PREDICTIVE AUDIT ANALYTICS: EVOLVING TO A NEW ERA

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ABSTRACT

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The traditional audit is retroactive in nature and requires some time to process and is subject to substantial latency. With the evolution of technology, assurance processes could be automated and accelerated to provide more frequent and may be preventive audits. This study contributes to the assurance literature by proposing an audit framework that is more responsive to current business needs.

Using the traditional continuous auditing as a basis, the first essay proposes the predictive audit framework. The predictive audit is a forward looking process that utilizes predictive analytics to estimate possible outcomes of business activities, and allow auditors to execute their work proactively. The predictive audit differs from the traditional audit in several aspects such as control approach, objective, and frequency. The preventive audit is defined as a predictive audit with filtering rules to block highly probable faulty transactions prior to their execution.

The second essay examines the application of the predictive audit on a bank's real business data set to determine potential irregularities. This study aims to assist internal auditors concerning the validity of sales transactions. The possible outcome of the sale transaction is identified using three machine learning techniques: decision trees, logistic regression, and support vector machine. The results show that logistic regression

outperforms other algorithms. With a proper sales variables selection, the predictive model could accurately predict results with high accuracy, true positive rates, as well as a reasonably low false positive rate. The robust results of the predictive audit can be used as a baseline to create screening rules for the preventive audit.

In the third essay, the predictive audit is deployed to determine the possible results of credit card sales transactions. Consequently, the filtering rule constructs are derived from the predictive model. These rules can be implemented at the beginning of the business process as the preventive audit to flag or block transactions before they are executed. Alternatively, the filtering rules can be applied to the results of the predictive audit to reduce a number of transactions that auditors have to investigate. The rules significantly increase the possibility of discovering problematic transactions.

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1.1 Introduction

> *"Clearly the vast majority of internal auditors think that the traditional retrospective audit process adds far less value than the ability to inform the organization of risk and control trends and issues that are of importance to management" (Verver, 2012).*

Most accounting and auditing standards were set prior to the advancements in information technology. This does not invalidate the necessity of these standards but raises questions about their desirability, efficiency, and effectiveness. Auditing is the process of validating the measurements provided by management to stakeholders. Auditing depends upon 1) the formality and quality of measurement rules, 2) the economics of the verification process, and 3) the purpose of the particular verification effort.

The *formality and quality of measurement rules* affects verifiability. Poor accounting rules that lead to vague accounting procedures allow for a wide range of allowable measures that are difficult to verify. On the one hand, historical cost measures are more reliable than fair value, and therefore, easier to verify. On the other hand, the measurement relevance may counterbalance the difficulties of its verification.

The *economics of the verification process* determine the acceptability and framework of audit rules. Sampling procedures balance the costs and benefits of audit verification, creating the concept of materiality. This allows for "fair representation" as opposed to exact measurement. The development of faster and more effective verification processes using information technology such as data mining, predictive analytics, and continuity equations, have changed this cost-benefit equation. However, the accounting and auditing standards have not yet been adapted to reflect this fact.

The *purpose of the verification effort* has been largely neglected in both accounting and auditing standards. The "one report for all" and the consequent "one audit standard for all[1]" neglect the different needs of various stakeholders such as employees, investors, banks, counterparties, etc. Although the customization of financial reports for groups, organizations, or even individuals was not economically feasible in the past, it has become feasible with extant technology (Vasarhelyi, 2012).

These issues lead to the need for a reconsideration of the axioms of the audit function with implications for both the external and internal audit roles. Furthermore, companies need more than just financial statement audits; they need assurance on a wider set of business information. Therefore, auditors should consider the need for impounding modern analytical methods and the acceleration and automation of business information technology. This approach of analysis with a retroactive or a predictive framework must be integrated into the assurance and auditing function.

