RISK MANAGEMENT TECHNIQUES IN BANKING SECTOR USING DATA MINING

Ramani Jaydeep R [1], Dr. Jayesh N Zalavadia[2]

[1] *P S Hirpara Mahila College, Jetpur 360370 (Gujarat), INDIA.*
[2] *Gyanyagna College of Science & Management Rajkot 360005 (Gujarat), INDIA.*

Abstract: *There is a growing power of data mining in business applications, with several solutions already applied and many more being discovered. Since the worldwide financial crisis, risk management in banks has increased more distinction, and there has been a continuous attention around how risks are actuality identified, measured, reported and managed. Significant research in academia and industry has concentrated on the expansions in banking and risk management and the current and evolving challenges. This paper, through an analysis of the accessible literature seeks to analyses and evaluates data mining techniques that have been researched in the environment of banking risk management, and to classify regions or difficulties in risk management that have been incompetently explored and are possible areas for further research. The review has exposed that the application of data mining in the managing of banking risks such as market risk, credit risk, ,liquidity risk and operational risk has been discovered; however, it doesn't appear proportionate with the present industry level of focus on both risk management and data mining. A huge number of regions persist in bank risk management that could pointedly advantage from the study of how data mining can be functional to address exact problems.*

Keywords: **bank risk management, data mining, fraud, credit scoring.**

1. INTRODUCTION

Since the worldwide financial crisis, risk management in banks has increased more importance, and there has been a continuous focus on how risks are being detected, restrained, reported and managed. In bank and risk management then the present and evolving challenges. In tandem, there has been a growing influence of data mining in business applications, with many solutions previously implemented and many additional being discovered.

The risk functions in banks, by 2025, would need to be basically different from what they are today. The enlargement and extending of guidelines, evolving customer expectations and the fruition of risk types are expected to initiative the change within risk management. New products, services and risk management methods are being allowed through the application of developing technologies and progressive analytics. Data mining, identified as one of the technologies with significant implications for risk management, can allow the building of more precise risk models by identifying complex, nonlinear patterns within large datasets. The prognostic power of these models can produce with every bit of information added, thus enhancing predictive power over time. It is predictable that data mining will be applied crosswise multiple regions within a bank's risk organization. Data mining has also been suggested as an initiative that could help in the alteration of the risk management function at banks.

The paper pursues to study the level to which data mining, which has been emphasized as an developing business enabler, takes been investigated in the situation of risk management within the banking industry and afterward to categorize potential areas for additional research. The purpose of this review paper is to measure analyses and evaluates data mining methods that have been functional to banking risk management, then to classify areas or difficulties in risk management that have been ineffectually discovered and make suggestions for additional research.

To regulator the risks exact toward banks, as an alternative to leveraging on present works, this paper delivers a classification of risks that is established based on a review of bank yearly reports. An analysis of the accessible works was approved out to estimate the areas of banking risk management where data mining techniques have been researched. The research assessed the risk regions where data mining has been applied in the risk categories and the specific risk procedure they addressed. The analysis also recognized the data mining algorithms being used, both for specific areas and in general.

Section 2.1 provides a summary of risk management at banks, the key risk types and risk management tools and methodologies. Section 2.2 gives a quick introduction to data mining and its use. Section 3 begins by providing an overview of the research methodology. The section additional examines the present research about the application of data mining in the administration of risk at banks. It offers an analysis of the regions where the application of data mining has been deliberate, highlighting regions where there is slight to no academic study. Section 4 deliberates the key explanations from the evaluation, stressing the possible challenges and topics that could be addressed in the forthcoming. Section 5 summaries the general findings from the study. The paper accomplishes by citation additional areas or difficulties in banking risk management where the application of data mining can be additional researched.

