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# Internal Audit Data Mining in Fraud Risk Management: Evidence from Nigeria Banking Sector

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ABSTRACT

This study investigates the extent to which internal audit data mining techniques ameliorates fraud in fraud risk management in banks. The main focus of the study is to broadly test the perceptions of fraud auditors, internal auditors and accountants on whether data mining techniques of: audit interrogation, neural network and machine learning in internal auditing ameliorate fraud in fraud risk management in Nigeria banks. A survey research design was applied for this study. Data was obtained through a survey in which questionnaire was administered on a sample of 400 fraud auditors, internal auditors and accountants using Taro Yamane's formulae on a population record of 668 from purposefully selected 15 banks in Nigeria. Three research questions and three hypotheses tested at 0.05 levels of significant guided the study. Likert Scale rating was applied to the research questions and its suitable descriptive statistics were used to analyze them, while ANOVA test statistics was used to test the hypotheses formulated. The major findings of this study indicated that data mining techniques of audit interrogation, neural networks and machine learning ameliorates frauds in fraud risk management in Nigeria banks. The main recommendation of this study is that various corporations in their daily operations should encourage their internal audit function to try data mining techniques in fraud risk management.

Key Words: Data Mining Techniques, Internal Audit, Audit Interrogation, Machine learning, Neural Networks, Fraud Risk Management.

## INTRODUCTION

Internal audit function in fraud risk management is a critical part of the corporate governance within an organization. Corporate governance is an effective tool in fraud risk management. Corporate governance includes those oversight activities undertaken by the board of directors and audit committee to ensure that there is effective fraud risk management and the integrity of the financial reporting process [1]. Three monitoring mechanisms have been identified in the corporate governance participation in fraud risk management literature. These are external auditing, internal auditing, fraud auditors and directorships, [2]; [3], as well as the audit committee [4] [5].

This study is narrowed to the monitoring mechanism of internal audit the form of participation in corporate fraud risk management using data mining techniques.

Risk management is the systematic application of management procedures and practices which provides the necessary information to address risk, [6]. Risk management is viewed as a relatively recent corporate function, [7]. The modern risk management started after 1955 and up-to 1970, the concept covered more on insurance market and through that it developed to complement several other risk management activities, [8]. This made companies to diversify portfolios of physical assets and began to develop other areas of risk insurance to cover many areas of risk in the business.

The necessity for risk management has come up based on the changes on the strategic corporate/business operating environment and the expansion in transaction volumes that have as well affected the methods corporations approach, and the way they handle risk, [9]. Every business increase has a

corresponding increase of uncertainties that drives corporate management to desire a better structured and systematic way to handle risks. It is through risk management that corporations address the increasing demand of the modern business operating environment and the consequent risks by endeavoring to address these risks whenever they are found.

It was the issues of risks that brought about the necessity of the word "fraud" risk management that covers numerous types of fraud caused by environment, technology, humans, organizations and politics.

The word Fraud on the other hand is an activity that takes place in a social setting and has severe consequences for the economy, corporations, and individuals [10]. Fraud is as old as corporations. The South Sea Bubble of 1720 is the best known early episode of fraud. The company formed in England in 1711 to trade with Spanish America, was allowed in 1720 to assume responsibility for Britain's National debt in return for a guaranteed profit. This complicated arrangement ignited a speculative boom with unscrupulous financiers that took advantage of the public excitement about assured profits to form other companies with dubious intentions. Many of the newly formed companies, some of which sought to extract gold from sea water soon failed together with the south sea company leaving thousands of shareholders to lose their investment. It caused financial catastrophe in London, Paris and Amsterdam. Subsequent investigations revealed fraud and corruption among ministers some of whom resigned and some committed suicide [11] [12].

Progressively, the Dictionary of Economics and Commerce confirmed that 200 banks failed in England alone between 1815 and 1850 just within a period of 35 years, one of the reasons attributed to the failure is improper fraud risk management [13].

Fraud risk management failure is the determining character of the global financial crisis [14]. In an effort to reduce fraud risk which culminated to global financial crisis, [15] stated that thirty five (35) official Anti-Fraud and regulatory bodies have been formed and recognized internationally to regulate, supervise and investigate organizations and their activities [16].

The fraud risk management sagas are the same even in Nigeria. These have had sever negative consequences on the country and its global image. Lack of Fraud risk management and related problems have caused instability in the Nigerian economy resulting to a high mortality rate of business organizations and the consequent losses of revenue, huge financial losses to business organizations and their customers, depletion of shareholders funds and capital base as well as loss of confidence in business investment [17].

A total number of one hundred (100) companies were estimated to have failed in Nigeria because of improper fraud risk management in 2010 [18]. The total number of frauds and forgeries case reported in one of the annual report of NDIC gave 10,719 cases of fraud which amounted to N168397.9 billion within a period of ten years i.e 2000-2009. The total depositor's loss in failed Banks amounted to ₦187.23 billion as of 2011. The CBN has also maintained that the dwindling situation is occasioned by weakness in the internal control system of the affected enterprise which is the key area where internal audit should function in fraud risk management, [19]; [20].

In Nigeria alone, several legislations were put in place to reduce and to alleviate and if possible to eradicate the occurrence and incidences of fraud risk in the industry [21]. Most popular and prominent among them are: (Company and Allied Matters Decree No 19. 1990 [22], now CAMA, Declaration of Asset Act 1990, National drug law enforcement Agency Act 1990; Special Tribunal (miscellaneous offences) Act 1990; The Central Bank of Nigeria (CBN) Decrees No 24 of 1995; The Nigerian deposit Insurance Corporation Decrees No 22 of 1998; The Bank and other financial Institution Decree (BOFID) 1999; Economic and Financial Crime Commission Act 2004; (CBN) Prudential guideline for Deposit of Money in Banks in Nigeria; Money Laundry Act and so on.

## Statement of the Problem

The truth is that, whatever the size of the organization, external audit is terribly bad at fraud detection and the scope of their responsibility do not cover fraud risk management. One of the survey by [23], showed that perhaps only about 2 percent of frauds were detected through external auditor [24].

Historically, management believed that external auditors would uncover fraud but the emergence of Sarbanes-Oxley specifically holds management responsible for fraud risk management and internal audit is an extension of management [25].

It is expected that internal audit detects weakness in management operations and provides a basis for correcting deficiencies that have eluded the first line of defense before these deficiencies become uncontrollable or are exposed in the external auditors report [26].