1.1.2 Continuous Auditing and the Predictive Audit

We are now living in a real time economy (Economist, 2002; Vasarhelyi *et al.*, 2010b) where businesses operate continuously with less geographic boundaries. This

[1] The emergence of the Internal and External audit professions actually created two standards, the first much less formal than the second (IIA, 2012).

necessitates very prompt responses to key events. Timely and reliable information is vital for business decisions and a competitive advantage. The traditional audit methodology cannot completely fulfill business and third party verification needs as it audits past transactions and provides substantially delayed and backward looking assurance. In this setting, most of the audit procedures, particularly substantive tests, are done manually with limited sample data.

A more frequent (closer to the event or continuous) audit can alleviate these problems (Vasarhelyi *et al.*, 2010a). Continuous auditing (CA) utilizes technologies to automate audit procedures and provides speed to audit processes so that auditors may accelerate their assurance processes and creation of audit reports. The Canadian Institute of Chartered Accountants (CICA)/ the American Institute of Certified Public Accountants (AICPA) define CA as the following:

> *A methodology that enables independent auditors to provide written assurance on a subject matter, for which an entity's management is responsible, using a series of auditors' reports issued virtually simultaneously with, or a short period of time after, the occurrence of events underlying the subject matter. (CICA/AICPA 1999)*

With the aid of advanced technology, tedious and time-consuming audit work could be automated (Teeter and Brennan, 2010; Teeter, 2013). Furthermore, the extent and timing of the audit can be expanded to cover the whole population and provide more timely assurance. Management and internal auditors have to continuously monitor their business processes and internal controls to ensure efficiency and effectiveness of their operations. While CA assists with audit work and is owned by auditors, continuous monitoring (CM) aims to support management monitoring tasks and is owned by management. Littley and Costello (2009) argue that management performs CM while internal audit focuses on CA, two complementary functions. CM is defined as the following:

> *A feedback mechanism used by management to ensure that controls operate as designed and transactions are processed as prescribed. This monitoring method is the responsibility of management and can form an important component of the internal control structure (KPMG, 2010).*

Management uses CM to monitor compliance with, and exceptions involving, transactions. Monitoring results can be used to support day-to-day or higher level management decisions as well as to improve performance and the integrity of processes and controls. CA lets internal auditors actively investigate internal control exceptions as soon as they occur. The exceptional transactions might typically be held for investigation before being released for further processing. Also, CA will reduce errors, anomalies, and/or fraud within the business processes.

Even though it is not necessary for a company to implement both CA and CM, they are complementary mechanisms. Companies may deploy both processes to maximize the usage of resources and benefit from resulting synergies. To implement CM, management can preliminarily select existing CA techniques that are suited to a firm’s operational processes and apply them as CM (Vasarhelyi et al. 2004, Littley and Costello, 2009). Likewise, auditors can take advantage of existing controls in CM and utilize them to support their CA initiatives (Vasarhelyi and Alles, 2005).

CA is the basis of the predictive audit or the next generation of audit methods that use both backward looking and predictive methods. The predictive audit uses analytical methods to predict the expected future outcome of process performance at the transaction, intermediate, and aggregate levels.

1.1.2.1 Definition

The predictive audit (PA) is a methodology that incorporates the traditional audit (backward) with the forward-looking audit procedure. This allows auditors not only to examine the past events and create adjustments based on changes or errors that have already occurred, but also perform an audit that could rapidly detect (predictive) or prevent (preventive) irregularities and anomalies. In addition, auditors will be able to create adjustments in an ex-ante manner.

Auditors and management can use this information for auditing and/or management purposes. For example, fraudulent service cancelations can be predicted to detect employees who violate corporate policies (Kuenkaikaew and Vasarhelyi, 2013). More importantly, external auditors can predict final audit results based upon quarterly and/or monthly data, and, thus do not have to wait to perform all the year-end data verification processes prior to issuing an opinion. For instance, at the accounting firm, Jane, a senior manager, has a number of clients and wants to plan her resources for efficient auditing. With information from the previous years, she uses PA to project business areas and accounts that are high risk and require special attention. Specifically, Jane estimates possible future account balances of the AB company, one of her clients. She found that the predicted interest income balance is 2 million and 25 million for accounts receivable. At the year end, if the actual amounts of these 2 accounts are significantly different from the predicted values (such as 10 million and 5 million for interest income and accounts receivable respectively) she can allocate more time and staff to scrutinize these two accounts. With this approach, Jane is capable to manage her time and resource prudently. Also, she is able to perform this task anytime, not only at the year-end.