2. Theoretical Background

2.1. Risk Management at Banks

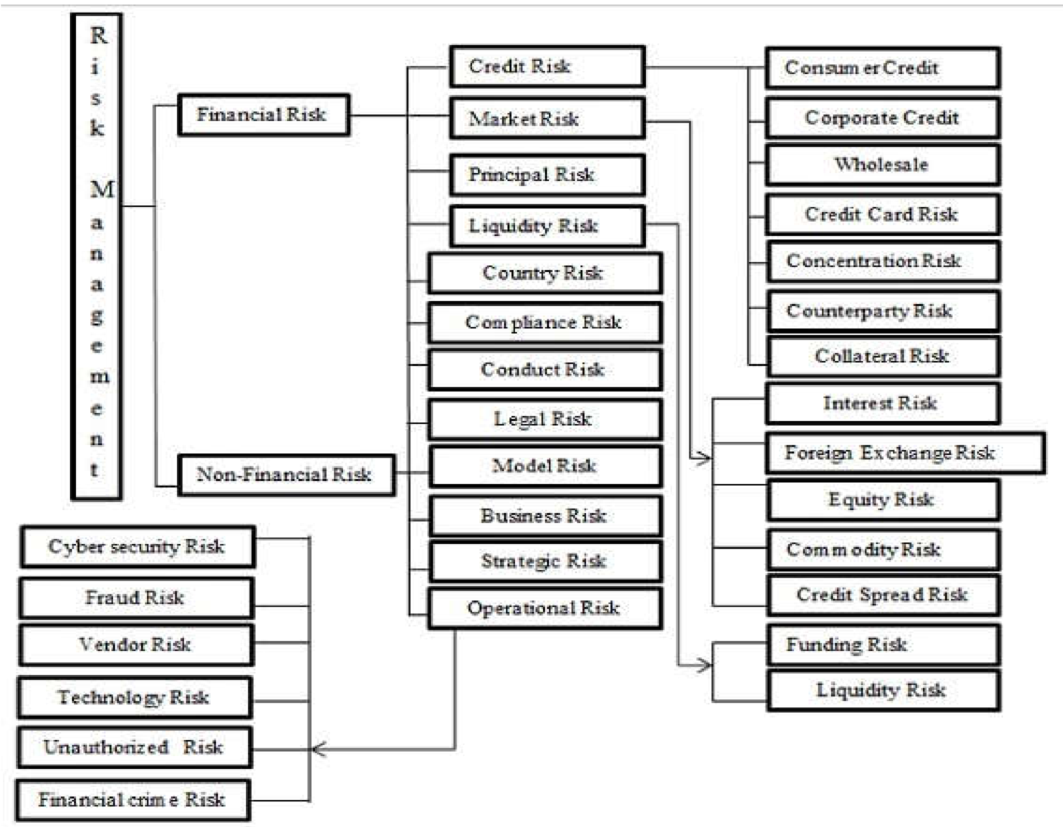
The bank's administration's search to growth returns for its owners incomes at the cost of increased risk. Banks are challenged with various types of risks— technology risk, operational risk, interest risk, credit risk, liquidity risk, balance-sheet risk, market risk, foreign exchange risk, liquidity risk. Actual controlling of these risks is important to a bank's presentation. It also, prearranged these risks and the protagonist that banks performance in financial classifications; they are matter to regulatory helpfulness. The regulators need banks to hold capital for the several risks that arise and are approved due to a bank's wide-ranging operations. The Basel standards for the determination of capital supplies were developed in 1998, and since then, have established and progressed. Capital is mandatory for each of the main risk types. Credit risk has usually been the highest risk facing banks, and typically the one requiring the most capital. Market risk rises principally from the trading operations of a bank, while operational risk is the risk of fatalities from internal system failures or outside events. In accumulation to calculating regulatory capital, most huge banks also calculate economic capital, which is founded on a bank's models rather than on preparations from regulators. The main risks that banks surface are credit, market, and operational risks, with other types of risk counting liquidity, business, and reputational risk. Banks are aggressively involved in risk management to monitor, manage and quantity these risks.

