):265-278.
21. Chanda K, Mbewe S, Tembo P. Enhancing Operational Efficiency in Zambian Banks Through Business Intelligence. African Journal of Business Management. 2020; 14(5):149-159.
22. Creswell JW, Creswell JD. Research Design: Qualitative, Quantitative and Mixed Methods Approaches. Sage Publications, 2018.
23. Caracota RC, Dimitriu M, Dinu MR. Building a scoring model for small and medium enterprises. Theoretical & Applied Economics. 2010; 17(9):117-128.
24. Castell MRF, Dacuycuy LB. Exploring the use of exchange market pressure and RMU deviation indicator for early warning system (EWS) in the ASEAN+3

region. DLSU Business & Economics Review. 2009; 18(2):1-30.
25. Chang Lee K, Lee N, Li H. A particle swarm optimization-driven cognitive map approach to analyzing information systems project risk. Journal of the American Society for Information Science & Technology. 2009; 60(6):1208-1221.
26. Chen YC, Chen SC, Huang MY, Tsai CL. Application of six sigma DMAIC methodology to reduce financial risk: A study of credit card usage in Taiwan. International Journal of Management. 2012; 29:166-176.
27. Ciampi F, Gordini N. Small enterprise default prediction modeling through artificial neural networks: An empirical analysis of Italian small enterprises. Journal of Small Business Management. 2013; 51(1):23-45.
28. Dalcher D. Why the pilot cannot be blamed: A cautionary note about excessive reliance on technology. International Journal of Risk Assessment and Management. 2007; 7(3):350-366.
29. Flores C. Management of catastrophic risks considering the existence of early warning systems. Scandinavian Actuarial Journal. 2009; 1:38-62.
30. Deloitte. The future of risk: New game, new rules. Deloitte Insights, 2020.
31. Gartner. Market Guide for Operational Risk Management Solutions. Gartner Research, 2019.
32. KPMG. Compliance transformation: Leveraging data and technology to meet today's challenges. KPMG Report, 2018.
33. Kunda J. Data Quality Challenges in the Implementation of Business Intelligence Systems in Zambian Banks. Information Systems Journal. 2020; 28(4):301-317.
34. Mwansa T. The Role of Business Intelligence in Risk Management in the Zambian Banking Sector. Risk Management Journal. 2021; 22(2):98-112.
35. Palinkas LA, Horwitz SM, Green CA, Wisdom JP, Duan N, Hoagwood K. Purposeful sampling for qualitative data collection and analysis in mixed method implementation research. Administration and Policy in Mental Health and Mental Health Services Research. 2015; 42(5):533-544. Doi:10.1007/s10488-013-0528-y
36. Phiri D. Strategic Planning and Competitive Advantage: The Impact of Business Intelligence in Zambian Banks. Journal of Strategic Management. 2022; 29(1):77-91.