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# Integrating Artificial Intelligence in Banking ERM Towards Efficient Mitigation of Contemporary Financial Risks in the Zimbabwean Banking Industry

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## Abstract
Artificial Intelligence (AI) has increasingly become a cornerstone of banking Enterprise Risk Management (ERM Since the early 2010s, AI technologies have been progressively integrated into ERM frameworks to complement traditional risk management approaches, particularly in areas such as fraud detection, credit risk assessment, anti-money laundering, and cost optimization. Despite these advancements globally, the Zimbabwean banking industry continues to face significant challenges arising from economic volatility, financial fraud, non-performing loans, and compliance-related risks. Traditional ERM methods in Zimbabwean banks are largely reactive, rule-based, and limited in predictive capability, thereby constraining effective risk mitigation. This study addresses this gap by assessing the impact of integrating AI-driven tools into banking ERM systems to enhance the mitigation of contemporary financial risks in Zimbabwe. The novelty of this study lies in its holistic evaluation of multiple AI technologies—machine learning algorithms, AI-based graphical analytics, robotic process automation, and natural language processing—within a unified ERM framework tailored to the Zimbabwean banking context. Adopting a quantitative explanatory research design, the study employed cluster sampling across selected Zimbabwean banking institutions. The data were analysed using both parametric and non-parametric techniques, including comparative descriptive statistics and Weighted Averaging Partial Least Squares regression using IBM SPSS. The findings indicate that AI integration significantly enhances the efficiency of ERM by reducing financial fraud, lowering non-performing loan frequency, curbing money laundering activities, and minimizing operational costs. The study concludes that AI-driven ERM systems offer a sustainable pathway for strengthening risk resilience in the Zimbabwean banking industry.

**Keywords:** Artificial Intelligence (AI), Enterprise Risk Management (ERM), Financial Fraud Detection, Machine Learning Algorithms, Non-Performing Loans (NPLs), Zimbabwean Banking Industry.

## 1. Introduction
Banking world is rapidly changing due to technological innovation, the change of regulations and the exposure to complex financial risks. ERM has long been used as a comprehensive model of risk identification, evaluation, and management of risk factors that compromise the stability and sustainability of banking institutions. The rise of modern financial risks, however, namely cyber fraud, money laundering, non-performing loans, operational inefficiencies and regulatory compliance breaches, has made many traditional ERM systems more than ineffective (Maguraushe and Matanda 2024). The threats are further exacerbated

by the digital banking, cross-country activity and advanced cyber threats, which require the implementation of highly developed technology-based risk management methods. An essential part of financial technology (FinTech), AI has become a revolution in the banking ERM of the present day (Dambudzo 2025). AI has been increasingly incorporated into ERM models in the early 2010s to supplement traditional risk management strategies by automating and predicting, as well as making decisions in real time. AI allows banks to gather, process and analyse abundant quantities of structured and unstructured information, thus increasing the risk identification, compliance supervision and strategic decision-making (Chingwaro et al. 2024). Banks can identify anomalies, predict possible losses, and reduce the risks in a more proactive way than with rule-based systems by deploying machine learning algorithms, graphical analytics, robotic process automation (RPA), and natural language processing (NLP) (Mwangi 2024).


Fig.1. AI Use in the Banking Industry

The Banking Industry use of AI is shown in Fig. 1. The application of AI-based ERM systems has proven to be very effective in reducing financial risks in the commercial, investment, savings banks, and credit unions in the global scene (J. Semwayo 2024). The use of AI-enabled models has enabled the detection of fraud, the monitoring of credit risks, the minimization of operational expenses, and the adherence to regulations. Modern machine learning methods like neural networks and deep learning allow banks to identify more intricate patterns in noisy data and, thus, in advanced cases, detect advanced fraud schemes and illegal financial transactions (Sagonda 2025). Also, graphical analytics that are based on AI can present visual data about the transactional networks and help detect the presence of money laundering and the presence of abnormal funds transfer. The use of NLP-powered systems and Chabot's also help to contribute to the efficiency of the operation and enable the communication of stakeholders, communication with customers in more than one language, and automatic reporting on compliance. The success of AI-based ERM systems is clearly seen both in developed and emerging economies. AI has been successfully implemented in countries like the United Kingdom, the United States, Japan, and Germany to decrease the level of fraud, increase capital adequacy, and improve the management of liquidity as well as resilience to financial crisis (J. K. Semwayo 2024). In the same vein, African economies like Nigeria and Egypt have also used AI in ERM, to minimize NPLs and enhance anti-money laundering systems. These international and continental experiences reveal the ability of AI in changing ERM into a reactive and rule-based system into an adaptive, proactive, and predictive system of risk management (Akinadewo et al., n.d.).

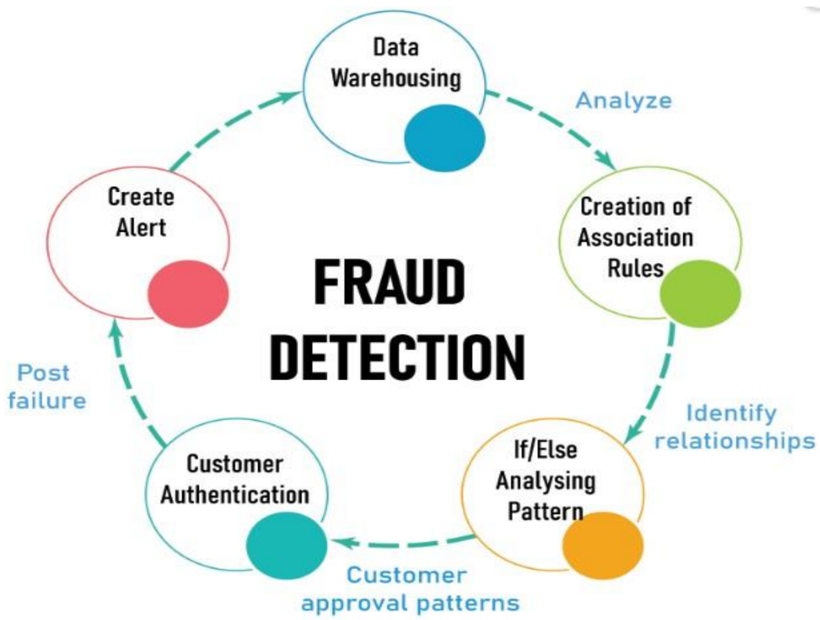



Fig. 2. AI Based Fraud Detection and Prevention

Fraud Detection and Prevention based on AI was given in Fig. 2. Although all these global developments have happened, the use and influence of AI in banking ERM in the Zimbabwean banking sector are still insufficiently explored and utilized. Banking in Zimbabwe has been exposed to a very volatile economic landscape and in the past it has been susceptible to financial fraud, cybercrime, inefficiencies in operations as well as loss of depositor trust (Masunda and Barot 2025). Despite the efforts of the reserve bank of Zimbabwe to promote the use of state of the art technologies to improve the risk management and compliance strategies, banks have been lagging in the uptake of AI in their ERM systems (Mazikana 2023). The research available suggests that this unwillingness is caused by resource limitations, technical skills deficit, regulatory ambiguity, and ethical issues related to the use of AI. Banking industry in Zimbabwe is still too dependent on the old-fashioned ERM systems that are mostly responsive, decentralized, and inadequate to respond to the fast changing digital and financial threats. Continuous cyber-attacks, information breaches, money laundering, and increased costs of operation have undermined trust in depositors and jeopardised business sustainability. These risks have only escalated with the digital transactions becoming the new way of doing business, and this has challenged the traditional ERM systems in terms of protecting sensitive financial information and system integrity. It is against this background that AI is a good answer to enhancing banking ERM in Zimbabwe. Incorporating machine learning, graphical analysis, robots process automation, and natural language processing into ERM systems enable banks to detect fraud, minimize non-performing liabilities, curtail illegal financial operations, and streamline the efficiency of operations. This paper thus aims at evaluating the potential of applying Artificial Intelligence in banking ERM in the context of effective mitigation of modern banking risks in the Zimbabwe banking sector. Through empirical investigation on the role of AI based tools in risk management, the study will inform policy formulation, managerial decision making and creation of sustainable, resilient and technology based ERM systems in banks in Zimbabwe.

### 1.1 Problem Statement

The banking sector in Zimbabwe is still operating on the threat of cybersecurity and financial risks because of the growing prevalence of online transactions. Even though the traditional ERM models and initiatives led by FinTech, the banks have witnessed repeated cases of financial fraud, data breach, money laundering, and operational inefficiencies, which damage the reputation of the banks, drive away customers, and reduce depositor trust. Currently used ERM mechanisms are mostly reactive, disjointed, and ill-adapted to address advanced cyber-attacks and new financial risks posed by new digital fraud methods and international cybercrime cartels. The increasing level of international cyber financial losses intensifies the depositor anxiety and reveals the weaknesses of the traditional risk reduction strategies in Zimbabwean banks. Although AI has come as an innovative solution in enhancing ERM around the world with regard to machine learning, graphical analytics, robotic process automation, and natural language processing, its application in Zimbabwean banking scenario is insufficiently investigated. As a result, the empirical evaluation of the effects of AI implementation in the banking ERM systems on the effective reduction of the modern financial risks in the Zimbabwe banking sector is also in high demand.