The institute of internal Auditors (11A) provides mandatory guidance for internal auditors in its internal professional practices framework (IPPF) through the International Standard for the practice of Internal Audit function in fraud risk management (Standards) (11A, 2009a). Several standards outline the role of the internal audit function in detecting, preventing, and monitoring fraud risks and addressing those risks in audits and investigation (11A, 2009c). 11A standard 1200, proficiency and due professional care, require that internal auditors have sufficient knowledge to evaluate the risk of fraud in their organization (11A Standard 2060). The Standards require that internal audit function report to the senior management and the board any fraud risks found during their investigations under 11A standard 2120, of fraud Risk Management [27].

There are, few research that were conducted in internal audit function in fraud risk management by Nigerian researchers. Even some of the researchers in these area like [28]; [29], did not inculcate internal audit use of data mining techniques.

However, observations from other literatures outside Nigeria on internal audit role in fraud risk management like [30]; [31]; [32]; [33]; [34]; [35]; [36]; [37]; [38] showed that some of these studies were not focused on internal audit data mining techniques in fraud risk management

Therefore, our observations from some of these literatures have shown that the subject matter is yet unsettle and hence the need for this study.

**Objective of the Study**

The main objective of this study is to determine the extent to which internal audit data mining techniques ameliorates fraud risk management in banks. Other specific objectives are to broadly test the perceptions of fraud auditors, internal auditors and accountants on whether:

1) Data mining audit interrogation techniques in internal auditing ameliorates fraud risk management in Nigeria banks;
2) Data mining neural network techniques in internal auditing ameliorates fraud risk management in Nigeria banks;
3) Data mining machine learning techniques in internal auditing ameliorates fraud risk management in banks.

**Hypotheses of the Study**

**$H_{01}$:** There is no significant relationship in the perception of fraud auditors, internal auditors and accountants on whether data mining audit interrogation techniques ameliorates fraud risk in banks;

**$H_{02}$:** There is no significant relationship in the perception of fraud auditors, internal auditors and accountants on whether data mining neural network techniques ameliorates fraud risk in banks;

**$H_3$:** There is no significant relationship in the perception of fraud auditors, internal auditors and accountants on whether data mining machine learning techniques ameliorates fraud risk in banks.

REVIEW OF RELATED LITERATURE

**Concept of Fraud Risk Management**

Fraud risk management is the proper development and implementation of an intelligence enabled fraud risk management framework and a conscious risk culture within an organization that can assist more effective decision making at all levels of any business management especially in the area of fraud risk management. There is no doubt that proper fraud risk management is seen as one of the guiding principles associated with modern business management, [39].

Further, Fraud risk management is the systematic application of management policies, procedures and practices to the tasks of establishing the context, and to those of identifying, evaluating and treating risks [40].

[41], agreed that fraud risk management is a process that seeks to eliminate, reduce and control risks, enhance benefits and avoid detriments from speculative exposures. The

main objective of fraud risk management is to maximize the potential of success and minimize the probability of future losses. Thus the risk that becomes problematic can negatively affect cost, time, quality, quantity and whole system performance.

Fraud risk management is an area of paramount importance to any organization. The fact being that every entity is exposed to risks but an effective fraud risk management is necessary for the improvement of any business performance [42]. It was stated by Committee of Sponsoring Organization of Tradeway Commission [43], that fraud risk management is a process, affected by an entity's board of directors, management and other personnel, applied in strategy setting and across the enterprise, designed to identify potential events that may affect the entity and manage risk to be within its risk appetite, to provide reasonable assurance regarding the achievement of entity objectives.

Fraud risk management is the process to manage the potential risks by identifying, analyzing and addressing them. The process can help also to reduce the negative impact and the emerging opportunities. This outcome help to mitigate the likely hood of risk occurring and the negative impact when it occurs.

In other words fraud risk management involves identifying, measuring, monitoring and controlling risks. It is to establish that those involved should have a clear view of fraud risk management and fulfill the business operational strategy and objectives.

**Concept of Internal Audit in data mining**

The internal auditor, being a company man, has a more vital interest in all types of company operations and its quite mutually more deeply interested in helping to make those operations as profitable as possible [44].

Internal auditing is a control which functions by examining and evaluating the adequacy and effectiveness of other controls. The objective of the internal auditing is to assist members of the organization in the effective discharge of their responsibilities. To this end, internal audit furnishes management with analysis, appraisal, recommendations, counsel and information concerning the activities reviewed. Therefore, the audit objective includes promoting effective control at reasonable cost. Nowadays, the computer environment in which firms functions, along with the controls within the environment, brings about complex systems, real time variances, and worldwide applications. This development is part of a major challenge for internal auditors to detect fraud in the electronic system, [45]. This challenge provides auditors the opportunities for the use of powerful interactive audit software and advance auditing techniques in the face of rapid complex business environment. It was noted by [46] that with the ever rising system complex these days, especially computer based accounting information systems including enterprise resource planning systems, and the vast amount of transaction, it is impracticable for internal auditors to conduct the overall audit manually. Data mining is not widely used for fraud risk management in all areas of banking sector. But, its important in the banking sector is that bank executives through that need to know whether the customer they are dealing with are reliable or not. Also when it comes to credit cards, accepting offer from new customers with credit cards, extending existing customer lines of credit, and approving loans can be risky decisions for banks if they do not know anything about their customers. Thus, data mining is important in the reducing of the risk of banks that issue credit cards by determining those customers who are likely to default on their account [47].

**Concept of Data Mining Techniques in Fraud Risk Management**

[48], defined data mining as the process of discovering interesting knowledge such as associations, patterns, changes, anomalies and significant structure from large amounts of data stored in a databases, data warehouse or other information repository. Data mining techniques in fraud risk management is a process which finds useful patterns from large amount of data in account. It is a logical way that is applied to search through huge data in order to extract useful information for decision purposes, [49]. Data mining is a set of computer- assisted techniques designed to automatically mine large volumes of integrated data, and also for new hidden or unexpected information, or pattern. It also supports customer relationship and fraud detection, [50]. Data mining is the process of extracting knowledge hidden in large volumes

of data. Data mining tools search for trends or anomalies without knowledge of the meaning of the data but the anomalies may not necessarily be an indication of fraud but can be the result of a range of different factors, [51]. Internal auditors can use data mining tools and techniques to examine the entire population of transaction in order to select samples for test controls and identify fraud. In other words internal auditors need to have access to the data and software tools as well as the techniques and knowledge necessary to make intelligent use of vast amount of financial and non-financial information in their aim of detecting and stopping fraud, [52]. There are things to note when there are anomalies in data. [53], observed that in many case they are as a result of faulty data entry, whereby the user has typed in one value instead of another. Sometimes errors can be as a result of software or hardware malfunctions, resulting in corrupt data but sometimes, it could be fraud.