Market risk can be distinct as the risk of victims "owing to arrangements in the level or volatility of market prices". Market risk contains interest rate risk, equity risk, commodity risk and foreign exchange risk. Interest risk can be well-defined as the possible loss due to activities in interest rates. Equity risk can be distinct as the possible loss following to an adverse change in the price of a stock. Foreign exchange risk can be distinct as the risk that the price of the assets or liabilities of a bank changes due to variations in the currency exchange rate. Commodity risk can be distinct as the possible loss due to an adverse modification in the price of commodities held. The market risk framework of the Basel accord consists of an internal prototypes approach and a identical approach. To incarceration tail risk improved, the reviewed framework also aphorism a shift in the measure of risk below pressure from the Value-at-Risk (VaR) to Expected Shortfall (ES).

Liquidity risk, preserved unconnectedly from the additional risks, takes two forms—asset liquidity risk and funding liquidity risk. A bank is unprotected to asset-liquidity risk when a operation cannot be executed at the predominant market prices, which could be a importance of the size of the location relative to the normal trading lot size. Funding liquidity risk mentions to the incapability to meet cash flow responsibilities, and is also known as cash flow risk. Banks are essential to begin a robust liquidity risk management structure that would ensure sufficient liquidity is maintained, counting the ability to withstand a range of stress proceedings. A sound procedure for the identification, measurement, monitoring and control of liquidity risk should be implemented.

Operational risk is separate by BCBS as the risk of defeat resulting from "insufficient or failed inside processes, people and classifications or from outside events" and is a "important element of risk management" at banks. This explanation includes legal risk, but eliminates strategic and reputational risk. It is measured characteristic in all banking activities, processes, products and systems. In the annual reports, operational risk was diversely presented and included a number of sub risks, and could be mentioned to more as non-financial risk. It included, between many others, cyber security, fraud risk, client's products and information risk, technology risk, business practices, money laundering financial crime risks, and vendor outsourcing risks, business disruption risks. In certain cases, banks have reported acquiescence and legal risk also under operative risk.

To control the risks specific to banks, as an alternative to leveraging the existing literature, a review was done of bank yearly reports. Based on the evaluation, classification was recorded of the different risk types that banks classically seek to manage as part of their business and the procedures and implements in use. The annual reports of 10 leading banks were reviewed to determine which risk areas were specifically being reported on by these banks. The review also included identifying the specific tools, methodologies or risk management framework components that were in use. To get broader attention, the list of banks involved a demonstrative from each region—US, mainly globally functioning banks, European banks, and also an Asian bank. Also, these banks functioned a extensive ranging of banking business lines—investment banking, consumer or retail banking, securities trading and corporate banking. Though there were differences in the technique the risks were deliberated and presented, including the top risks, sub risks were largely the same and included credit risk management, liquidity risk, and market risk management, operational risk. A diagram (Figure 1) showing the classification of the various risk types deliberated in bank yearly reports and also the several methodologies or implements (Figure 2) applied to manage these risks is encompassed above.



The principal risk officer has admittance to risk understanding and intelligence that was more reconsidering in nature, such as occurrence analyses focusing on understanding what happened and why. Now, progressively, they are gearing up with tools that allow for an appearance ahead that facilitates the forecasting of potential risk occurrences. Data mining, scenario demonstrating and forecasting are integral geographies of most risk management clarifications. Reasoning (pattern appreciation by visualizing and classifying apparent and later tendencies in historical data) and algorithmic (establishing causal relationships among miscellaneous events and data sets) intellect is making way for increased (natural language processing and data mining) and assistive (appropriate virtual intelligent assist) intellect that augments and quickens decision making.