### 1.2 Research Objectives

1. To determine the effect of machine learning algorithms on financial fraud reduction in the Zimbabwean banking industry.
2. To analyse the effect of AI-based graphical analytics on NPL frequency in the Zimbabwean banking industry.
3. To analyse the effect of RPA on money laundering schemes in the Zimbabwean banking industry.
4. To determine the influence of NLP on banking financial operational costs in the Zimbabwean banking industry.

### 1.3 Research Hypothesis

H1: ML algorithms have a significant positive effect on financial fraud reduction in the Zimbabwean banking industry.
H2: AI-based graphical analytics have a significant negative effect on NPL frequency in the Zimbabwean banking industry.
H3: RPA has a significant negative effect on money laundering schemes in the Zimbabwean banking industry.
H4: NLP has a significant negative effect on banking financial operational costs in the Zimbabwean banking industry.

### 1.4 Structure of the Paper

Section 1 presents the background of the research, research motivation, research objectives, and contributions. Section 2 is a review of related literature on AI-driven banking risk management and determines the research gaps. Section 3 outlines the suggested methodology and the model development. Section 4 provides the findings and comments on the most important results. Section 5 is a conclusion of the study and gives the future research directions.

## 2. Literature Review

The literature review briefly presents the empirical evidence synthesized on each and every objective area. This gives purpose, direction and the basis for the study to make more impact.

### 2.1 The Effect of Machine Learning Algorithms on Financial Fraud Reduction

Machine Learning (ML) is a branch of AI that aims at defining supervised, unsupervised learning, and reinforcement learning that allow computers to learn and use data to make decisions (Sultan and Sultan 2024). It has become an effective tool in the reduction of financial frauds within the banks because of its capacity to analyse huge amounts of data at an unprecedented speed and accuracy. It is a standard technology utilized in the determination of bank account fraud detection system. ML algorithms like Random Forest, Support Vector Machines, and Gradient Boosting machines detect and reduce fraud in complex manners that cannot be understood by human analysts and conventional systems of ERM. Banks save the information of the clients on proprietary database on which ML models are built on to ensure that any attempt that may be fraudulent is identified. ML has emerged as a powerful instrument in enhancing the reduction of financial frauds by banks. ML basically performs predictive analytics, whereby algorithms run on past data to anticipate possible financial fraud.

ML models such as logistic regression, decision trees, and neural networks have proved to be more correct and competent in detecting fraudulent behaviour, resulting in improved mitigation of financial fraud (Paleti 2022). There are ML algorithms that can process large volumes of transaction data and identify the patterns that may suggest some kind of fraudulent activity, thus allowing the banks to prevent fraud and avoid losses by taking preemptive actions. They also determine abnormal transactional patterns that are not in line with normal financial systems that enable one to easily identify financial fraud. ML algorithms will automatically identify suspicious transactions and allow the banks to react rapidly to possible fraud attacks.

The analysis of a huge amount of data in real time makes it possible that the ML algorithms can search for anomalies and suspicious designs that indicate fraud. The credit card fraud detection based on analysing transaction patterns, identification of outliers, and the identification of suspicious activities that are outside the banking norms has been successfully achieved through the use of ML algorithms. They also make financial fraud reduction decisions quicker and reliable that provide banks with financial transaction sustainability.
The deep learning branch of ML has improved its abilities to identify complex financial fraud in banks. Deep learning can be used to conduct further and more detailed financial fraud risk analysis by detecting more winding patterns that cannot be found in ERM traditional systems. It produces warnings on detecting deviations automatically, via deep neural networks. This enhances the level of cybersecurity and secures banks against cyberattacks. ML may be developed in the cloud as a part of Federated Learning of bank accounts, and can identify and minimize fraud involving two or more banks without divulging sensitive information (Brown 2024).

The study conducted by (Pallathadka et al. 2023) indicates that ML algorithms are effective in predicting of fraud risks and enhancing the levels of cybersecurity against fraud plans. A study conducted by (Khan et al. 2024) indicates that machine learning algorithms are strong and highly efficient in detecting fraudulent financial transactions with minimal or no human presence. It was also realised that, ML algorithms minimise false positives significantly that improves the accuracy and effectiveness of the created fraud detection systems. An analysis of one of the European banks that were leading to minimize financial fraud by applying ML algorithms indicates that there was an increase in fraud detection by 35% because of applying the ML techniques. The paper (Bani Ahmad 2024) discusses the case study of an application of ML algorithms by a Middle Eastern bank in forensic validation. ML algorithms helped to decrease the number of fraudulent reversals of payments by about 30 percent because the audits were more thorough. A study conducted by Deloitte discovered that the ML algorithm-based fraud detection systems reduced false positives by half and increased detection rates by 30%.

### 2.2 The Impact of AI based Graphical Analytics on NPL Frequency

In credit scoring and risk measurement, visual representation of past data can provide outstanding insights that cannot be easily seen in tabular and textual data. The AI based graph analytics relates the ability of visualization by mapping the credit transactions to a network or graph structure that leads to decision making in the provision of loans. Graphs that are generated by AI reflect nodes that are typically associated with entities such as individual accounts, and edges between such accounts are a reflection of transactions or networks between such accounts (Bello 2023). The graphs can then be refined using AI-based graphical analytics, when it comes to credit risks and NPLs. It also has the benefit of identifying credit and NPL anomalies within a holistic setting of the whole network of transactions as opposed to individual events, thereby improving the accuracy and the fullness of credit risks and NPLs (Farazi 2024). The graphical analytics using AI are not limited to conventional credit scoring mechanisms because it uses diverse data sets, which will give a more comprehensive understanding of the credit worthiness of customers.

Graphical analytics on the basis of AI enhances the credit risk analysis by processing the data about the borrower and identifying factors that are defined by default to make more accurate lending decisions and reduce NPLs. It enables credit scoring to be automated and fast processing of substantial data to help curb credit risks and at the end, lower the rate of NPLs. The AI based graphical analytics are known to enhance speed and accuracy of credit decision making that leads to customers receiving a loan decision within a short period of time after application. The quality of the loan portfolio and the minimization of the credit risks are facilitated by the use of AI based graphical analytics (Edunjobi and Odejide 2024). In support of the same thought, concludes that application of AI on graphical analytics in credit scoring and credit risk assessment has helped banks to be more efficient in their processes, decrease loan default risk, and enhance customer service, which has a direct proportional impact on the financial stability of a bank. After 1 year of application to the banks of Middle East, the use of AI based graphical analytics could reduce by 30 percent the time taken to approve the loan and by 20 percent the default rate. This demonstrates how AI is actually useful in automating credit risk assessments, enhancing their decision making and reducing the total frequency and exposure to NPLs. A case study conducted by HSBC shows that the credit risk is accurately analysed by the use of AI based graphical analytic algorithms which leads to better informed lending decisions and reduced default rates.

### 2.3 The Effect of Robotic Process Automation on Money Laundering Scheme

RPA is computer technology that allows banking employees to organize computer software that fit and connect human systems, and it creates large quantities of replicable tasks using multiple applications. As a result of RPA, bankers with nominal programming skills can easily automate all their daily operations to make them easy to use, faster to deploy, and their output can be one to one plotting of the automated human procedure bots. It enables human oversight in ERM procedures and reduce the losses of money laundering.

The RPA also automates repetitive procedures including updating risk registers and produce reports that strengthen anti-money laundering (AML) systems. This work well to reduce false positive, whereas, increased accuracy in suspicious activity predicting to greater well-organized compliance with regulatory requirements is saved. The RPA has the capability to identify a rapid sequence of funds flowing among perfectly structured accounts to depict the money laundering arrangements or layered transactions that are aimed at disguising the source of funds. It also operates contrary to the high speed transfer of funds which portend to the existence of money laundering. (Javaid and others 2024) understands that there were fund movements to be realised by RPA that were intended to cover illegal activities. RPA enhances the anti-money laundering processes by examining the transactions of customers in real time. It was praised in identifying suspicious behavioural patterns, abnormal volumes or frequency of dealings, and the transfer of money to accounts at high risk countries. According to (Thach et al. 2021) RPA has been used in anti-money laundering and contradicting terrorist financing where automation allowed the anti-money laundering and countering terrorist financing to align itself with the advice of the Financial Action Task Force (FATF). RPA helps to make the actual detection and prevention of unlawful financial transaction (Force 2021).

### 2.4 The Influence of Natural Language Processing on Banking Operational Costs

The NLP can help to achieve the Know Your Customer (KYC) procedures where the artificial intelligence scans text information across a wide variety of sources, and the legitimacy of a customer is verified. The KYC essentially can allow financial institutions to identify the actual identity and goodwill of depositors that prevent operational inefficiency (Haque et al. 2024). NLP is applied to automatize and enhance KYC process by processing the textual data contained in the customer documents, digital communications, social media activity, and other digital traces (Moscato et al. 2021). NLP algorithms are able to value context, emotion, and are also able to identify fraudulent activity. Banks also justify their KYC procedures by using NLP and can achieve a better level of accuracy in verifying the authenticity of their customers (Bussmann et al. 2021). This saves on operation expenses and less human error which translates to greater efficiency and accuracy in financial operations.