Fraud audit is defined as a set of audit procedure performed over a business transaction population in order to increase the likelihood of identifying fraud. Thus using data mining in fraud audit or fraud data mining is the process of obtaining and analyzing transactional data to identify anomalies or patterns indicative of a specific fraud scheme, [54].

Objective of use of data mining in fraud risk management is to find a discrete number of transactions that can be examined using fraud audit procedures. Fraud auditing final purpose is to identify one fraudulent transaction and afterwards have the audit plan dictate how the sample containing the transaction will be extended. There are various data mining tools and techniques that can be applied to identify transactions consisted with a specific fraud scheme, [55].

**Concept of Data Mining Audit Interrogation Techniques in Fraud Risk Management**

Audit interrogation is a data mining tool that can be used to highlight, data anomalies and pattern recognition, [56]. Audit interrogation is a computer assisted audit techniques that has a programmed procedures known as edits or validation controls. It performs test on transaction data to ensure they are errors free before processing. There are three types of audit interrogation input controls in data mining. Field interrogation which involves program procedures to examine the characteristics of the data in the field such as common data input that have the following: transcription truncation or substitution and transposition error. These types of problems are controlled with check digits. Missing data checks are used to check for blank spaces. Numeric alphabet checks identity data in the wrong form. Limit check test for amount that exceed the authorized limits. Range checks for upper and lower limits of acceptable values, and validity checks compares actual against acceptable values. Another input controls record interrogation procedure valid is recorded by examining the interrelationship of its values, while another file interrogation is to ensure that correct file is being processed. There are run to run processing controls that monitor a batch as it moves from one run to another and ensures that all records are processed, no record is processed more than once and finally output process and to output controls.

**Concept of Data Mining Neural Network Techniques in Fraud Risk Management**

Neural network is a set of connected input or output units and each connection has weight present with it. Neural Networks works as a set of connected input and output units and each connection has weight present within it. At this time, during the learning phase, network learns by adjusting weight in order to be able to predict the correct class label of the input tupelos. There is this remarkable ability that neural networks has to drive meaning from a complicated or imprecise data and can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques, [57]. A neural network is a series of algorithms that endeavors to recognize underline relationships in a set of data through a process that mimics the way human brains operates. [58], confirmed that neural network is a structure similar to the neurons in a human brain. It is an information processing system that mimics biological nerves and that can receive and combine multiple inputs to make predictions. Neural networks can adapt to changing input; so the operations generates the best possible result without needing to be redesign for the output criteria. There is artificial neural networking that serves as a type of artificial intelligence machine where the mathematical method is used to make the

computer to have ability to deduce the outcome through the computer's rapid calculation ability, [59]. There are several types of neural network. But the common one is feed-forward perception. This network consists of three layer nodes. These are the input layer, the hidden layer and the output layer. Within this data passes forward through the network. During this process, a transaction presented to the input will result in a score at the output, which can be used to tag the corresponding transaction as suspicious fraudulent or legitimate. When a neural network produces a score it is very difficult to understand why it produces the result it did [60]. Neural network can be very good at dealing with highly skewed data like card fraud data. It was stated by [61], that the purposes of any fraud detection system is to produce a score that reflects the probability of fraud given the evidence. According to [62] neural networks are well suited for continuous valued input and output.

**Concept of Data Mining Machine Learning Techniques in Fraud Risk Management**

Machine learning is a data analytics technique that teaches computer to do what comes naturally to humans and animals and also learn from experience. Machine learning algorithms use computational methods to learn information directly from data without relying on predetermined equation as a model. One of example of machine learning is medical diagnosis, image processing, prediction, classification, learning association, regression, decision tree, logistic regression etc. It is an intelligent system built on machine learning algorithms to have the capability to learn from past experience or historical data. Machine learning works by finding a function, or relationship, from input x to output y. The most accepted definition of machine learning is the ability for computers to learn and act without being explicitly programmed. According to [63], machine learning techniques is the scientific study of algorithms and statistical models that computer systems use to perform a specific task without using explicit instructions, relying on patterns and inference instead. It is seen as subset of artificial intelligence. Machine learning algorithms builds a mathematical model based on sample data, known as training data in order to make predictions or decisions without being explicitly programmed to perform the task, [64]. Machine learning anomaly detection in data mining, detect anomaly known as outlier detection. It is the identification of rare items, events or observations which raise suspicions by differing significantly from the majority of data, [65]. A typical anomaly items represents an issue such as bank fraud, structural defect, medical problems or error in a text. Anomalies are referred to as outliers, novelties, noise, deviations and exceptions, [66].

**Empirical Review**

A review on internal auditor's role in the detection and prevention of fraud on a post SAS No 82 analysis was conducted by [67]. They employed non-parametric ANOVA and Kruskal Wallis to evaluate the effect and the results provided evident that internal auditors are moderately knowledgeable about 11A and AICPA standards for fraud. However, they are, at best, neutral with regard to acknowledging fraud detection and prevention as primary roles for themselves in the organization.

Internal audit function in fraud risk [68] surveyed (ACFE) regarding actual incidence of fraud with which they were familiar. They collected a total of 2,573 case of known fraud and found that organizations with internal audit functions were significantly more effective in detecting fraud than those without internal audit function.

The use of risk management principles in planning an internal audit engagement was conducted by [3]. The conclusion was that the term risk-based internal auditing is fairly new, in that the terminology is used to describe the audit of the risk management strategy as well as the development of the internal audit function's annual plan, the chief audit executives are unsure how frequently the risk register is being updated with emergent risk which could involve internal audit function's activities and that internal auditors are still unclear about the differences between risk management and risk –based internal auditing as regards terminologies, methodologies and rule. Another research by [7] examined the effects of internal audit function structure on perceived financial statement fraud prevention in USA. The study found that users perceived greater financial statement fraud protection when internal audit function reports to the audit committee than when it reports to senior management. They also concluded that there is lack of evidence

supporting enhanced user confidence resulting from outsourcing the internal audit function in fraud risk management.