	Market Risk	Credit Risk	Liquidity Risk	Non-Financial Risk (Operational Risk)
Risk Management Tools				
Risk Limits	Y	Y	Y	
Credit Risk limits		Y		
Value at Risk	Y			
Earnings at Risk	Y			
Expected Shortfall	Y			
Economic Value Stress Testing	Y			
Economic Capital	Y	Y	Y	Y
Risk Sensitivities	Y			
Risk Assessment(RCSA)				Y
Operational Risk Losses				Y

Loss Distribution Approach				Y
Scenario Analysis	Y	Y	Y	Y
Tail Risk Capture	Y	Y	Y	Y
Stress Testing	Y	Y	Y	Y
Scoring Models		Y		
Rating Models		Y		
Exposure -Probability of Default - Loss Given Default -Exposure at Default		Y		
Back Testing	Y	Y	Y	

Risk Management Framework Components				
Risk Appetite	Y	Y	Y	Y
Risk Identification	Y	Y	Y	Y
Risk Assessment	Y	Y	Y	Y
Risk Measurement	Y	Y	Y	Y
Risk Testing	Y	Y	Y	Y
Risk Monitoring	Y	Y	Y	Y
Risk reporting	Y	Y	Y	Y
Risk Oversight	Y	Y	Y	Y
Capital Management (calculation and allocation) - CCAR - ICAAP	Y	Y	Y	Y

2.2. Data Mining

Data mining has been clarified as untruthful at the connection of computer science, statistics and engineering. It has been emphasized as a implement that can be functional to different problems particularly in fields that require data to be under-stood and represented upon. Data mining brings the competence to detect meaningful designs in data, and has become a collective tool for almost any task faced with the obligation of extracting meaningful information from data sets. When faced with the condition of removing meaningful information from data, and the resulting complexity of designs to be studied, a programmer might not be able to deliver clear and detailed explanation on the implementation process. Data mining addresses this experiment by “bestowing programs” with the ability to “learn and adapt”. The Data mining packages learn and progress and can be applied when the problem that has to be distributed has the dual challenge of difficulty and the need for flexibility

Data mining tools that are dynamic the improvements in and self-driving cars and search engines container be accepted and functional in the financial sector. A diversity of technological developments have underwrote to the financial sector being able to discover and mine a huge data infrastructure that comprises diverse sets of unstructured forms of financial data about markets and consumers. Economists are progressively adopting data mining, in combination with other tools and knowledge to assess complex relationships, despite manual data limitations in being able to control connection. The acceptance of data mining has been interested by the possible opportunities for cost reduction, improved risk management and improved productivity. New rules have also lacking the banks to automate with the need to have well-organized regulatory compliance.

Data driven and computational-based, data mining algorithms depend on less on expectations about the data, including about the circulation. While they are measured more robust and better at addressing complex non-linear relationships, they also are understood as being difficult to interpret.

Recent years have understood a surge in the amount of data collected within financial institutions (FI). A big thrust towards the digitalization of services and improved regulatory reporting supplies has resulted in a large amount of formless data being created and/or collected at a high incidence. This data comes from various sources, including client interactions, consumer apps, metadata and other external data sources. The desire to improve their analytical capabilities and mechanize across business lines, including risk management, by managing and mining these increased volumes and a variability of data has led financial institutions to discover controlling and analytical solutions, an importance of which is the rise in interest and the acceptance of data mining and artificial intelligence within the FI community. Data mining is widely understood in the financial services sector as consuming the possible to deliver the analytical competence that FIs desire. Data mining is accomplished of impacting every feature of the FI's business model—improving understanding client partialities, risk management, conducts monitoring, fraud detection, client support automation and even automated identity verification when coupled with biometrics.

The Institute of Worldwide Finance and technology ventures explain use cases within financial institutions. He considers applications in the part of credit risk modeling, money laundering, and discovery of credit card fraud and surveillance of behavior openings at FIs. He also highlights that data mining pursues to predict "out-of-sample" while learning "found in-sample" (past) correlations, while dwindling short of providing an explanation for the analyzed relationship. This could create complexities around model development and evaluation.