NLP is helping the banks to achieve operational efficiencies through automating of timely feedback and also responding to the clients concerns thus lowering the cost of operation. Responding to customer queries enable banks to be more strategic and tactical in terms of operations and it makes the operational costs lower. NLP lead to fast service delivery, which leads to increased customer satisfaction. Erica is the NLP virtual assistant at the Bank of America that provides clients with personalized financial insights and advice that lead to them making smart decisions (Sultan and Sultan 2024). The NLP project enhanced customer retention and enhanced cross -selling by 10 and 15 percent respectively which reduced the cost of operation. How well NLP can be used in assessing credit risks of operational costs of banks in peer- to-peer lending platforms. ML algorithms such as Naive Bayes and Support Vector Machines were used in analysing textual data of loan applications. The study realised that NLP that used unstructured data on loan applications that resulted in improved lending decision. Over 50 percent of banks that apply NLP algorithms saves 5-10 percent of the operations costs.

## 3. Methodology

The research was conducted using a quantitative explanatory research approach to explore the impact of introducing AI in banking ERM systems to reduce modern financial risks in the

Zimbabwe banking sector. The research was based on the Technology Acceptance Model (TAM) and Institutional Theory and it was aimed at management-level employees working in the risk management, compliance, audit and operations of the selected Zimbabwean banking institutions. Analogous to the sampling technique, a cluster sampling was employed to group the banks into various types and the sample size was calculated by the Krejcie and Morgan (1970) table. Structured and closed ended questionnaires were used to gather primary data in order to understand the levels of adoption of AI and effects on financial fraud, frequency of non-performing loans, money laundering schemes, and operational costs. Comparative descriptive statistics and inferential analysis were adopted to screen, code, and analyse the obtained data. The IBM SPSS Version 31 was used to test hypothesis by weighted averaging partial least squares (WA-PLS) regression, which also made it possible to examine the causal associations between AI technologies and risk mitigation outcomes. The methodology allowed to conduct strong empirical analysis of the effectiveness of AI-driven ERM, as well as to maintain objectiveness, reliability, and applicability to the dynamical environment of the Zimbabwean banking.

### 3.1 Research Design

The research design of the study is a quantitative explanatory research design since it is used to investigate the causal relationships in a systematic manner between the integration of AI technologies and the mitigation of the current financial risks in the banking industry of Zimbabwe. The design is suitable as it allows testing the pre-established hypotheses and measuring the size and strength of the relationships between independent variables (ML algorithms, AI-based graphical analytics, RPA, and NLP) and dependent variables associated with financial risk reduction. Following statistical inference, the explanatory design allows interpreting the numerical data taken on the level of management among the respondents of the selected banking institutions and generalizing the results to the rest of the banking industry. Moreover, the quantitative method proves to justify the use of superior statistical methods, including regression analysis, to identify cause-and-effect relationships as opposed to association. The design is specifically appropriate in the current study since it complies with the theoretical underpinnings of the Technology Acceptance Model and Institutional Theory and presents empirical data on the impacts of AI-driven ERM practices on reducing fraud, prevalence of non- performing loans, and money laundering control, and cost-efficiency in operations of the banks in Zimbabwe.

### 3.2 Theoretical and Conceptual Framework Development

The theoretical framework that supports the study is the TAM and the Institutional Theory, which offers a strong basis of explaining the adoption of AI and its impact on ERM practices in the banking sector of Zimbabwe. The authors use TAM to describe the influence of perceived usefulness and perceived ease of use on the acceptance and use of AI-based ERM tools by management. TAM can be used to explain why risk managers and decision makers would feel more inclined to embrace AI technologies like machine learning, graphical analytics, robotic process automation and natural language processing when such technologies are proven to increase fraud detection, increase the accuracy of risk monitoring, and decrease the complexity of operations. The model thus aids the comprehension of personal and organizational preparedness to merge AI to ERM systems.

The Institutional Theory is a complement to TAM as it describes the more general organizational and environmental forces that impact AI adoption by banks. These pressures are regulatory demands, industry practices, competitive forces, and stakeholders demand, regulatory, depositors, and investors. In Zimbabwe, institutional influences like the advice of the Reserve bank of Zimbabwe, the adherence to global banking practices, and reputation are factors that are critical in determining ERM practices. The Institutional Theory, thereby, explains why banks might consider resorting to AI-driven ERM systems in order to get not only efficiency benefits, but also to gain legitimacy, comply with the regulations, and follow the global best practices.

On these theoretical foundations, the conceptual framework is formed which is shown in Fig. 3, which connects the independent variables, the specific AI tools, which include machine learning algorithms, AI-based graphical analytics, robotic process automation, and natural language processing, to the main risk mitigation outcomes, which include the reduction of financial fraud, the decreased frequency of non-performing loans, controlling the money laundering schemes, and the decrease in the banking operational costs. The framework presumes that successful incorporation and institutional encouragement of AI technologies can boost ERM capacity and, therefore, reinforce the banks in their proactive awareness, evaluation, and well-being of the contemporary risks in financial matters.

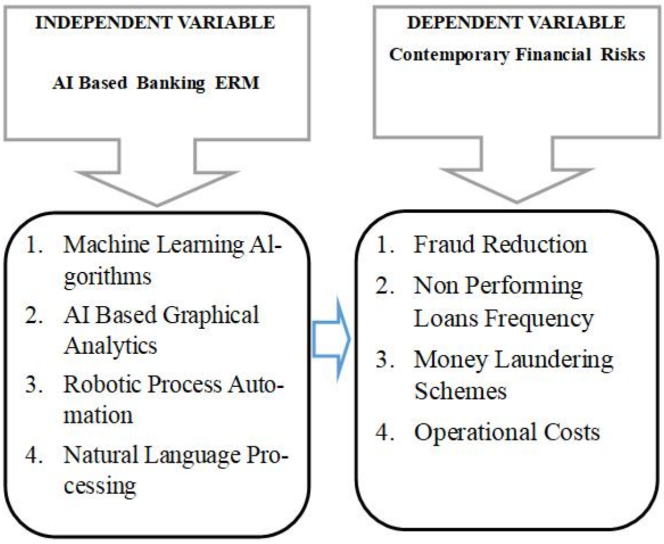



Fig. 3. Conceptual Framework

### 3.3 Population Identification

The population of the study will be characterized as employees at the management level as direct participants in the risk management, compliance, audit, and operational activities at the Zimbabwean banking institutions. The population captured in this group comprises personnel in commercial banks, savings banks, merchant banks, building societies and development or infrastructure banks as these institutions are at the center of financial intermediation and risk governance. The employees on the management level were chosen since they already have the necessary knowledge, the power to make decisions, and the experience in the field of ERM frameworks and the introduction of AI technologies in their organizations. Their roles can help them to deliver informed guidance on AI-based risk mitigation practices, compliance and regulatory matters, and operational issues. The targeting population is critical in that it guarantees the relevancy, credibility, as well as reflectiveness of the collected data with the ERM practices at the institutional level thus increasing the validity and reliability of the study findings in the Zimbabwean banking environment.

### 3.4 Sampling Technique and Sample Size Determination

In the research, a cluster sampling methodology was used to make proper representation of various groups of the banking institutions in Zimbabwe. Initially, the banks were organized into clusters in terms of institutional type i.e. commercial banks, savings banks, merchant banks, building societies and development banks. This was the right tactic based on the heterogenous nature of the banking industry and helped to collect data effectively and to make sure that every type of banks was represented in appropriate proportions. After clustering, the respondents were chosen in the level of management employees at each cluster. The size of the sample was calculated on Krejcie and Morgan (1970) table of sample size determination which offers statistically accurate sample sizes at a specific level of population. This approach also made sure that the sample that was selected was large enough to enable any generalizations regarding the findings, reduce the sampling error, and assist in conducting the quantitative analysis of the relationship between AI-driven ERM practices and modern financial risk mitigation in the banking sector in Zimbabwe to the maximum.

### 3.5 Research Instrument Design

A structured, closed-ended questionnaire was used as the major data collection tool in this study to guarantee consistency, objectivity, and quantitative analysis. The questionnaire has been well constructed and structured to suit the study objectives and research hypotheses with questions being grouped as per the key constructs being studied. The instrument was divided into sections that gauged the use and implementation of particular AI technology- machine learning algorithms, AI-based graphical analytics, robotic process automation, and natural language processing, in banking ERM systems. Other areas included the financial risk mitigation results, such as reduction of fraud, non-performing loans frequency, prevention of money laundering schemes and operational cost efficiency. The measure of responses was based on Likert-scale items, which gave the respondents a chance to show the levels of their agreement or perception on a standardized scale. It made it easier to quantify attitudes as well as practices, increased the reliability, and allowed the use of statistical methods to test the correlation between AI adoption and the current financial risk mitigation in the banking sector of Zimbabwe.