The following [9] investigated alternative internal audit structure and perceived effectiveness of internal audit function in fraud prevention. The methodology used simple questionnaires sent to fifteen banks in Jordan. A simple one-t-test, using mean, standard deviation, frequency and percentages were used to analyzed and test the hypotheses. The study found that respondents perceived internal audit units effect in fraud prevention. They also found that senior managers consider that in-house internal audit units are more effective in preventing fraud than outsourcing internal auditors.

In Nigeria, [12] studied empirical evidence of antecedents of internal audit function effectiveness in fraud risk management from Nigerian perspective. The data were obtained by questionnaires administered to internal auditors, audit committee and chairman of local governments using descriptive statistics and factor analysis. The result reveals the significant effect of the entire antecedents on the internal audit effectiveness in local government, which implies that for local government or other public sector to attain the effectiveness of their internal audit, such antecedents need to be given due consideration.

The study made by [16], was aimed to investigate where the responsibility for computer fraud prevention and detection reside within an organization and to examine the role of internal audit department in prevention and detection of fraud in fraud risk management. They concluded that information services function is most commonly held responsible for computer fraud prevention and detection. Thus organizations do not consider use of computer to be a high priority matter in fraud risk management.

While, [20] conducted a survey of data-mining techniques used in fraud detection and prevention and concludes that effective use of data mining techniques detect and prevent fraudulent activities and categorized four computer frauds where data mining tool can be employed: Management fraud; customer fraud; network fraud; and computer based fraud.

Then, [21] researched on prevention and detection of financial statement fraud: a data mining approach and concludes that management fraud is a deliberate and wrongful act carried out of public companies using material misleading financial statement that cause damage to investors, creditors and the economic market.

Also [24] conducted a research on data mining techniques for the detection of fraudulent financial statement. The study used a sample of 76 Greek manufacturing companies in order to inquire and draw an analogy between the performances of the various factors that are associated with the financial statements fraud. Neural networks Decision tree and Bayesian belief networks were the data mining techniques employed and the input data was the published financial statement contained falsified indicators; Bayesian belief networks performance was found out to be the best with 90.3% correct classification of the cross validation procedure, neural network had 80% success rate and decision tree model 73.6% success rate.

In another development, [27] had a further study in which they used generic data mining framework for fraud prevention along with fraud risk-reduction for the financial statement fraud. The study divided data mining tasks into two groups of predictive tasks and descriptive tasks. Predictive data mining, along with machine learning helped in better fraud prevention, while performance evaluation of various data mining techniques using metrics such as error rate, information gain and Gini index for decision trees were employed.

[33] conducted a research to assist auditors in identifying any possible fraud records and evaluating datasets by developing a fraud detection mechanism based on Zipf's law through simulation test and a case study. They used four key performance indicators, Audit Hit Rate, Bayers Audit Hit Rate, confusion matrix and the misclassification cost matrix. Finding showed that ZipF's mechanism could be identified by ZipF's Analysis and this is more effective than a 100% sampling.

[35], investigated the efficiency of the machine learning techniques in identifying firms that publish fraudulent financial statements. This they did by implementing a hybrid decision support system through

combining algorithms that uses a stacking variant methodology. The data came from 164 non-financial Greek manufacturing firms listed, 41 of which had issued fraudulent financial statement. The study variables were collected from the financial statements of the firms. Results from this experiment indicated that the falsification indicators and a small list of ratios largely determined the classification result in published financial statements.

[38], investigated the similarities and differences between two models of fraudulent financial reporting detection and the business failure prediction that helped in identifying firms that procured losses. It aimed to find the effectiveness of the approach and the explanatory variables using data mining algorithms such as regression logistic, neural network, and classification trees to construct detection/prediction models using data from Taiwan Economic Journal data bank and Taiwan stock exchange corporation website. The financial variables were from 2003 to 2004. The findings show that the variables were significant in detecting fraudulent financial reporting and predicating business failures, logistic regression was considered the best of the three data mining algorithms.

[39], researched on learning from skewed class multi-relation database. They focused the use of new strategy to address the imbalance in multi-relational data wherein one class in the target relation is higher than the others. The imbalances assist in diagnosing a disease or detecting a fraud case such as a credit-card fraud. Six benchmark data-sets were used for the experiment. The results indicated that imbalance in multi-relational method was better than other prevailing data mining algorithms in comparison, especially when there was a high class imbalance with regard to receiver operating characteristics curve and area under the curve.

[45] employed the use of neural network technology and the rule-based components to develop credit-card fraud detection system using four clusters of low, high, risk and high risk using the two staged models that is frequently used in fraud detection. They developed a model identifying the behavior of a cardholder and evaluating the transaction characteristic to detect fraudulent transactions using the self-organizing map algorithm. Other several models were generated by applying the artificial neural network trained with the unsupervised learning methods. This experiment further indicated that generation was done to secure a correct result and minimize the wrongful classification in which genuine transaction is considered fraudulent.

[41] also used data mining algorithm on simulated and real data to create user profile for identifying customer behavior in detecting fraudulent transactions in an online system through a set of association rules. Anomalies were identified by comparing the incoming transaction of the user against that users profile based on his/her recent transaction. Conclusion is that the differences between the anomaly behavior and the profiled user behavior can be correctly interpreted by the proposed algorithm.

[48] also found in their studies that classification of network traffic helps to identity abnormal behaviors by detecting any derivations from the normal activity, [47] also examined network fraud and found out it is possible to use data mining-based network intrusion detection system and track the problem of solving the multi-class classification.

[52] discussed different strategies and techniques used in the detection of the telecommunication-fraud history. They developed a fraud-management system to manage different types of fraud using call details, database required for storing data, fraud detection, algorithms fraud types and corrections and visualization cool that can help in diagnosis. [55] also examined the need for an effective and automated system for network forensic. The experiment results indicated that 91.59% of the attack types could be classified by the system thereby providing understandable information of forensic experts.

[57] also compared the different data mining techniques, benchmarked each technique and identified Adaptive Neuro Fuzzy Inference for telecom-fraud detection in Turkey. The results showed that it provided 97% of sensitively, 99% of specificity, where 98.37 of the instances were correctly classified.

On the other hand [66] used machine learning and data mining to discover and classify malicious executables. The research selected executable which would appear undetected on a user's hard drive, without preprocessing or

removing any obfuscation. The results showed that the boosted decision tree had an area under the ROC curve of 0.996, surpassing other models in fraud risk management. [66] showed that the ensemble of artificial neural network, SVM and Multivariate Adaptive Regression Splines, was superior to individual approach for intrusion detection in terms of classification accuracy. They used data from Massachusetts with five different classes of patterns. The results showed that 100% classification accuracies can be achieved if appropriate intelligent paradigms are chosen.