At the XY company, Jim, an internal audit manager, wants to audit an expenditure cycle. He decides to apply the PA to this audit cycle. As a result, he does not have to select a sample data for testing. The analytical model in the PA evaluates every transaction. Spending transactions that have a high probability of being suspicious are automatically flagged and his team will get the exception report. They can further investigate the transactions or keep looking at the outcomes. If flagged transactions turn out to be fraudulent, Jim will find out in time to rectify the problem. Finally, Jim and his team can continuously review the expenditure cycle, not just at a specific period.

1.2 Progressive Audit Automation

Enterprise resource planning (ERP) software has become a common platform for many businesses in all areas from manufacturing to service. With many system configurations, numerous user settings, and an excessive volume of transactions continuously processed through each system, it is generally infeasible for auditors to manually audit ERP systems. CA and CM are methodologies to address this difficulty. To adopt CA and CM, companies have to be well prepared and organized. They must also be able to incorporate new technologies and adjust their processes to support CA and

CM. Most extant audit automation is progressive rather than comprehensive. The progressive audit is applicable to existing audit procedures by automating the traditional audit, which entails a backward looking audit. In this progressive audit automation domain, the actual audit processes are modularly formalized. As such, these processes are broken down into small steps or subcomponents and automated where possible.

Alles et al. (2006) experimented with audit automation concepts in the pilot implementation at Siemens, stating "*The pilot implementation confirmed the Vasarhelyi et al. (2004) hypothesis that CA would first automate existing audit procedures rather than reengineer them to better suit the needs of the CA system*." In the pilot project, the research team classified audit programs into the following two groups: audit programs that are automatable and those that require reengineering. Ultimately, the internal audit management team believed that the automated audit programs facilitated cost savings and increased efficiency of the internal audit department.

Teeter and Brennan (2010) extended the pilot implementation project of Alles et al. (2006). They experimented with automating the audit programs of a newly acquired division of the company and created a universal rule set that could be used as a standard for other divisions. While evaluating the existing audit programs, they found that some types of control tests are easier to automate than others. These are typically targeted for initial automation. The researchers considered these controls easy targets of implementation. "*Easily automatable controls tests were identified as 'low-hanging fruit' because they didn't require intense work to automate. These tests included authorization, configuration, separation of duties and use-as-is (UAI) tests*" (Teeter and Brennan, 2010). The challenges of the automation process consisted of three major issues. The first issue pertained to prioritizing rules that are relevant to company operations. The second issue related to incompatible programs or bugs in the current software platform. The last issue dealt with the proper functioning of basic controls. Eventually, the researchers concluded that 63 percent of the audit actions could be automated such that alarms could be set to notify management in the event of control violations. Consequently, a continuous control monitoring rule-book was created as a set of standards and guidelines for conducting an internal IT audit. Thus, the audit process can be shifted from testing transactions to testing the rules themselves. The result of automation can be a reduction in time and travel expenses for the audit as auditors could remotely review automated controls.

Hammer (1990) states, “Reengineering requires looking at the fundamental processes of the business from a cross-functional perspective. [It uses] modern information technology to radically redesign our business processes in order to achieve dramatic improvements in their performance.” As such, audit re-engineering is a systematic review and alteration of audit processes. It aims to align audit processes with the flow of data in a company and improve audit procedures. An organization may decide to reengineer audit processes to improve audit efficiency (Alles et al. 2006). Warren et al. (2012) formalized the audit process and re-engineered the structure of the order-to-cash process of a consumer business firm. Specifically, they focused on the elimination of redundant processes and inefficient attributes in that audit cycle. Initially, formalized rules and audit questions were generated. Those rules and questions were then converted into queries, dashboards, and analytic procedures. Available data was assessed and audit procedures were reengineered according to data behavior and characteristics. Some of the criteria used to evaluate data in Warren et al. (2012) included *"…how data is generated (manual vs. automated), when and at what intervals data is updated (discrete vs. continuous), and where the data is located (local vs. remote)."* As a result, audit procedures were more in line with available business data. In addition, audit timing and location were revised according to the findings. In conclusion, they found that audit reengineering could improve audit efficiency and allowed auditors and managers to focus more on business risks.