### 3.6 Data Collection

The data collection process entailed administration of structured questionnaires on the respondents who were respondents at management level within the identified banking clusters namely commercial, savings, merchant, building society and development banks. The questionnaires were only given within a well-specified time period so that there was consistency as well as timely retrieval of data. Distribution was done in both physical and electronic modes where necessary with a view of maximizing the response rates. The ethical considerations were perfectly followed during the data collection process which involved the informed consent of respondents, the assurance of voluntary participation and the guarantee of confidentiality and anonymity of all the responses. No personal identifiers were gathered and the data utilized was only to acquire academic research. Such a methodology guaranteed adherence to the ethical standards of research and increased the validity and authenticity of the primary information.

### 3.7 Data Screening and Preparation

Once the data was collected, a systematic screening and preparation of the responses were performed to guarantee the lack of mistakes and the appropriateness of the consequences to be analysed statistically. First, the data were edited to ensure completeness, consistency and clarity of answers after which valid responses were coded and fed into the statistical software. Data cleaning steps were then implemented in recognition and correction of missing data, outliers and inconsistent data that may bias the analysis. The integrity of the dataset was preserved with the help of appropriate methods of dealing with missing data and extreme values. Moreover, reliability testing was done to determine the internal consistency of the measurement scales that were used in the questionsnaire so that the constructs could reliably predict the results of AI adoption and mitigation of financial risks. These steps increased the quality of the data and demonstrated that the further analyses yielded valid and reliable results.

### 3.8 Descriptive Data Analysis

The analysis of descriptive data was performed through comparative descriptive statistics to obtain the primary idea of the data and summarize the main features of the respondents and AI use patterns in the banking sector of Zimbabwe. The average responses about the adoption of and perceived effectiveness of AI-driven ERM tools were measured using the measures of central tendency, in particular, means. Respondent demographics, representation of the institutions and their degree of implementation of AI were described using frequencies and cumulative percentages. Such a methodology allowed making a clear comparison of the levels of AI use and risk management practice across the banks and discover the prevailing trends, as well as gave a good basis to further inferential and hypothesis testing studies.

### 3.9 Inferential Data Analysis

The inferential analysis of data was utilized to determine the interrelation between AI technologies and the modern financial risks mitigation results within the Zimbabwean banking sector. As it was necessary to support the nature of the data as well as to enable the strength of the findings, both parametric and non-parametric statistical tools were implemented. This method made it possible to make meaningful inferences beyond descriptive summaries and it also enabled the testing of causal relationships. Weighted Averaging Partial Least Squares (WA-PLS) regression that is installed in IBM Statistical Package of Social Sciences (SPSS) Version 31 was used to specifically test the research hypotheses. WA-PLS regression was selected as it is suitable because of its capability to use complex models, smaller sample sizes, and test relationships between two or more constructs. The analysed method allowed estimating the strength, direction and significance of the effects of AI-driven ERM tools on financial fraud reduction, the frequency of non-performing loans, and money laundering schemes, as well as operational cost efficiency, and then proved empirical evidence to confirm or deny the stated hypotheses.

## 4. Results and Discussion

The findings suggest that the aspect of Artificial Intelligence implementation in the banking Enterprise Risk Management has a robust and significant impact on addressing the present-day financial risks of the Zimbabwean banking sector. The results of the regression indicate that AI-based tools have a positive influence on reducing financial frauds, and a negative impact on the frequency of non-performing loans, money laundering, as well as the cost of doing business in banks. These results indicate that the more successful implementation and use of ML, AI-driven graphical analytics, RPA, and NLP can increase the predictive, monitoring, and control of ERM systems. In general, the findings indicate that the integration of AI can enhance the effectiveness of risk mitigation, operational performance, as well as more proactive and resilient banking risk management practices.

**AI-ERM**

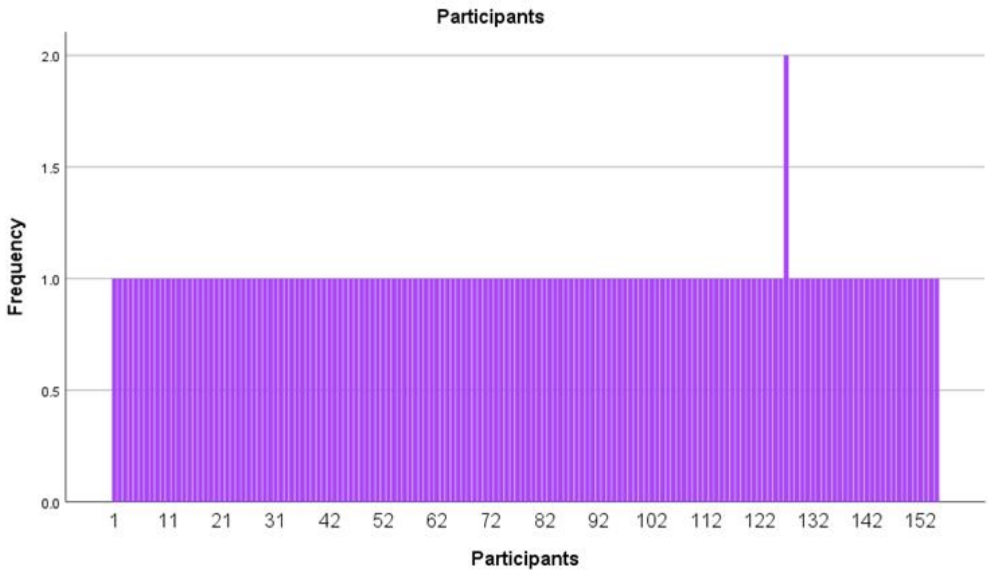


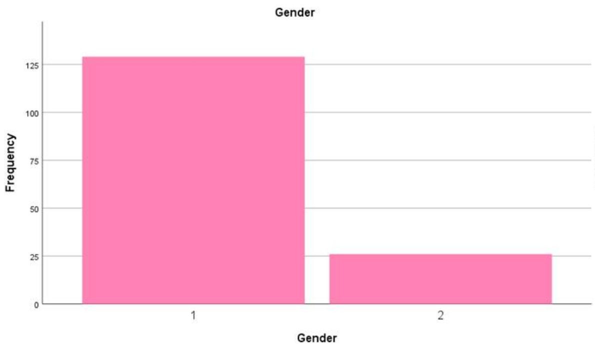

Fig. 4.Frequency Distribution of Study Participants

This fig. 4 depicts the frequency of the participants who are going to be used in the study demonstrating the equal representation of the individual respondents within the sample. The bars represent the different participants and the frequency is mostly concentrated on one implying that the respondent made only one valid answer to the data set. The visualization will ensure the lack of duplication and emphasize the completeness and consistency of the gathered data. All in all, the figure shows that the sample of participants is evenly distributed, which justifies the validity of the further descriptive and inferential analyses made in the study.

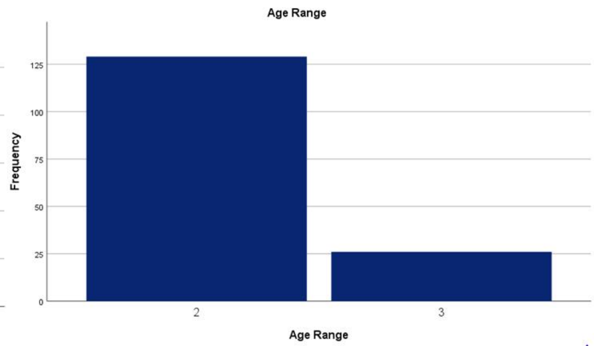
Table 1: Demographic Profile of Study Respondents

| Variable | Category / Value | Frequency (f) | Percent (%) | Valid Percent (%) | Cumulative Percent (%) |
|---|---|---|---|---|---|
| Gender | 1 (Male) | 129 | 83.2 | 83.2 | 83.2 |
| | 2 (Female) | 26 | 16.8 | 16.8 | 100.0 |
| Age Range | 2 | 129 | 83.2 | 83.2 | 83.2 |
| | 3 | 26 | 16.8 | 16.8 | 100.0 |
| Education Level | 2 | 51 | 32.9 | 32.9 | 32.9 |
| | 4 | 104 | 67.1 | 67.1 | 100.0 |
| Experience Level | 1 | 51 | 32.9 | 32.9 | 32.9 |
| | 2 | 52 | 33.5 | 33.5 | 66.5 |
| | 3 | 27 | 17.4 | 17.4 | 83.9 |
| | 4 | 25 | 16.1 | 16.1 | 100 |

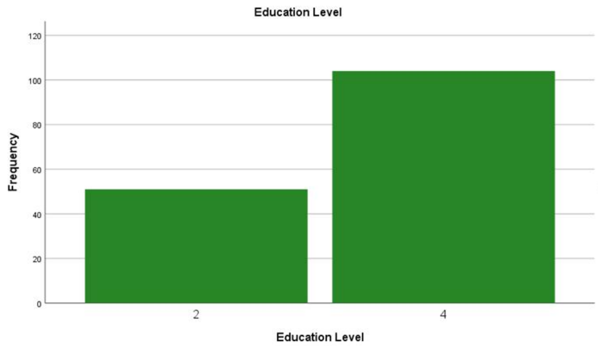
The table 1 gives the demographic features of the study respondents. Most of the participants were male (83.2%), and the females made up 16.8% of the sample. The vast majority of the respondents belonged to Age Range category 2 (83.2%), with fewer of them being in the 3 category (16.8%). On the educational status 67.1 percent of the respondents fell in category 4, which represents high level of academic achievement and 32.9 percent fell in category 2. As to the work experience the highest percentage of respondents were of category 2 (33.5) and category 1 (32.9) then category 3 (17.4) and category 4 (16.1). On the whole, as can be observed in the table, the sample consists of mostly experienced and highly educated professional people, which is suitable to investigate the AI integration in banking ERM.