In their study [5] proposed practical approaches for selecting and implementing organizational information security and presented three models for security business information system ISS offensive model, ISS defense model and sati guard model. He concludes that these help system security and prevent the breaches respectively and other frauds. Also, [14] came out with risk-assessment model to assess the financial damages resulting from the cube attacks. Another research on the use of business intelligence tools to detect fraud [16] found out that there is an increase in the use of data mining to detect fraud, but also lamented an overall underutilization.

[7] made a review of the extent of the use of business intelligence to detect fraud by internal auditors. They came out with the following as regard the use of data mining: 15% use relational reporting; 13% use online analytical processing for fraud risk management; while other respondents complained that all the tools suggested were deficient and some noted that they use MS Access and the rest stated that they monitored email looking for transmission of credit card numbers.

[11] researched on using Data mining to detect fraud of internal audits by application of fraud deductive methods. The result shows that data analysis technology enables auditors and fraud examiners to analyze an organization's business data to gain insight into how well internal controls are operating and to identify transactions that indicates fraudulent activity or the highest risk of fraud.

Finally, [51] surveyed on Global Economic Crime, Cyber crime (digital fraud) and reported that 45% indicated rising cybercrime fraud risks; 40% indicate that it is damaging reputation; 40% did not have capability to detect and prevent cyber crime; 56% said the most serious fraud was an inside job and senior executives made up almost 50% who did not know if a fraud occurred and no indication of internal audit commitment in the use of data mining in cyber fraud risk management.

## METHODOLOGY

The methodology of this research used a simple survey research design to elicit information from respondents to address internal audit data mining techniques in fraud risk management in Nigerian banks. The reason for the choice of a simple survey research design is to determine from those who have primary interest on banks on whether the explanatory variables of data mining techniques have the potentials of ameliorating fraud risk management in Nigeria banks.

### Population of the study

The population of banks in Nigeria comprising either international or national or regional authorization was 21. The numbers of banks studied were selected in a balloting through systematic sampling technique. The names of all the banks were represented in a paper and reshuffled, after which fifteen papers where picked that made up the sample size of the banks for the study [23]. The targeted population element of the study consists of the internal auditors, accountants and fraud auditors in each of the banks of interest in this study. Questionnaire was used to collect data from these banks, (refer to appendix). The outcome indicated that the total population of internal auditors, fraud auditors and accountant from the fifteen banks used for this study is 668 as described in the table below:

**Table 1: Population of the Study was made up of the internal audit staff, fraud audit staff and accountant staff in each of the 15 Banks used for the study**

| S/N | Description of Institution | Internal Audit Staff | Fraud Audit Staff | Accountants | Total |
|---|---|---|---|---|---|
| 1. | Bank A | 3 | 5 | 16 | 24 |
| 2. | Bank B | 3 | 4 | 30 | 37 |
| 3. | Bank C | 5 | 9 | 53 | 67 |
| 4. | Bank D | 2 | 3 | 40 | 45 |
| 5. | Bank E | 4 | 6 | 44 | 54 |
| 6. | Bank F | 1 | 2 | 8 | 11 |
| 7. | Bank G | 2 | 3 | 21 | 26 |
| 8. | Bank H | 3 | 5 | 50 | 58 |
| 9. | Bank I | 1 | 1 | 14 | 16 |
| 10. | Bank J | 3 | 8 | 77 | 88 |
| 11. | Bank K | 8 | 10 | 41 | 59 |
| 12. | Bank L | 1 | 2 | 15 | 18 |
| 13 | Bank M | 6 | 7 | 58 | 71 |
| 14. | Bank N | 2 | 3 | 76 | 81 |
| 15. | Bank O | 1 | 2 | 10 | 13 |
| | | **45** | **70** | **553** | **668** |

**Source: Primary Survey Data sourced from the Banks by the Researcher.**

### Sample and Sampling Technique

The researcher employed Taro Yamane's formulae to determine the sample for the study. The formula is given as: $n = \frac{N}{1+N\,(e)^2}$

where, n = Sample Size, N = Population Size (668)

E = Level of Significance (0.05), 1 = Constant. Using the formula, therefore, we have:

$$\text{Sample Size} = \frac{668}{1+668(0.05)^2} = \frac{668}{669(0.0025)} = \frac{668}{1.67}$$

= 400.

Therefore, the sample size for this study is 400 respondents (accountants, internal and fraud audit staff). Each of the 15 chosen commercial /deposit money banks represents a sample frame and the 400 determined sample size is distributed among these institutions as follows:

**Table 2: Distribution of sample size on proportion among the 15 Banks studied.**

| S/N. | DESCRIPTION OF INSTITUTIONS | SAMPLE SIZE FOR EACH INSTITUTION | | |
|---|---|---|---|---|
| 1. | Bank A | 24/668 x 400 | = | 14 |
| 2. | Bank B | 37/668 x 400 | = | 22 |
| 3. | Bank C | 67/668 x 400 | = | 40 |
| 4. | Bank D | 45/668 x 400 | = | 28 |
| 5. | Bank E | 54/668 x 400 | = | 32 |
| 6. | Bank F | 11/668 x 400 | = | 6 |
| 7. | Bank G | 26/668 x 400 | = | 16 |
| 8. | Bank H | 58/668 x 400 | = | 35 |
| 9. | Bank I | 16/668 x 400 | = | 10 |
| 10. | Bank J | 88/668 x 400 | = | 52 |
| 11. | Bank K | 59/668 x 400 | = | 35 |
| 12. | Bank L | 18/668 x 400 | = | 11 |
| 13 | Bank M | 71/668 x 400 | = | 42 |
| 14. | Bank N | 81/668 x 400 | = | 49 |
| 15. | Bank O | 13/668 x 400 | = | 8 |
| | | **Total Sample Size =** | | **400** |

***Source: Researcher's Proportion of the 400 sample size to each of the banks' population***

**Sources of Data**

This study made use of questionnaires which were used to collect primary data from fraud audit staff, internal audit staff and accountant staff. The questionnaire was to elicit information from the respondents to address the variables of this study. This section of the questionnaire is based on Likert Scale response format of Strongly Agree (5 points), Agree (4 points), Strongly Disagree (3 points), Disagree (2 points), and Undecided (1 points). The researcher distributed and retrieved some of the questionnaire to the respondents while others were distributed through agents.