All companies in the US SEC jurisdiction or a conglomerate must comply with a number of rules and regulations. Examples of such legislation include the Sarbanes-Oxley Act, Foreign Corrupt Practices Act (FCPA), USA Patriot Act, and other industry specific regulations (KPMG, 2010). Given this situation, a company must consume significant resources in fulfilling the requirements of such legislation. Fortunately, there is an opportunity for firms to substantially automate compliance with existing and new regulatory requirements. This will allow companies to better address the associated compliance burden. Compared with manual audits, automated audits (Alles et al., 2013) could substantially improve the monitoring of regulatory compliance, which is very detailed and should be continuously monitored.

1.3 Predictive Auditing

Continuous auditing notably supports real time business needs. A number of CA studies have been evolving, and many companies have started to adopt some type of continuous audit. Additionally, these organizations are trying to improve and expand the application of CA in their companies (PricewaterhouseCoopers, 2006; Brown et al., 2007, Vasarhelyi et al., 2012a). When using CA technology, a number of audit tasks can be automated and efficiently performed. Therefore, auditors can focus more on business risks and continuously or frequently (rather than periodically) act on the entire transaction population instead of a mere sampling of transactions. This allows auditors to detect errors on a timelier basis and simultaneously increase audit effectiveness.

Technology plays an important role in contemporary and future auditing. Audit automation greatly facilitates the development of forward-looking audit techniques that can be used either as a measurement benchmark for “close to the event” auditing (predictive audit) or, in certain cases, as a way to avoid likely defective transactions from being executed (preventive audit). Figure 1.1 depicts contemporary auditing. The traditional audit is still needed and will be a foundation of the predictive audit. This predictive audit is an approach for performing CA. It applies a prognosticative analytic methodology to the audit and focuses on upcoming events. Results of the predictive audit (not the preventive audit) could be used to identify a process or set of processes that have a high probability of irregularities or errors. If these results are found to be robust, they can be used to construct additional rules or filters, and implemented as preventive controls (the preventive audit) in those processes.