(a)




(b)




(c)


(d)

Fig. 5.Demographic Distribution of Study Respondents by (a) Gender, (b) Age Range, (c) Education Level, and (d) Experience Level

The fig. 5 display the demographic data of the respondents in four major characteristics. There is a gender disparity with male respondents dominating over the female respondents. The age range distribution shows that the distributions of the majority of the participants can be considered as one dominating age category, which points to the age profile being relatively homogenous. The results of the education level indicate that most of the respondents have higher education levels, which represent the sample which is well-educated and has a high level, which can be considered to test an advanced technology like AI in banking ERM. Lastly, the distribution of experience level reveals that the respondents are evenly distributed in the various categories of experience with the greater proportion being on the lower to mid-level experience. On the whole, the numbers reveal that the sample used in the study is sufficiently diversified but professionally skilled enough to offer valuable information on AI-controlled risk management activities in the banking industry.

Table 2: Descriptive Statistics and Reliability Analysis of AI Constructs

| AI Construct | Item | Mean | Std. Deviation | N | Cronbach's Alpha |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| ML | Random Forest is useful in our ERM to identify fraudulent activities | 3.70 | 1.276 | 155 | |
| | Vector Machines play important roles in ERM since they determine identity fraud | 4.11 | 1.160 | 155 | |
| | Gradient Boosting Machines execute excellent roles in ERM systems specifically prediction of cyber-attacks | 2.95 | 1.186 | 155 | |
| | Deep Learning is effective on complex ERM operations to swiftly communicate suspicious transactions | 3.56 | 1.123 | 155 | 0.971 |
| AI Graphical Analytics | Visual modalities are used to easily execute credit scoring | 3.76 | 1.094 | 155 | |
| | Mapping techniques make all processes transparent which makes credit risk assessment effective | 4.09 | 1.286 | 155 | |
| | Client dynamic datasets can be integrated to realise accurate loan defaults | 3.54 | 1.539 | 155 | |
| | Complicated historical data can be computed to easily profile credit worthiness | 3.94 | 0.880 | 155 | 0.949 |
| RPA | Process automation reduces ERM workload which minimise financial losses | 3.55 | 1.033 | 155 | |
| | RPA empowers employees in generating money laundering reports | 3.49 | 1.360 | 155 | |
| | RPA repetitive tasks are efficient in realizing suspicious funds transfer | 3.92 | 1.279 | 155 | |
| | RPA minimises human error in ERM which determine concealed accounts | 3.03 | 1.170 | 155 | 0.955 |
| NLP | Chatbots easily interact with stakeholders which reduce costly errors | 4.03 | 1.200 | 155 | |
| | Drone-bots offer rich reports and documents which have adequate instructions | 3.77 | 1.247 | 155 | |
| | Cloud-based AI chatbots foster compliance which improve customer retention and brand equity | 3.59 | 1.445 | 155 | |
| | Virtual assistants improve interaction which facilitate the Know Your Customer processes | 3.75 | 1.429 | 155 | 0.981 |

The table 2 provides the summary of descriptive statistics and reliability findings of the Artificial Intelligence constructs to be applied in the study, which include Machine Learning, AI Graphical Analytics, Robotic Process Automation, and Natural Language Processing. The average scores of the items show a positive perception of the AI tools to improve banking ERM functions, though most of the items demonstrate moderate to high levels of agreement. ML items demonstrate high levels of reliability with a Cronbach alpha of 0.971 whereas AI Graphical Analytics, RPA, and NLP exhibit high internal consistency with alpha = 0.949, 0.955, and 0.981 respectively. These reliability coefficients are high, which proves that the measure items are consistent and appropriate to measure how AI technologies help to back up contemporary financial risks in the banking sector.

**BRM-AI**

Table 3: Descriptive Statistics of Respondents' Demographic Characteristics

| Variable | Category / Value | Frequency (f) | Percent (%) | Valid Percent (%) | Cumulative Percent (%) | Mean | Std. Deviation |
|---|---|---|---|---|---|---|---|
| GENDER | 2 | 2 | 33.3 | 33.3 | 33.3 | 2.33 | 1.211 |
| | 4 | 1 | 16.7 | 16.7 | 50.0 | | |
| | 5 | 2 | 33.3 | 33.3 | 83.3 | | |
| | Concealed accounts | 1 | 16.7 | 16.7 | 100.0 | | |
| AGE | 1 | 1 | 16.7 | 16.7 | 16.7 | 2.83 | 1.169 |
| | 2 | 1 | 16.7 | 16.7 | 33.3 | | |
| | 4 | 2 | 33.3 | 33.3 | 66.7 | | |
| | 5 | 2 | 33.3 | 33.3 | 100.0 | | |
| EDU | 1 | 2 | 33.3 | 33.3 | 33.3 | 3.00 | 1.265 |
| | 4 | 1 | 16.7 | 16.7 | 50.0 | | |
| | 5 | 3 | 50.0 | 50.0 | 100.0 | | |
| EXP | 1 | 2 | 33.3 | 33.3 | 33.3 | 3.33 | 1.633 |
| | 2 | 1 | 16.7 | 16.7 | 50.0 | | |
| | 4 | 1 | 16.7 | 16.7 | 66.7 | | |
| | 5 | 2 | 33.3 | 33.3 | 100.0 | | |

The table 3 represents the descriptive statistics of demographic characteristics of the respondents depending on the pilot study data. In gender distribution, there is dissimilar representation in the categories and the calculated value of the means is 2.33 and the standard deviation of 1.211 indicating moderate dispersion. The age distribution is balanced considering the percentage distribution, the mean value is 2.83 and the standard deviation is 1.169. The qualification level is rather medium with an average of 3.00 and standard deviation of 1.265 whereas the experience level is relatively higher with an average of 3.33 and standard deviation of 1.633. In general, the table shows that the sample is rather diverse but comparatively balanced, which can be used to analyze the preliminary AI integration in banking ERM.

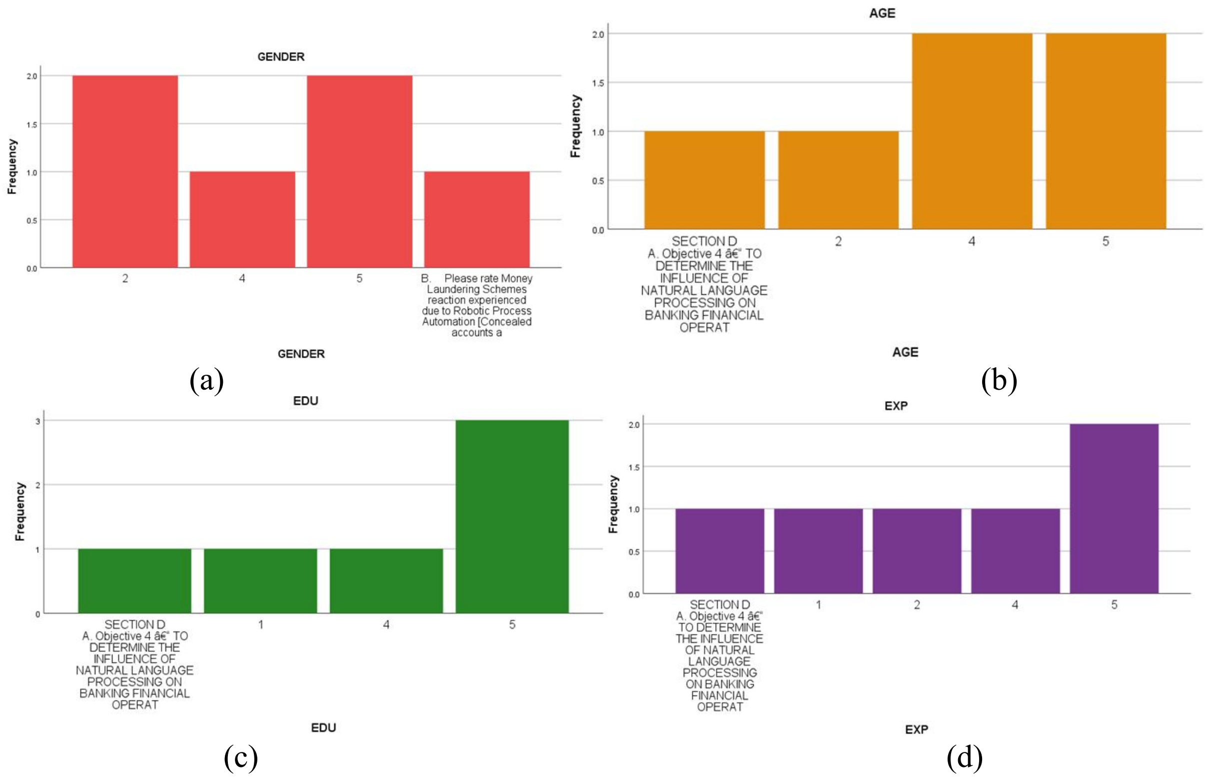



Fig. 6. Pilot Study Demographic Distributions by (a) Gender, (b) Age, (c) Education, and (d) Experience

The fig. 6 demonstrates the demographic profiles of the sampled respondents within the pilot study along four dimensions, namely, (a) gender, (b) age, (c) level of education, and (d) level of experience. The charts describe a balanced but diverse representation in categories, which means that the respondents are diverse. Gender distribution involves input of various categories, whereas age distribution implies the attendance of the initial to advanced career stages. The education level shows that the majority of the respondents have moderate to high academic background, experience levels are spread over various years of professional exposure. Generally, the figure indicates that the pilot study sample is varied enough to help preliminarily evaluate the issue of AI adoption and its effect on enterprise risk management within the banking industry.