**Methods of Data Collection, Analyses and Justification of the Statistical Tools Used.**

Only questionnaires correctly filled and returned were used for analysis. In order to determine the degree of respondents' position in each of the variables of interest, normal values were assigned to the options in each variable as has been stated above, that is 5, 4, 3, 2, and 1. A cut off was determined by finding the mean of the nominal values assigned to the options in each variable using the formula: $\overline{X} = \frac{\Sigma X}{n}$; where; $\overline{X}$ = Mean; X = the score; n = number of items.

Thus we have $\overline{X} = \frac{5+4+3+2+1}{5} = \frac{15}{5} = 3$. Our decision rule, therefore, is that any mean within 3.0 and above was considered as significant by the respondents, while a mean that is below 3.0 is taken as not significant. Likert Scale was used to measure the extent of the respondents' agreement on each variable factor. Descriptive statistics of percentage,

mean and standard deviation were applied in the study.

To further strengthen the empirical analyses and test the posited hypotheses, ANOVA was employed to test the equality or otherwise of the perceptions of the three categories of staff, namely, the fraud auditors, the internal auditors and the accountants on whether internal audit use of data mining techniques ameliorate fraud risk management in Nigeria Banks. SPSS statistical analyses software was employed to carry out the analyses.

**Validity of the instrument**

Validity has been defined as the degree to which a method or instrument is able to measure what the researcher intends to measure. This research used both face and content validity to check whether the instrument covered what were required and the appropriateness of the measuring instrument on the study. The appropriateness of the face and content was validated by the researcher [5].

**Reliability of the Instrument**

Reliability of the instrument was established. Reliability is defined as the consistency of repeated measurements taken under similar conditions [7] [8]. The Cronback Alpha correlation of items calculated yield, 0.6 and above which is very high above the minimum stated by Cronback. The table of the reliability of the instrument of the study is found in appendix, (See appendix 2). Further, this research applied analysis of variance (ANOVA). This was used to analyze and test the hypotheses of the study and the mean perceptions of the fraud audit staff, internal audit staff and the accountant. The application of ANOVA was denoted by the formula:

$$\Sigma = V_b \quad \int = \frac{Vb\ between\ group\ Varance}{Vw\ within\ group\ variance} = \frac{\int B^2}{w^2}$$

Where $V_1$ or $\int\frac{2}{j}$ = the variance of the scores for all the groups combined into one composite group known as the total group $\int\frac{2}{w}$ or $V_w$ = the mean values of the variance of each group computed separately known within groups of variance $V_{ß}$ or $\int\frac{2}{w}$ 1 ($\int\frac{2}{w}$ - $\int\frac{2}{w}$ = the difference between the total groups variance and within group variance. One of the reasons why the research used parametric data analysis is that it allows for independence of score [8]. The collection of the data for the study was based on the responses of the respondents' independent perception. There was no influence of scores. Parametric techniques data analyses are required when the scores assume independence [23]; [24]; [25]; [26]; [27]. Likert scale method is applicable when instrument is coded strongly agree, agree, etc. and Parametric test is also one of the appropriate statistical techniques that could be used to analyze Likert Scale responses, [44].

DATA PRESENTATION AND ANALYSIS

The response data set from this study met with the assumptions of parametric techniques. Presentation of the study analyses are as follows:

**Table 3: Questionnaire Responses**

| Items | Number | % |
|---|---|---|
| Total administered instrument | 400 | 100 |
| Instrument not returned | 169 | 42 |
| Returned but invalid | 18 | 5 |
| Valid copies returned | 213 | 53 |
| Total | | 100 |

**Source: Researchers report of instrument survey, 2019**

The report from the table 3 above showed that 400 questions were distributed, and 213 (53%) were returned valid, while 169 (42%) were not returned and 18 (5%) were also returned but were invalid due to irregularities found in the responses

**Research Question One Analyses**

**Question I**: To what extent do you agree that internal audit data mining interrogation techniques ameliorates fraud risk in banks?

**Table 3 Respondents view on data mining audit interrogation in fraud risk in banks.**

| Job description | To what extent do you agreed that data mining audit interrogation ameliorates fraud risk in banks | | | | | Total |
|---|---|---|---|---|---|---|
| | Strongly disagree | Disagree | Undecided | Agree | Strongly agree | |
| Internal auditor | 2<br>4.9% | 1<br>2.4% | 2<br>4.9% | 17<br>41.5% | 19<br>46.3% | 41<br>100.0% |
| External auditor | 0<br>0% | 1<br>1.9% | 7<br>13.5% | 25<br>48.1% | 19<br>36.5% | 52<br>100.0% |
| Accountant | 3<br>.25% | 8<br>6.7% | 4<br>3.3% | 48<br>40.0% | 57<br>47.5% | 120<br>100.0% |

**Source: Research's response analysis in Likert scale Survey, 2019**

Responses above show that only, 2 internal auditors representing the frequency mode of 4.9% and the accountants disagreed that data mining audit interrogation techniques ameliorates fraud risk, and that 3(2.5%) accountant also disagreed on the subject matter, while no fraud auditor disagreed. The extent of the disagreement is represented by 2.4% for internal auditors and 1.9% for fraud auditors, and a higher rate of 6.7% represented as disagreed by the accountants. The undecided opinions represented the mode of 4.9% of internal auditors, 13.5% of fraud auditors and a lesser 3.3% for accountants. The respondents who rated "agreed" and "strongly agreed" that data mining audit interrogation ameliorate fraud risk were as follows: Internal auditors had a frequency mode of "agree" and "strongly agree" of 41.5% and 46.3% respectively. The fraud auditors' responses also showed a high percentage mode of 48.1% and 36.5% respectively for both "agreed and strongly agreed". But, Accountants' responses had a high rating mode of 40% and 47.5% for "agreed" and "strongly agreed" respectively. Fraud auditors had the higher rating of "agreed" opinion with a mode of 48.1% indicating that data mining audit interrogation is a technique that ameliorates fraud risk in banks.