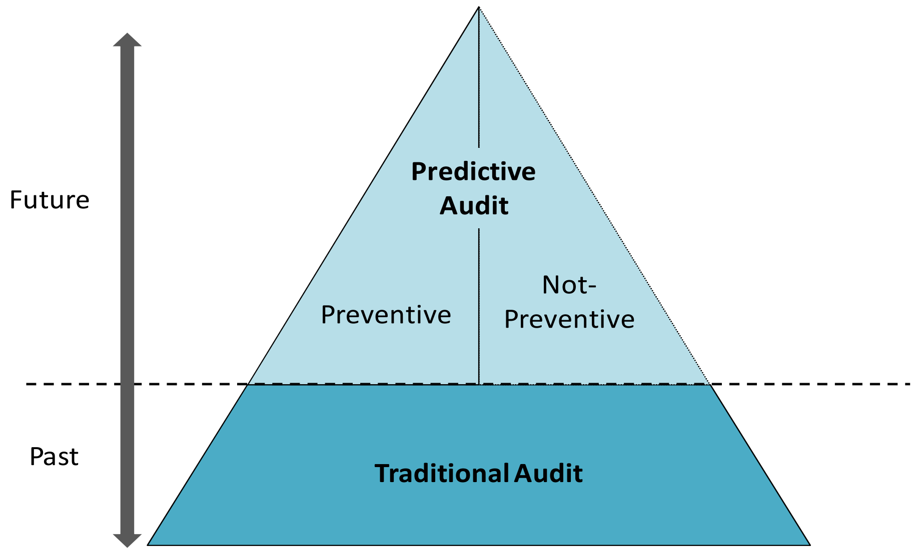

Figure 1.1 Contemporary Auditing

1.3.1 Contemporary Audit

In the coming age of close to real time auditing and control, auditors and management not only want to verify past activities, they want to predict future events for improved control and prevention of faulty transactions. The predictive audit is an emerging concept that could fulfill this vision. The predictive model can be executed before knowing the outcome of the transaction or before the transaction is passed the next process. An analytical model in the predictive audit will compare estimated results of transactions to timely normative models. For example, when sales information is put into the system, the model can analyze whether this transaction has a high probability of becoming a channel stuffer. Based upon such analyses, auditors and management are able to be notified beforehand about any problematic transactions and/or processes. As a result, individuals may investigate and resolve these issues prior to conducting any associated recording activities. Consequently, the predictive audit may turn an audit towards the future by taking a proactive stance in conducting audit activities. Consequently, audit paradigms will change from a backward and periodic audit to a forward and continuous audit, and from a detective to, when possible, preventive stance.

The predictive audit could strengthen the control environment of a company and create better feedback mechanisms for management. In particular, auditors and management could examine errors and irregularities that cause transactions to be flagged. They can also monitor transactions to ensure that when problems occur, resolutions could be promptly implemented. Flagged transactions could be examined to determine if they are allowable. If they are not allowable, these transactions could be subjected to further investigation. In addition, companies could consistently refine preventive controls by establishing additional checkpoints to improve business process rules. Accountants who are responsible for period-close adjustments could use the predictive audit findings to create and enter preventive adjustments. For example, by comparing results from predictive models with operational budgets, auditors and accountants could identify possible variances that may occur and make plans to address them. Figure 1.2 shows the predictive audit flow.