Table 4: Summary of Descriptive, Reliability, Correlation, and Regression Results for AI Constructs

| Construct | Indicators | Mean (Range) | Std. Dev. | Cronbach's α | Correlation (r) | $R^2$ | β (Std.) | t-value | Sig. (p) | Outcome Variable |
|---|---|---|---|---|---|---|---|---|---|---|
| ML | ML-FFR1–ML-FFR4 | 2.67 (1–6) | 1.47 | 0.124 | 0.743 | 0.552 | 0.743 | 2.219 | 0.091 | Financial Fraud Reduction (FFR) |
| AI Graphi | AI-NPL1– | 2.04 (1–4) | 1.08 | 0.909 | 0.818* | 0.668 | 0.818 | 2.840 | 0.047 | NPL Frequen |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| cal Analytics | AI-NPL4 | | | | | | | | | cy |
| RPA | RPA-ML1–RPA-ML4 | 2.46 (1–5) | 1.04 | 0.915 | 0.961** | 0.924 | 0.961 | 6.967 | 0.002 | Money Laundering Schemes |
| NLP | NLP-COST1–NLP-COST4 | 2.54 (1–5) | 1.18 | 0.953 | 0.942** | 0.888 | 0.942 | 5.629 | 0.005 | Operational Cost |

The table 4 will give an overall summary of the descriptive statistics, reliability estimates, and inferential findings of the AI constructs to be studied by our research. The mean score of Machine Learning, AI Graphical Analytics, Robotic Process Automation, and Natural Language Processing is different, which demonstrates the moderate level of adoption of the constructs. Internal consistency reliability analysis indicates acceptable to high levels of reliability in most constructs with especially high values of Cronbach, alpha in AI Graphical Analytics, RPA, and NLP. The results of correlation and regression indicate that AI constructs have strong positive relationships with their corresponding risk mitigation outcomes, which are indicated by high correlation coefficients, R S, standardized beta coefficients and statistically significant p-values of most of the relationships. In general, the table shows that AI-based technologies can contribute to financial fraud reduction, decrease non-performing loans rates, cover money laundering attempts, and decrease the operational expenses in the banking industry.

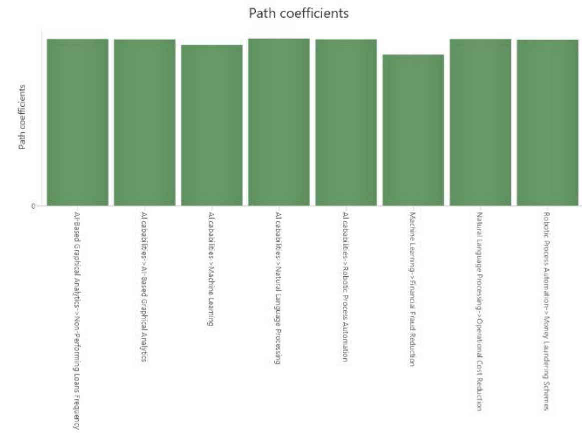
**PLS-SEM**

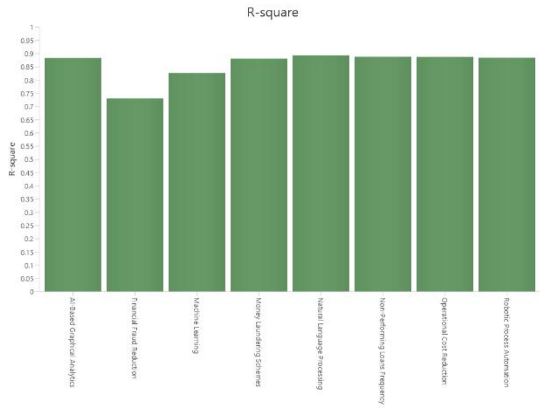
Table 5: PLS-SEM Structural and Measurement Model Results Using SmartPLS 4

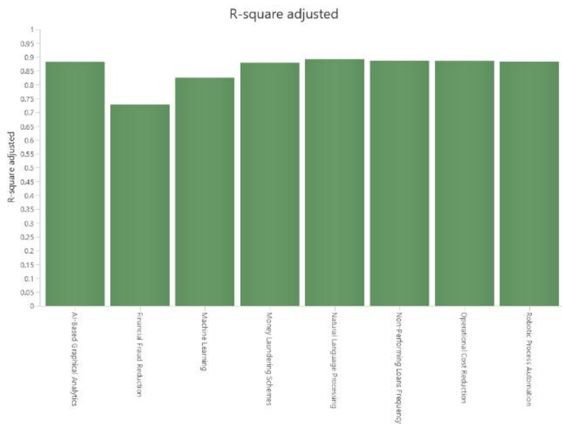
| Component | Key Results Summary |
|---|---|
| Structural Model (Path Coefficients) | Strong direct effects are observed, including AI-Based Graphical Analytics → NPL Frequency (β = 0.942), Machine Learning → Financial Fraud Reduction (β = 0.854), NLP → Operational Cost Reduction (β = 0.942), and RPA → Money Laundering Schemes (β = 0.938). AI capabilities significantly drive all AI dimensions (β = 0.909–0.945). |
| Indirect Effects | AI capabilities show substantial indirect effects on outcomes through mediators, such as via NLP on operational cost reduction (0.890), via AI graphical analytics on NPL frequency (0.885), via RPA on money laundering schemes (0.882), and via ML on fraud reduction (0.776). |
| Total Effects | Total effects confirm AI capabilities as the dominant driver influencing all risk outcomes both directly and indirectly, with overall effects ranging from 0.776 to 0.945 across constructs. |
| Measurement Model – Outer Loadings | All indicators exhibit high outer loadings (0.926–1.000), exceeding recommended thresholds and confirming strong convergent validity across ML, AI graphical analytics, NLP, and RPA constructs. |
| Outer Weights | Indicator contributions are acceptable, with dominant weights for key |

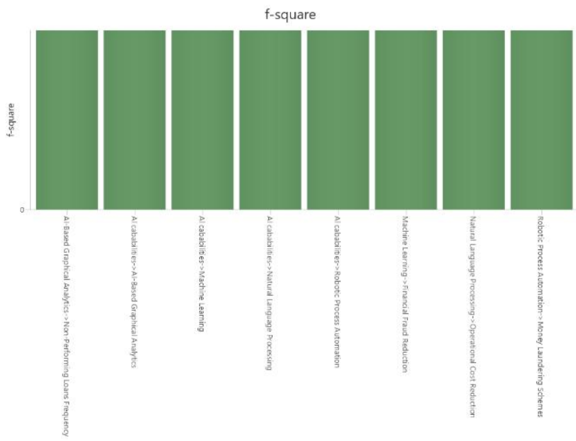
| | |
|---|---|
| | items such as reduce costly errors (0.611), RPA minimises human error (0.566), and gradient boosting machines (0.538), supporting construct relevance. |
| Estimation Details | Results are based on the PLS-SEM algorithm in SmartPLS 4 with standardized estimates, ensuring robustness of both structural and measurement assessments. |

The table 5 shows the integrated PLS-SEM results that were obtained with the aid of SmartPLS 4, which combines structural paths, indirect and total effects, and the evaluation of measurement model. The results show that AI capabilities and core AI technologies are strongly related and statistically significantly, thus, preventing major financial frauds, non-performing loan frequency, money laundering schemes, and operational cost. The mediating position of AI-based graphical analytics, ML, NLP and RPA is indicated by high path coefficients and significant indirect effects. Moreover, the robustness of the outer loadings and accuracies of the weightings ratify the accuracy and soundness of the measurement framework, which proves that the suggested AI-based banking risk management framework is both statistically sound and practically effective.