**Table 4 Respondents view on data mining neural network in fraud risk management in banks**

| Job description | To what extent do you agreed that neural networks as data mining techniques ameliorates fraud risk in banks | | | | | Total |
|---|---|---|---|---|---|---|
| | Strongly disagree | Disagree | Undecided | Agree | Strongly agree | |
| Internal auditor | 1<br>2.4% | 2<br>4.9% | 6<br>14.6% | 18<br>43.9% | 14<br>34.1% | 41<br>100.0% |
| External auditor | 1<br>1.9% | 2<br>3.8% | 11<br>21.2% | 27<br>51.9% | 11<br>21.2% | 52<br>100.0% |
| Accountant | 3<br>.25% | 10<br>8.3% | 18<br>15.0% | 55<br>45.8% | 34<br>28.5% | 120<br>100.0% |

**Source: Research's response analysis in Likert scale Survey, 2019**

Respondents' opinion from table 4 above indicates the opinions of the respondents on whether neural networks ameliorate fraud risk in banks. There was a high rating on "agreed" and "strongly agreed" by the respondents. Internal auditors who "agreed" had 43.9%, and those who indicated "strongly agreed" had 34.1%. The fraud auditors who "agreed" had 57.9%, and those with strongly agreed scored 21.2%, while the accountants who indicated

"agreed" had a rating frequency mode of 45.8% and those who indicated strongly agreed had 28.3%. From the analyzed table above there is a higher rating indicating that neural network ameliorate fraud in fraud risk management. Those that stood on the "undecided" position had 14.8%, 21.2% and 15% among internal and fraud auditors and accountants respectively

**.Table 5: Respondents view on data mining machine learning techniques in fraud risk in banks.**

| Job description | To what extent do you agreed that neural networks as data mining techniques ameliorates fraud risk in banks | | | | | Total |
|---|---|---|---|---|---|---|
| | Strongly disagree | Disagree | Undecided | Agree | Strongly agree | |
| **Internal auditor** | 1<br>2.4% | 0<br>0% | 5<br>12.2% | 22<br>53.7% | 13<br>31.7% | 41<br>100.0% |
| **External auditor** | 1<br>1.9% | 4<br>7.7% | 5<br>9.6% | 25<br>48.1% | 17<br>32.7% | 52<br>100.0% |
| **Accountant** | 3<br>25% | 4<br>3.3% | 14<br>11.7% | 59<br>49.2% | 40<br>33.3% | 120<br>100.0% |

**Source: Researchers Responses Analysis in Likert Scale, Survey 2019.**

Analysis above indicated that 53.7% of internal auditors agreed, and 48.1% of fraud auditors also agreed, while 49.2% accountants also agreed that data mining machine learning techniques ameliorates fraud in fraud risk management. Internal auditors who strongly agreed were 13 with 31.7% mode and fraud auditors were 17 with 32.7% mode, while accountant who stated "strongly agreed were 40 representing 33.3% of the respondents. Internal auditors who stood in undecided position showed 12.2% and fraud auditors showed 9.6% while accountant had 11.7%. The responses of strongly disagreed showed internal auditors with 2.4%, fraud auditors had 1.9% and accountant scored 2.5%, while disagreed respondents showed 0%, 7.7% and 3.3% respectively for internal auditors, fraud auditors and accountants respectively. The summary indicates that greater percentage of the respondents rated "agreed" that data mining machine learning techniques ameliorates fraud in fraud risk management in Nigeria banks.

**Table 6: Mean and standard deviation scores on data mining techniques that ameliorate fraud risk in Nigeria bank.**

| Variables | Internal Auditors | | | Fraud Auditors | | | Accountants | | |
|---|---|---|---|---|---|---|---|---|---|
| | Mea | Std | N | Mea | Std | N | Mean | Std | N |
| **Data mining audit interrogation** | 4.35 | 0.75 | 41 | 4.13 | 0.87 | 52 | 4.06 | 0.95 | 120 |
| **Data mining Neural Net works** | 4.30 | 0.91 | 41 | 3.85 | 1.30 | 52 | 4.85 | 0.60 | 120 |
| **Data mining machine learning** | 4.12 | 0.94 | 41 | 3.97 | 1.19 | 52 | 4.93 | 0.10 | 120 |

**Source: Researchers analysis from survey, 2019.**

Information from table 6 above showed that all the mean scores of the respondents were above 3.00 which is the mean score acceptance limit set for the study.

Accountants scored the highest mean of 4.93 with the least standard deviation of 0.10 indicating that data mining machine learning is one of the main variable techniques that ameliorates fraud in fraud risk management in banks. Fraud auditors had the least mean scores of 3.85 with the highest standard deviation of 1.30.

If you compare the average mean of the various groups within this job description, you will notice that accountants had the highest mean scores of 4.61 and the smallest standard deviation of 0.55 indicating homogeneity in agreement among them than the other groups [14] [15]. Internal auditors scored second with a mean of 4.26 and a standard deviation of 0.87 showing that the score are tightly clustered around the mean [3]. The fraud auditors on the other hand had an average mean of 3.98 and a standard deviation of 1.12. The standard deviations of the internal and fraud auditors and accountants do not differ much in variability that data mining techniques ameliorates fraud in fraud risk management, [24]. In order words, the individual persons within the three groups of job description were united in their opinion that internal audit data mining techniques ameliorate fraud risk in banks. The opinion of the three groups of job description did not differ much in the mean and standard deviation.

**Testing of the Hypotheses of the Study**

**Table 7: ANOVA Hypotheses**

| | | Sum of Squares | Df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| To what extent do you agree that audit interrogation techniques ameliorates fraud risk in banks | Between Groups | 5.101 | 4 | 1.275 | 0.04 | 0.97 |
| | Within Groups | 177.528 | 208 | .854 | | |
| | Total | 182.629 | 212 | | | |
| To what extent do you agree that neural networks techniques ameliorates fraud risk in banks | Between Groups | 8.705 | 4 | 2.176 | 0.37 | 0.69 |
| | Within Groups | 184.601 | 208 | .888 | | |
| | Total | 193.305 | 212 | | | |
| To what extent do you agree that machine learning techniques ameliorates fraud risk in banks | Between Groups | 4.295 | 4 | 1.074 | 0.15 | 0.86 |
| | Within Groups | 165.648 | 208 | .796 | | |
| | Total | 169.944 | 212 | | | |

**Source Researches Analysis Result Using SPSS**

The ANOVA output of SPSS demonstrated that all the P values of 0.97, 0.69, 0.86, were more than the significant level of 0.05 which was chosen as a base for the study. The overall P value is 0.84. Applying the decision rule P value 0.84 > 0.05, we therefore reject the null hypothesis and accept the alternate hypothesis that all the explanatory variables of data mining techniques are all significant in fraud risk management. The research further conclude that there is no significant difference among the opinions of internal auditors, fraud auditors and accountants that internal audit data mining techniques are significant in ameliorating fraud in fraud risk management in Nigerian banks. In other words data mining techniques of audit interrogation; neural network and machine learning are considered significant in ameliorating fraud in fraud risk management in banks.