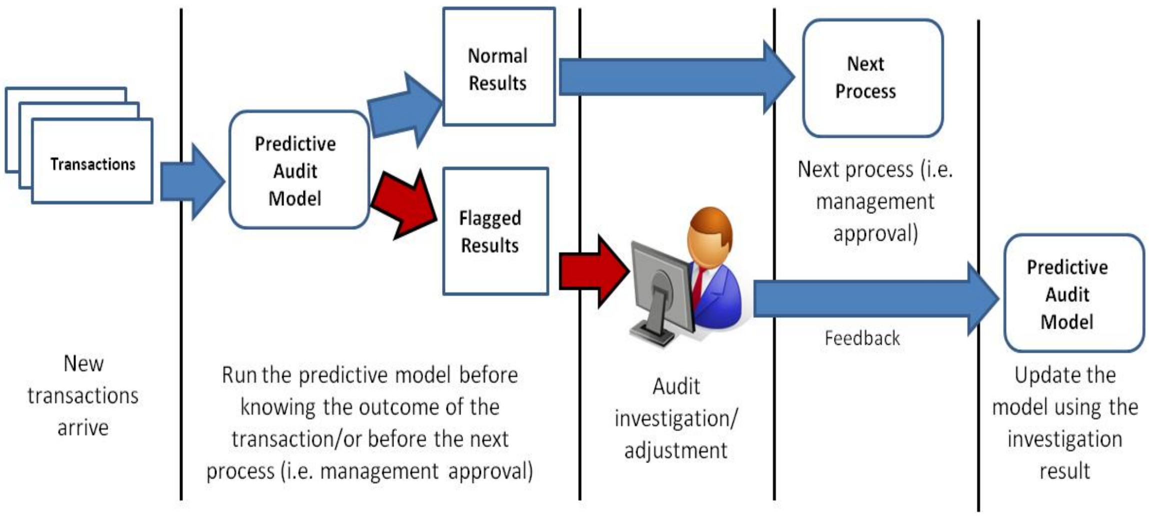

Figure 1.2 The Predictive Audit Flow

There are several differences between the predictive audit and the traditional audit. These differences relate to control approach, objectives, audit area, frequency, measurement, and method. For convenience, Table 1.1 compares the different perspectives between the traditional and predictive audits in greater detail. Data that is used in a predictive model must be in an electronic format. Therefore, hard copy data must be digitized prior to inclusion. In addition, audit procedures should be automated where possible to gain the most benefit from this new audit paradigm. Similar to other CA projects, an initial implementation and conversion will require considerable investment in technology, human resources, and management support (Vasarhelyi et al., 2012b). Even though it entails substantive effort initially, it is expected that the benefits will justify the costs in the future.

Table 1.1: Predictive Audit Characteristics

Area\Audit	**Traditional Audit**	**Predictive Audit**
Control Approach	Detective (Backward)	Preventive (Forward)
Objective	Support audit opinion on financial statements	Support not only for financial purposes; include but not limited to operational audit, compliance, and control monitoring
Audit area	Financial statements at an account balance level	High risk areas in financial statements and operation processes at transaction, sub-account, and account levels
Frequency	Periodic	Continuous or close to the event or frequent
Measurement	Static	Dynamic
Method	Manual - Manual confirmations - Document vouching by sampling - Inventory counts Use statistics and/or ratios	Automated - Automatic confirmations - Data analysis of entire population - RFID, barcode Use data analysis and/or data mining techniques

1.3.2 Types of Prediction

The predictive audit connects past and exogenous data with knowledge of the processes to predict risks, control trends, level and flows, and other parameters of the business process. These predications are compared with the actual results revealed by management for monitoring and assurance purposes. Where discrepancies of substance arise, alerts are generated (the predictive audit not the preventive audit) and potentially block (preventive) execution.

1.3.2.1 Risks

Moon (2013) divides the risks to be monitored in the Continuous Risk Monitoring and Assessment (CRMA) methodology into the following three major categories: 1) operational, 2) environmental, and 3) black swans. These risks are monitored and when substantive changes are observed, analytical methods are used to rebalance audit procedures and potentially refine management actions. This is aimed at improving the balance of audit procedures being applied. The prediction of risk changes would allow CRMA to improve situations in a proactive manner.

1.3.2.2 Control Trends

Controls were evaluated before the enacted of the Sarbanes-Oxley (SOX) Act but the requirement for the evaluation was strengthen by this regulation. The quality of the controls is reflected in the quality of auditee data. The structure, current trends in the evaluation, and frequency of data alerts provided by control systems, serve as predictors of future trends in the control evaluation. While the measurements of control effectiveness proposed in the literature (Debreceny, 2006; Doyle et al., 2007; Ashbaugh-Skaife et al., 2009) are still coarse, they may serve as predictive measures of irregularities and proxies for management quality.

1.3.2.3 Levels and Flows

The traditional audit attests to the reliability of measurements presented by management concerning data levels (Balance Sheet) and flows (Income Statement and Funds Flow). The auditors' prediction allows for the creation of a more competent benchmark for continuous monitoring and continuous auditing relative to the more traditional "standards" used by Vasarhelyi and Halper (1991). For example, a company could predict a level of sales returns before the year-end using historical information related to sales and returns in previous periods, and could create adjustments in advance or monitor for irregular returns.

1.3.3 Predictive Audit: The Framework

1.3.3.1 Forward Audit

Auditors review past transactions to support their opinion on financial statements. They investigate past events to ensure that controls were obeyed and no significant exceptions occurred. Auditors periodically review business transactions. Some processes will be audited monthly, quarterly, annually, or even every other year (Vasarhelyi et al., 2010a). Although traditional audits have retroactive value, this backward looking audit creates a time lag between the occurrence of an event and the time of the associated assurance that influences the decision making of stakeholders.