Data mining also plays a role at the Securities and Exchange Commission (SEC) in the risk assessment process in identifying misconduct. While this is applicable from a supervisory perspective and for the oversight of systemic risks, it can also help as a guide for a bank on how similar data mining techniques can be functional in risk assessments for the discovery of misbehavior (internal or external) counting risk assessments on counterparties or corporate issuers. In computational finance, data mining has great possible and could be variedly used, fluctuating from the complete exploratory data analysis to the presentation/visualization of modeling results

Some of the cons of data mining, as contended, are that they are more "black box" in countryside, with results at times existence difficult to understand. It is claimed that they are also delicate to outliers, resulting in the over appropriate of the data and counterintuitive forecasts. They are also argued to have the pros of being able to be a better fit for non-linear relationships between the explanatory variables and explained variables, and also that the ability for them to apply a wider set of variables tends to improve accuracy.

3. Materials and Methods

To convey out the review of literature that researches the application of Data mining in bank risk management, two sets of key words were used in the exploration for related papers. The exploration for documents was done expending the scholar.google.com, SSRN and ProQuest databases. The search was largely focused on papers after 2007 to capture developments since the global financial crisis; however papers prior to that period were also included if they were referenced in other recent papers.

The first group of words was 'Data mining', in line with the topic. The second group comprised terms that were identified from the review of the bank annual re-ports. This includes risk types, as listed in the risk taxonomy and risk management tools or methods that were identified from the bank annual reports. Taxonomy is as exposed in Figure 1 and methods as in Figure -2.

The search and review was limited to conference papers, journal articles and selected theses (post graduate or doctoral). The review has not considered articles, white papers, vendor papers or web articles that have just made reference to Data mining without providing details on how, or that made references to the application of any specific algorithm, though many such articles did come up in the search. In particular, there are a huge number of articles, web and magazines, and publications that include Data mining as a solution or as a generic and general recommendation without providing further details on how a given specific problem can be addressed.

The review has looked at only papers that have analyzed the topic with a level of depth, namely, by making references to specific algorithms or providing a design or model for how ML can be implemented. Articles or papers or conference proceedings that have made only a cursory or a general reference to the application of ML in the risk management space have not been considered for this research. It is noted that there are many references available where the authors or speakers have proposed that DM or Big data can be functional in the management of risk; however, many of them stop short of providing clarity on which algorithms, or fail to provide examples of how DM /BG has been applied in a test or industry setup.

The methodological framework for this research was determined by analyzing the various problem areas related to Data mining and risk management in banks. The articles were classified to understand: (i) the risk area they focused on; (ii) the risk management tool or risk management framework component they targeted; or (iii) the algorithms that were applied/studied/proposed. The survey was also seeking to review papers that focused more on risk assessment and measurement.

Risk regions such as cyber security and fraud risk have remained dealt with extensively; how-ever, the attention in this appraisal has been only on cases where they exactly relate to banking risk management use cases. Papers that focus the research on operational matters, such as credit risk management solutions that address the operational process of credit review and approval, or tools that are focused on supporting traders and trading risk managers in the order and trade management process, have not been considered. Moreover, operational risk management explanations that appropriate within the operational procedure to alleviate operational events/incidents (e.g., robotics procedure mechanization, STP, irregularity detection) have not been researched.

3.1. Credit Risk

The assessment of credit risk remnants an significant and challenging research topic in the arena of finance, with initial exertions dating back to the last century. On the back of the worldwide financial crisis events and the consequent increased regulatory focus, the credit risk assessment process has seen an increased interest within the academic and business community. The general method to credit risk assessment has been to put on a classification technique on historical customer data, including on delinquent customers, to analyses and evaluate the relation between the characteristics of a customer and their potential failure. This might be used to regulate classifiers that can be functional in the categorization of new candidates or existing client as good or bad.

Credit risk evaluation occupies an important place within risk management. Techniques such as Logistic reversion and discriminant analysis are conventionally recycled in credit scoring to determine likelihood of default. Support Vector machines are successful in categorizing credit card client who avoidance. They were also found to be competitive in determining features that are most significant in determining risk of default when tested and compared against the traditional techniques. Credit risk modeling for the calculation of credit loss exposure involves the estimation of the Possibility of Default (PD), the Experience at Default (EAD) and the Loss Given De-fault (LGD). This is emphasized by the Basel II accord. Predominant methods to develop models for PD are arrangement and survival analysis, with the concluding involving the approximation of whether the client would default and when the default could occur. Classifier algorithms were found to perform suggestively more precisely than standard logistic regression in credit scoring.