## FINDINGS

After the analysis, the testing of the hypothesis showed that the null hypotheses were rejected, i.e. the alternative hypotheses were accepted. Thus all the proposed data mining techniques are significant in ameliorating fraud in fraud risk management in banks. In other words, the respondents strongly agreed that internal audit data mining techniques of audit interrogation, neural networks and machine learning are significant in fraud risk management in banks.

### Discussion of Findings

The null hypotheses were all rejected, while the alternatives were accepted. This is a proof that the respondents accept that data mining of audit interrogation, neural networks and machine learning techniques ameliorates fraud risk in banks. In other words, they were united in both individual and group perception on the subject matter. Any observed difference in their opinions was due to chance [11].

The result does not in any way differ from the findings of some studies in other countries, [59]; [60]; [61]; [62]; [63] who found that application of data mining detect and prevent fraudulent financial activities.

This result also differ from the conclusion of [4], who applied data mining tool only on fraudulent financial reporting and [34] who also applied it on fraudulent financial reporting and loss on production and not generally on fraud risk management.

Other findings from this study were the statistical significant of the combination of data mining audit interrogation, data mining neural networks and data mining machine learning techniques. These findings do not differ much in any form from the opinion of [24], who found that data mining neural network detect fraud direction and [25], who also found out that data mining detect fraudulent transaction.

The findings do not differ from the findings of [7]; [8]; [9]; [10] who also agreed with the result that the application of data mining is significant in fraud risk.

The finding, by the agreement of the respondents that data mining techniques of audit interrogation, neural network and machine learning, when applied in fraud risk, ameliorates fraud risk: is therefore not misleading, [34]; [35]; [36].

If we discuss this finding considering the mean and standard deviation scores of the individual and group responses on the items within the data mining tools, we will see that they were very high. Their mean scores were found to be above the study chosen limit of 3.0. Also, the standard deviations were reducing significantly to proof harmony in both the individual and group responses. However, considering the result of the Likert Scale analysis findings in all the items within the data mining; showed that respondents had greater opinions of ‘‘strong and strongly agreed’’ opinions of responses.

From the literature reviews, we consider it along with one of the findings of [28], that conclude that data mining-neural networks had 80% success in detection of fraud. It was concluded in [29], that the application of neural networks helps to detect fraudulent transaction and the wrongful classification in which genuine transaction is considered fraudulent. [34], also, found that audit interrogation can identify abnormal behaviors by detecting any derivation from normal activity.

Further, [1] suggested that machine learning can discover and classify malicious executables; more so [47], agreed that neural networks can be a good intrusion detection in terms of classification accuracy, while [36]; [37]; [38]; [39]; [40], all suggested that data mining impact fraud.

### Summary of Findings

The study results revealed that all the null hypotheses tested were rejected and the alternate hypotheses were accepted. In others words, the respondents were of a strong opinion that: internal audit data mining techniques of audit interrogation, neural network and machine learning techniques are found significant in ameliorating fraud in fraud risk management in banks

## CONCLUSION

The major findings of this study serve as a basis for making the following conclusions. Internal audit data mining techniques of audit interrogation is significant in fraud risk management in banks; Internal audit data mining neural network is significant in fraud risk management in banks and Internal audit

data mining of machine learning is significant in fraud risk management in bank,

## RECOMMENDATION

This study makes the following recommendations based on the findings:

**a)** Internal audit can apply data mining techniques in fraud risk management and by ensuring that a functioning internal audit is put in place;

**b)** Banks and other financial institutions that are susceptible to more fraud risk factors are encouraged to adapt and fully try to apply these variable techniques in fraud risk management;

**c)** Banks should broaden their horizon in internal audit data mining techniques in fraud risk management processes and ensure that management pay more attention in risk areas.

Finally, every corporation will have to ensure that there is an effective fraud risk management using internal audit function.

### Research Contributions

The followings are considered as the current contributions of this study.

**a)** This study found three variables and gave a construction of a new conceptual framework that showed how internal audit data mining techniques can apply in fraud risk in banks. Also the conceptual framework of this study suggested a broad view that covered data mining techniques in fraud risk management;

**b)**The study also, has tried to bridge the gap of the paucity of academic studies and also provides a systematic empirical review of literatures covering internal audit data mining variables techniques in fraud risk management which may also serve as a reference to other researchers.

Finally, it provided a more understanding of the various ways to ameliorate fraud risk through the suggestions of the research findings, implications, and recommendations.

### Suggestions for Further Study

We suggest here that further study can be carried out on the same topic internal audit data mining techniques in fraud risk management choosing a different industry instead of banking. The study can be conducted in a manufacturing industry. Another study can also be carried out to determine the impact of internal audit function in fraud risk management instead of the application.

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**Appendix 1: Questionnaire Instructions:**

i) Please tick ( √ ) in your opinion as provided in each of the questions. ii) State other comments if need be.

Please, indicate the extent to which you agree or disagree using the key. Key: SA = Strongly Agree; A = Agree; SD = Strongly Disagree; D = Disagree; U = Undecided. 1

**To what extent do you agree that the following data mining techniques ameliorates fraud risk in banks:**

| | | SA | A | UN | D | SD |
|---|---|---|---|---|---|---|
| **A** | **Data-mining techniques** | | | | | |
| **1** | -Employment of a type of a computer that uses a systematic sentence enquiry? (Data-mining audit interrogation) | | | | | |
| **2** | - Make use of different computer programs that work together through trial and error in audit to detect fraud? (Data-mining neural networks) | | | | | |
| **3** | -Include capable programmed languages that identify fraud patterns in an audit functions? (Data-mining machine learning techniques) | | | | | |
| **4** | -Include capable programmed languages that identify fraud patterns in an audit functions? (Data-mining machine learning techniques) | | | | | |

**APPENDIX 2**

**Reliability Statistics**

| Cronbach's Alpha .622 | N of Items 3 |
|---|---|
| .622 | 3 |

**Item-Total Statistics on data mining techniques**

| | Scale Mean if Item Deleted | Scale Variance if Item Deleted | Corrected Item-Total Correlation | Cronbach's Alpha if Item Deleted |
|---|---|---|---|---|
| Audit Interrogation | 22.73 | 46.064 | .873 | .699 |
| Neural networks | 23.20 | 46.209 | .730 | .653 |
| Machine learning | 22.89 | 47.101 | .756 | .710 |