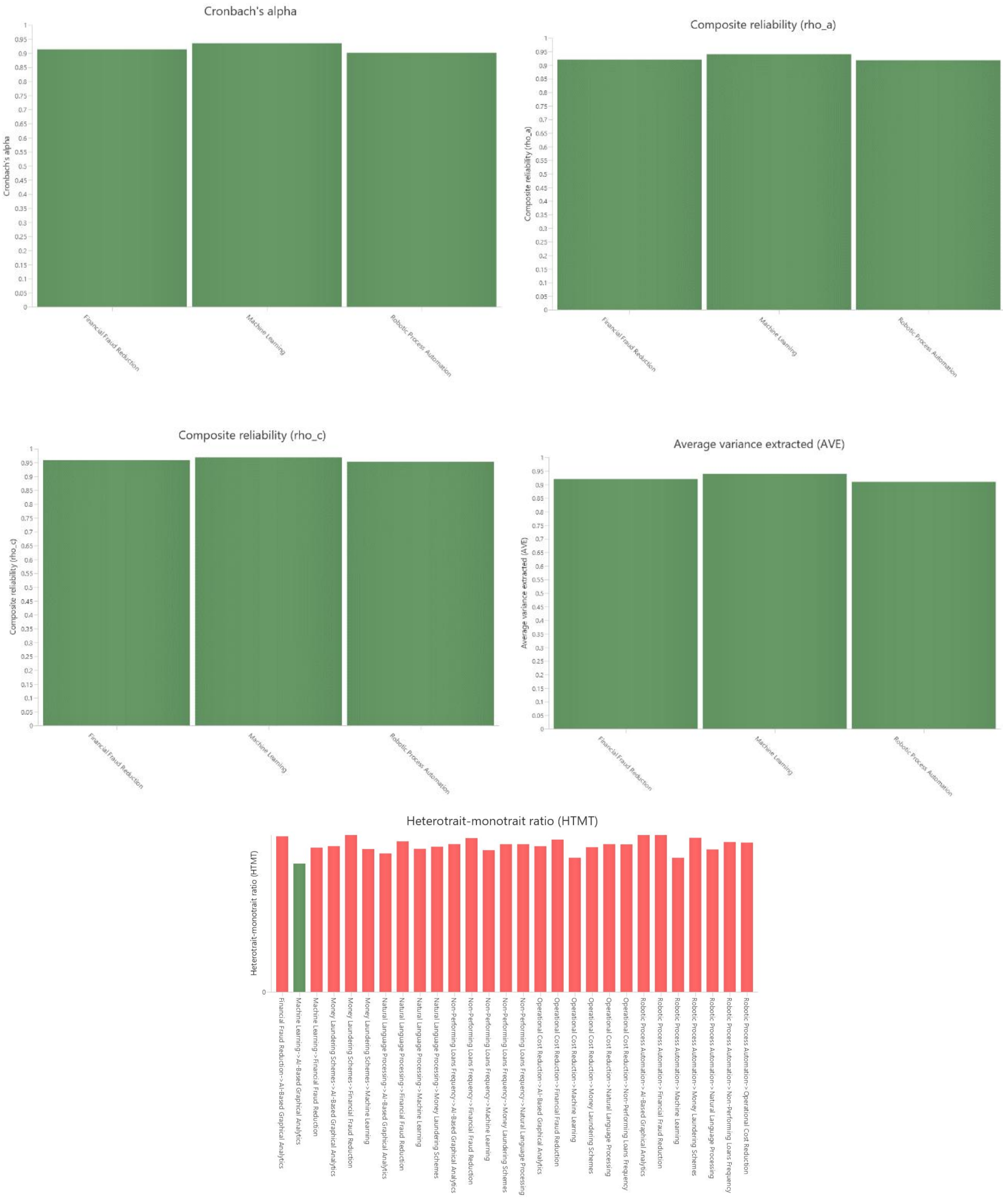



Fig. 7. Comprehensive PLS-SEM Model Evaluation Results

The fig.7 comprises a thorough analysis of the PLS-SEM model in that it summarizes the structural relationships, explanatory power, effect sizes, reliability, validity and discriminant validity. It demonstrates the path coefficients that indicate the strength of the relationships between constructs and the value of R-square and adjusted R-square that indicates that endogenous variables explain a lot. The f-square outcomes prove that the effects of important paths are large in nature, which proves the substantive influence of AI capabilities and other technologies associated with it. The high Cronbach alpha, composite reliability (rhoa and r, and rhoc) and AVE scores are found to be supportive of reliability and convergent validity, which are above the suggested limits. Lastly, the ratios of the HTMT are presented to

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determine the discriminant validity, where most of the pairs of constructs are within the reasonable levels, which confirms that the constructs are conceptually different and overall quality of the measurement and structure model is good.

**Bootstrapping**

Table 6: Structural Path Coefficients and Bootstrapping Results

| Path Relationship | Original Sample (O) | Sample Mean (M) | Std. Deviation (STDEV) | T-Statistic | p-Value | 95% CI (Lower–Upper) | Bias-Corrected 95% CI |
|---|---|---|---|---|---|---|---|
| AI-Based Graphical Analytics → NPL Frequency | 0.942 | 0.942 | 0.006 | 166.395 | 0.000 | 0.930 – 0.953 | 0.930 – 0.952 |
| AI Capabilities → AI-Based Graphical Analytics | 0.940 | 0.940 | 0.007 | 140.694 | 0.000 | 0.926 – 0.952 | 0.924 – 0.951 |
| AI Capabilities → ML | 0.909 | 0.908 | 0.013 | 71.273 | 0.000 | 0.880 – 0.931 | 0.880 – 0.930 |
| AI Capabilities → NLP | 0.945 | 0.945 | 0.008 | 117.956 | 0.000 | 0.929 – 0.961 | 0.928 – 0.959 |
| AI Capabilities → RPA | 0.940 | 0.940 | 0.008 | 113.273 | 0.000 | 0.922 – 0.955 | 0.921 – 0.954 |
| ML → Financial Fraud Reduction | 0.854 | 0.854 | 0.019 | 44.289 | 0.000 | 0.812 – 0.888 | 0.810 – 0.886 |
| NLP → Operational Cost Reduction | 0.942 | 0.942 | 0.009 | 107.001 | 0.000 | 0.924 – 0.958 | 0.923 – 0.958 |
| RPA → Money Laundering Schemes | 0.938 | 0.938 | 0.010 | 97.652 | 0.000 | 0.917 – 0.955 | 0.916 – 0.954 |

The table presents the structural path coefficients, which were found in the course of bootstrapping analysis, original sample estimates, sample means, standard-deviations, t-statistic, p-values, and uncorrected and bias-corrected standard and confidence interval. Each of the hypotheses suggested is positive and statistically significant with the $p = 0.001$, indicating that AI capabilities are closely related to AI components and banking risk mitigation outcomes. The low amount of bias and the thinness of the confidence intervals can attest to the strength and stability of the estimates and demonstrate that AI-based technologies are significant in reducing the non-performing loans, financial fraud, money laundering schemes, and operational expenses in the banking industry.

Table 7: Summary of Structural, Indirect, and Measurement Model Results

| Relationship / Indicator | Effect Type | Original Sample (O) | Sample Mean (M) | Std. Dev. | t-value | p-value | 95% CI (Lower–Upper) |
|---|---|---|---|---|---|---|---|
| AI Capabilities → Financial Fraud Reduction | Total / Indirect | 0.776 | 0.776 | 0.027 | 28.468 | 0.000 | 0.718 – 0.824 |
| AI Capabilities → Money Laundering Schemes | Total / Indirect | 0.882 | 0.881 | 0.015 | 57.807 | 0.000 | 0.849 – 0.909 |
| AI Capabilities → NPL Frequency | Total / Indirect | 0.885 | 0.885 | 0.011 | 78.846 | 0.000 | 0.862 – 0.906 |
| AI Capabilities → Operational Cost Reduction | Total / Indirect | 0.890 | 0.891 | 0.014 | 65.909 | 0.000 | 0.863 – 0.916 |
| AI Capabilities → ML → Fraud Reduction | Specific Indirect | 0.776 | 0.776 | 0.027 | 28.468 | 0.000 | 0.718 – 0.824 |
| AI Capabilities → AI Graphical Analytics → NPL | Specific Indirect | 0.885 | 0.885 | 0.011 | 78.846 | 0.000 | 0.862 – 0.906 |
| AI Capabilities → RPA → Money Laundering | Specific Indirect | 0.882 | 0.881 | 0.015 | 57.807 | 0.000 | 0.849 – 0.909 |
| AI Capabilities → NLP → Cost Reduction | Specific Indirect | 0.890 | 0.891 | 0.014 | 65.909 | 0.000 | 0.863 – 0.916 |
| ML → Financial Fraud Reduction | Direct | 0.854 | 0.854 | 0.019 | 44.289 | 0.000 | 0.812 – 0.888 |
| AI Graphical Analytics → NPL Frequency | Direct | 0.942 | 0.942 | 0.006 | 166.395 | 0.000 | 0.930 – 0.953 |
| RPA → Money Laundering Schemes | Direct | 0.938 | 0.938 | 0.010 | 97.652 | 0.000 | 0.917 – 0.955 |
| NLP → Operational | Direct | 0.942 | 0.942 | 0.009 | 107.001 | 0.000 | 0.924 – 0.958 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Cost Reduction | | | | | | | |
| Measurement Indicators (Outer Loadings) | Loading Range | 0.926 – 1.000 | — | — | > 80.000 | 0.000 | > 0.90 (all) |
| Measurement Indicators (Outer Weights) | Weight Range | 0.199 – 1.000 | — | — | > 4.959 | 0.000 | Stable |

The findings of the analysis of bootstrapping in this table 7 have provided a synthesized account of the structural model, indirect and total effect and findings of the measurement model. The findings suggest the overall and statistically significant total and indirect effect of AI capabilities on financial frauds, money laundering, non-performing loan frequency, and operational costs reduction at $p < 0.001$. The specific indirect paths testify to the fact that machine learning, AI-specific graphical analytics, robotic process automation, and natural language processing fully reflect the impact of AI capabilities on the banking risk outcomes. Further, it appears that everywhere that the effect size is large, and the outer loading and weights are excessively high, which is the demonstration of the high-indicator reliability, construct validity and the overall strength of the enterprise risk management model created by the AI.