Through the necessity to assign capital in an efficient and moneymaking manner has leads FIs to build credit scoring replicas to assess the avoidance risk of their customers. Over, SVM has been exposed to yield meaningfully improved results in credit scoring. An exact estimate of projected likelihood of avoidance delivers more cost to risk management in assessment to a binary classification of clients as either trustworthy or not-credible. A number of techniques are used in credit scoring, such as discriminant analysis, logistic regression, nearest neighbor, Bayes classifier, artificial neural networks and classification trees. Artificial neural networks must been shown to perform classifications more accurately than the other five methods.

Methods and models are being constantly developed to address a significant issue at banks, namely, the correct classification of customers and the estimation of credit risk. The numerous methods applied in these methods seek to increase the correctness of credit earnestness forecasts that could lead to a better and profitable loan portfolio. Neural networks have proven to be of significant value in the credit risk decision process, and their application in company distress predictions was reported to be beneficial in credit risk evaluation.

Neural networks, Support Vector Models and Random Forest appear to be the most researched algorithms in the credit risk management area.

3.2. Market Risk

Risk can be measured by the standard deviation of unexpected outcomes, also called volatility. Value at Risk (VAR) calculates the nastiest loss over a board horizon that will not be surpassed with a given level of sureness and captures the combined effect of underlying volatility and acquaintance to financial risks. Volatility forecasting in the financial marketplaces is important in the regions of risk management and asset pricing, among others. By using NN models, the performance of the instability approximation method can be improved.

A prototypical that is founded on the Generalized Autoregressive Conditional Heteroskedastic (GARCH) prototypical and Extreme Data mining (ELM) algorithm to approximation volatility. The model predicts the unpredictability of target time sequence using GELM-RBF and inferring the predicted volatilities allows for the control of VaR with better presentation in terms of correctness and efficiency. The model utilizes a stochastic mapping method that doesn't need the Gaussian likelihood for estimation and is a not linear data driver model.

Market risk also includes interest rate and equity risk. Interest rate curves, which is the relative between the interest rate and the time to adulthood of the debt for a given debtor in a given currency, is widely used in financial engineering and market risk management. A clustering method called the "Gaussian Mixture Model" can be used to develop nonlinear models of the evolution of the parameters and then to forecast interest rate curves. This can allow for better visualization of interest rates. Data mining clustering methods calculated to discourse Stochastic Differential Equation (SDE) can be functional to develop anticipatable VAR models that aim at being a leading risk measure of market regime change. This can partly address some of the difficulty introduced by the stimulating regulatory environment, such as scenario consistency.

3.3. Liquidity Risk

A number of liquidity risk problems can be resolved over the use of Data mining. Measurement of liquidity risk, the analysis of important factors with the study of the interconnections between the factors can be realized through the use of Data mining. For the purposes of estimating a risk measure Artificial Neural Networks (ANN), a genetic algorithm can be applied. ANN can be used in the approximation of the general risk trend and determination of the most powerful factors. The likelihood that a liquidity risk occurrence will occur can be projected by the application of Bayesian Networks. The ANN and the BN applications were capable of individual the most dangerous liquidity risk factors calculating the risk by a distributional approximation and a functional approximation and, correspondingly.

3.4. Operational Risk

Data mining is also functional in operative areas that allow the justification of risk, i.e., detection and/or prevention of risks. In the area of operational risk, sideways from cyber security cases, Data mining is mainly focused on problems connected to fraud detection and suspicious transactions detection.

A prototype for the group of a report that permits for the detection of doubtful transactions. The prototype uses a logistical regression algorithm. It is noteworthy that they have also comprised a survey of six software explanations that are currently applied at various banks for the automation of suspicious transaction detection and monitoring processes. While the authors make a reference to algorithms, it is unclear whether these products apply Data mining techniques, and if so, with which algorithms. No further research was done on these products as this was not in the scope of the paper.

One such region where an analysis system based on Data mining is recognized to add value is in the defense against spammers where the attackers' techniques evolve. Losses from spam potentially include lost productivity, disrupted communications, malware attacks and theft of data, including financial loss. Proof point's MLX technology usages progressive Data mining techniques to deliver complete spam detection those protectors in contradiction of the threat of spam. Millions of messages can be analyzed by the technology, which also automatically refines the detection algorithm to identify and detect newer threats. While it was not in scope for this research, being more of an operational control to manage risk, it has been highlighted as a case of how Data mining is used in dealing cyber security risks.

Also, in the regions of operational risk, there are a few papers on fraud risk detec-tion in credit cards and online banking. They concern credit card fraud detection in domains not specifically related to bank risk management or the banking industry. One would note that the algorithms they refer to were SVM, KNN, Naïve Bayes Classifier, Bagging ensemble classifier based on decision tree.

4. Discussion

Credit scoring includes the task of a mathematical value to the business (or client) representative whether the business (or client) is likely to avoidance or not. Maximum of the research has remained focused on addressing this area by handling it as a classification problem, predicting a prospective customer as "good" or "bad" so as to facilitate the credit decision and management of credit risk. There is therefore a dominance of classification related algorithms. Many papers have gone beyond only providing a classification of creditors, and have addressed how to predict of the possibility of avoidance or recovery rate i.e., estimating the possibility of avoidance (PD), loss given avoidance (LGD), exposure at avoidance (EAD). It would be of significant value to banks and their risk management functions to have research and models for predicting or estimating the PD, LGD, EAD, and therefore, estimating the credit loss exposure.

Data mining techniques have been proven to perform better than traditional statistical techniques, both in classification and also predictive accuracy. The support vector mechanism is seen to be a widely tested and proven Data mining approach. Much empirical work is based on observational data. Selection mechanisms could result in non-random samples, either owing to sample design or the performance of the sampled units. In the former, data are usually missing, and in the latter, there is a self-selection of the sample units. This leads to sample selection bias.

When the sample data being studied has a proportional representation of certain dependent variable outcomes (e.g., default, fraudulent transaction) different from their proportional representation in the population they are drawn from, it is supposed to be 'choice based'. This 'choice based' sampling induces a bias in the estimation. As Data mining bases much of the modeling upon learning from available data, it could be prone to the same problems and biases that affect traditional statistical methods. As Data mining methods are compared to traditional statistical techniques, it would be beneficial to evaluate and understand how problems inherent to traditional statistical research methods fare when treated by Data mining techniques.

The application of Data mining for market risk management also doesn't appear to have been adequately studied. Numerous papers have investigated market instability or market risk from a portfolio or speculation risk management perception. However, from a bank risk management perspective, the papers appear limited. Further research on this, especially from the point of view of stress testing or tail end risk capture, is merited. Liquidity risk that has, meanwhile the financial crisis, involved a lot of consideration from controllers, has a few use circumstances researched.

In the operational risk area, trainings have been principally attentive on fraud and doubtful transaction detection—problems that are characteristically addressed by classification algorithms. Clustering analysis, Bayesian networks, decision, classification trees, SVM are commonly noted in the application of Data mining algorithms. Neural networks have also been referred to as a very prevalent and prominent technique in credit card fraud detection.

Much of the other regions of non-financial risk management, nation risk management, compliance risk management—aside from money laundering related uses—cases haven't been explored adequately. Conduct risk, which has become a key risk and assumed a high priority for regulators and banks driven by the spate of conduct issues in Europe, US and Asia Pacific also appears to be deficient in research papers, though data mining is obtainable as an explanation to manage conduct risk. Further-more, many of the standard risk management tools such as risk assessments, risk monitoring and risk reporting appear as areas that could meaningfully benefit from further research.