Table 8: Overall Model Quality, Reliability, Validity, and Effect Size Assessment

| **Construct / Relationship** | **$R^2$** | **$R^2$ Adj.** | **$f^2$** | **AVE** | **Cronbach's α** | **CR (ρc)** | **CR (ρa)** |
|---|---|---|---|---|---|---|---|
| AI-Based Graphical Analytics | 0.883 | 0.882 | 7.554 | 1.000 | 1.000 | 1.000 | 1.000 |
| ML | 0.826 | 0.825 | 4.746 | 0.939 | 0.935 | 0.969 | 0.940 |
| NLP | 0.893 | 0.892 | 8.347 | 1.000 | 1.000 | 1.000 | 1.000 |
| RPA | 0.884 | 0.883 | 7.595 | 0.910 | 0.901 | 0.953 | 0.918 |
| Financial Fraud Reduction | 0.730 | 0.728 | 2.701 | 0.920 | 0.914 | 0.958 | 0.921 |
| Money Laundering Schemes | 0.880 | 0.879 | 7.334 | 1.000 | 1.000 | 1.000 | 1.000 |
| NPL Frequency | 0.887 | 0.887 | 7.887 | 1.000 | 1.000 | 1.000 | 1.000 |
| Operational Cost Reduction | 0.887 | 0.886 | 7.848 | 1.000 | 1.000 | 1.000 | 1.000 |

The table 8 gives a vivid description of the quality measures of the model, which will be the explanatory power ($R^2$ and adjusted $R^2$), the effect sizes ($f^2$), convergent validity (AVE) and the reliability measures (Cronbachs alpha, composite reliability ρc and ρa). Such results suggest that the data is very explanatory in all the endogenous constructs of 0.73 to 0.89 of R 2 which is high variance explained. The $f^2$ values are highly preferably large than the recommended values which testify to large effects. All major constructs have value of AVE that are more than 0.90 that indicate high convergent validity but reliability measures are never below acceptable level. The power, consistency, and robustness of the proposed AI-based banking risk management model were demonstrated by strong t-values and statistically significant p-values ($p < 0.001$) and small confidence intervals.

Table 9: Discriminant Validity, Latent Correlations, Model Fit, and Estimation Settings

| Category | Measure / Relationship | Key Results (Range / Summary) |
|---|---|---|
| Discriminant Validity (HTMT) | HTMT values across construct pairs | HTMT values ranged from 0.818 to 1.052. Several pairs (e.g., RPA–FFR, RPA–AI Analytics, MLS–FFR) exceeded the strict 0.90 threshold. |
| | HTMT Confidence Intervals (95%) | Lower bounds ranged from 0.770 to 1.035, and upper bounds from 0.855 to 1.072, indicating strong conceptual overlap among related constructs. |
| Latent Variable Correlations | Inter-construct correlations (r) | Correlations ranged from 0.794 to 0.976, all statistically significant ($p = 0.000$), with very high t-values (up to 311.22). |
| Model Fit | SRMR | Saturated model = 0.048, Estimated model = 0.111 |
| | d_ULS | Saturated model = 0.240, Estimated model = 1.304 |
| | d_G | Saturated model = 1.551, Estimated model = 3.270 |
| Estimation Method | Algorithm | PLS-SEM with Bootstrapping |
| | Bootstrapping samples | 5000, two-tailed test, $\alpha = 0.05$ |
| | Weighting scheme | Path weighting, standardized results |
| | Missing data treatment | Mean replacement |
| | Construct measurement modes | MODE_A for most constructs; MODE_B for AI capabilities |

This table 9 provides a summary of the discriminant and latent variables correlation, and model fit measures, along with estimation parameters of proposed PLS-SEM model. According to the results of HTMT, construct correlations tend to be high and construct-to-construct pairs are generally beyond the conservative levels, which demonstrates a high degree of theoretical interdependence in AI-based banking risk management. The degree of correlation between the latent variables is reproducible and statistically significant, which confirms the high interrelationship between AI capabilities, methods of analysis, and risk management outcomes. The model fit indices show that the saturated model is fitted appositely and the estimated model is more complicated. In the analysis, 5000 bootstrap samples were used, the path weighting was calculated on a standardized scale, and the strict estimation options were used, and the results were statistically robust and reliable.

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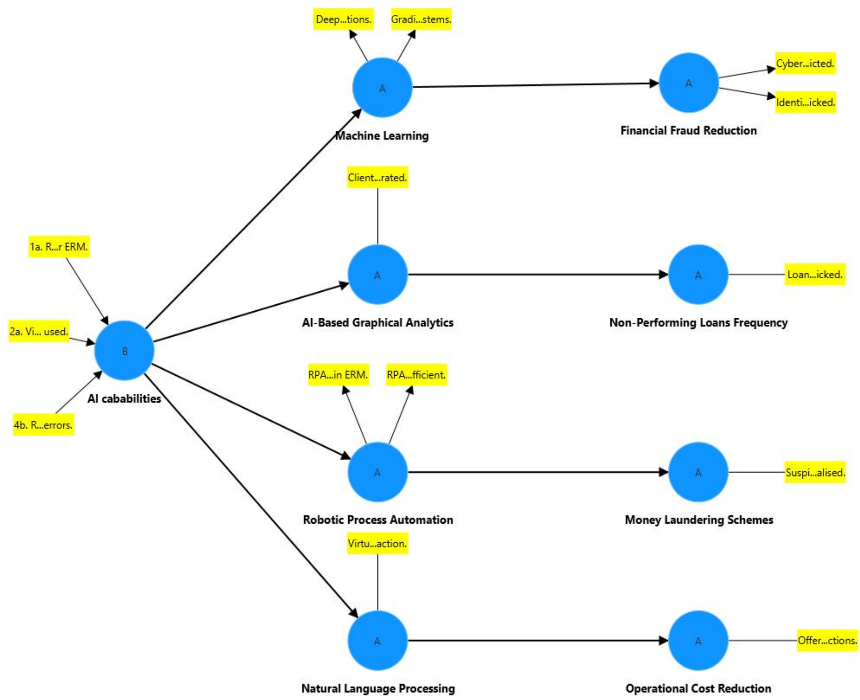


Fig. 8.Proposed AI-Driven PLS-SEM Structural Model for Banking Risk Management

The fig. 8 is used to show the PLS-SEM structural model proposed that shows how the AI capabilities impact the main banking risk management results by using various AI-based technologies. The introduction of AI capabilities, as the key exogenous variable, is the impetus towards implementing Machine Learning, AI-Based Graphical Analytics, Robotic Process Automation, and Natural Language Processing. These technologies, in their turn, have direct influences on such critical risk management results as the reduction of financial fraud, the number of non-performing loans, money laundering schemes, and the reduction of operational cost. The arrows are the postulated causal relationship and the observed indicators at the end of each construct depict the measurement model. In general, the figure has graphically described both quantitative and structural elements of the model that emphasized the mediating nature of certain AI methods to convert organizational AI competencies to better risk control, compliance, and operational efficiency in the banking setting.

## 4. Conclusion and Future Works

This research indicates that AI potentials are vital and essential in enhancing risk management in banking by facilitating sophisticated analytical and automation-based technologies. The PLS-SEM results, which are based on empirical findings, support the idea that AI capabilities have a strong impact on the adoption of the Machine Learning, AI-Based Graphical Analytics, Robotic Process Automation, and Natural Language Processing that have significant and statistically significant impacts on the critical risk management outcomes. Machine Learning can significantly increase the reduction of financial fraud, AI-Based Graphical Analytics can detect non-performing loans more effectively, Robotic Process Automation can eliminate the risk of money laundering by minimizing the error rate and enhancing productivity, and Natural Language Processing will help reduce the costs of the operations by means of intelligent automation and better decision support. The high values of path coefficients, the high explanatory power (R 2 values), and the high levels of reliability and validity are all pointers that show that the proposed model is not only statistically valid but also practical. On the whole, the results validate that AI-based strategic integration can contribute to the enhancement of risk detection, compliance, cost- and decision-making accuracy to a considerable extent and put AI-driven systems in the banking industry as critical elements of the contemporary enterprise risk management systems.

Further studies can build on this study by testing the model hypothesis with longitudinal and real-life operations data of various banking institutions to determine the performance in both the long run and in dynamic risk environments. Other AI methods, like explainable AI, reinforcement learning, and hybrid deep learning models can be applied to enhance transparency, flexibility, and regulatory oversight. More research can also be conducted on the effect of the data quality, ethical factors, and cybersecurity resilience on AI-based risk management systems. The model can be extended to the external environment and regulatory pressure, as well as organizational preparedness, to give more information about AI adoption issues. Lastly, the comparison between the results of various nations or financial sectors would contribute to the verbalization of the findings and contribute to the creation of scalable, reliable, and policy-oriented AI-based risk management programs.

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