Dataset sources used by researchers for their studies are varied, with some receiving data from commercial banks or from databases provided by financial services providers (e.g., Moody's), and with some researchers conducting their studies using publicly-available data. Difficulties emphasized are that the data can be highly slanted (e.g., low default rates), data incompleteness and data truthfulness (e.g., might not be categorized correctly or as expected. A wider accessibility of real world data sets would definitely encourage more research in evaluating the many problems faced by risk management functions..

5. Conclusions

The future of Data mining in the banking and financial industry is well recognized, and it is expected that the field of risk management will also seek to apply Data mining methods to enhance their capabilities. Despite being evaluated for functioning like a black box, the ability of Data mining techniques to analyses capacities of data deprived of being forced by expectations of distribution and deliver much value in exploratory analysis, classification and predictive analytics, is significant. This offers the potential to transform the area of risk management. Data mining, identified as one of the technologies with significant suggestions for risk management, can allow the building of more precise risk models by classifying complex, nonlinear patterns within large datasets. This paper has presented an assessment, analysis and evaluation of the research around the application of Data mining in risk management within the banking industry. Most of the research appears to be focused around credit risk management. One could characteristic this to the detail that credit risks are careful the most important risk to a banking organization. More specifically from a methodology perspective, credit risk management problems researched have been around credit scoring; it would go a long way to research how Data mining can be applied to measurable regions for better calculations of credit risk exposure by forecasting possibilities of default, loss given avoidance given the many complexities and the varied factors that are involved. Market risk has understood some research with Data mining existence used to forecast unpredictability, interest rate curves, and market command change. Liquidity risk, despite the increased attention in the industry post the concern from Regulators, has seen limited research. Assumed the suggestions to a bank's effectiveness and comfort as a importance of a liquidity risk occasion materializing, liquidity risk would be a very good applicant to be research lengthily, more particularly, research about calculating liquidity risk actions in isolation or as a network of issues or events. Operational risk has also seen very limited research. Research has focused on application of Data mining to prevent or detect operational risk events; however, there is very limited application to operational risk management practices especially in the areas of risk identification, assessments, monitoring, reporting. Given the vast amounts of operational data available (internal to a bank) Data mining could be applied in effectively developing operational risk management capabilities, which has mainly relied on qualitative factors to measure, report and manage risk. The evaluation has exposed that areas of tail risk capture, stress testing, scenario analysis—areas that rely on prognostic analysis of huge volumes of data—have also seen only limited research. The benefit and drawbacks of the different Data mining techniques in solving specific risk management problems can also be further evaluated and studied to maximize the value.

The evaluation has presented that the application of Data mining in the administration of banking risks such as market risk, credit risk, liquidity risk and operational risk has been discovered; however, it doesn't seem proportionate with the present industry level of attention on both Data mining and risk management. In regions of operational risk, market risk, and liquidity risk research appear lacking, and there is important possibility for further study. The application of Data mining could be further researched for some areas where analysis or modeling on sizes of data with complex and non-linear computations is required. As one of a group of topics that requires a lot of analysis of different data types to predict potential events or estimate losses, these include tail risk analysis and stress testing. Measuring and reporting technology risk is still a new area and might be further researched, especially as this risk is rising up the charts and senior managers and risk managers in bank are starting to seek more insight into what the technology risk is. As banks look to mature their enterprise risk management capabilities, it would be beneficial to study how Data mining can be functional in the aggregation of risks, and enhancing risk reporting capabilities. While areas such as conduct risk could also be researched, it is noted that these areas would benefit more from application in the operational area such, as behavior monitoring and activity monitoring. Although these go towards management risk (risk qualification, risk discovery) at the bank, they are not the risk administration systems (risk measurement, risk assessment) that are the focus of this research.

In conclusion, although there has been research on the application of Data mining in risk management over the years, it still falls short and is not on par across the numerous regions of risk management or risk methodologies. There still remain a large number of areas as highlighted above in bank risk management that could significantly benefit from study on how Data mining can be applied to address exact problems.