In the current auditing paradigm, errors or irregularities that occur may not be uncovered in a timely manner and this may be detrimental. Conversely, continuous auditing and continuous control monitoring allow for an immediate response in the ever-changing business environment. Using these methods, management and auditors may explore emerging problems soon after the event. As result, they will optimize the likelihood of recovering from errors and/or irregularities.

In a competitive business environment, the value of a company is equivalent to its future economic performance. From an auditing and control perspective, if auditors could identify processes that have a high probability of producing irregularities or controls that deviate from benchmarks, they could use this information to prepare for audit planning and consequent procedures. The predictive audit utilizes historical and/or current data to predict potential future outcomes. Predictive models can identify patterns, trends, and/or benchmarks, and predict processes or transactions that may deviate from predefined controls. As such, auditors can plan ahead for the audit and scarce resources such as time and personnel can be allocated more efficiently. If anomalies are detected, auditors may examine source transactions to intervene and/or prevent possible adverse consequences. Also, management can use a predictive model to identify high-risk areas that will need greater attention. Moving forward, management can then apply more preventive controls or filters to processes in those areas.

1.3.3.2 Beyond the Financial Purpose

As stated earlier, the primary objective of the traditional audit is to assess and validate financial statements in an effort to provide reasonable assurance that they are free of material misstatement. Audit work focuses on testing and verifying the accuracy of account values and balances. By comparison, the objective of continuous auditing is *"to provide assurance on both financial and non-financial data at a more detailed level and on a much wider set of data"* (Vasarhelyi et al., 2004). In addition to supporting the requirements of the financial audit, the predictive audit can be applied to non-financial audit tasks such as operational auditing, compliance testing, and controls monitoring. Furthermore, it can be applied to areas such as customer relationship management, supply chain, and manufacturing.

In many organizations the implementation of ERP systems and relational databases facilitate the automation and electronization of processes and data (Vasarhelyi and Greenstein, 2003). In these systems, the controls are shifted from the account level to the transaction level so that "*The proliferation of business processes and the ubiquity of technology and automation will…change the minimum level of control from accounts (embodying multiple transactions) to individual transactions….*" (Vasarhelyi, 2011). The predictive audit can identify possible exceptions at both aggregated and disaggregated levels, depending upon input data. As such, it can be applied to account balances or to individual transactions. Because predictive audits require significant investments in technology and automation as well as concentration in data analytics, companies may only consider its application in high-risk areas of accounting systems and operational processes to be cost-effective (Chan and Vasarhelyi, 2011).

1.3.3.3 Continuous Measurement

Businesses need measurements to track their performance in various dimensions. They need both financial and non-financial measurements. Financial statements are used to identify the financial value of a business and accounting is the method for measuring that status. As the nature of business has evolved, measurements have been adapted to continue to effectively evaluate and reflect the actual status of the business. For example, in the digital era, companies' possess both tangible and intangible assets such as intellectual property, human resources, and digital assets. Given this fact, accountants and auditors are faced with the challenge of valuing these intangible assets (Vasarhelyi and Alles, 2008). Existing tangible asset measurement schemes such as LIFO and FIFO inventory methods would not be appropriate for intangible assets.

A company can select many financial or non-financial measures that are applicable to its strategic goals and define expected levels of accomplishment. This will be used as a guideline for employees. Well-known and widely used non-financial measurements include the balanced scorecard (Kaplan and Norton, 1992) and key performance indicators (KPIs) (Venkatraman and Ramanujam, 1986; Ahmed and Dhafr, 2002; del-Rey-Chamorro et al., 2003). A balanced scorecard as defined by Kaplan and Norton (1992) is a measurement schema that includes one financial measure and three operational measures. These operational measures include customer satisfaction, internal processes, and organizational innovation and improvement activities. The balanced scorecard allows management to simultaneously monitor an organization's performance in various views. Figure 1.3 shows four perspectives of the balance scorecard. A key performance indicator (KPI) is "*a number or value which can be compared against an internal target, or an external target benchmarking to give an indication of performance. That value can relate to data collected or calculated from any process or activity*" (Ahmed and Dhafr, 2002).

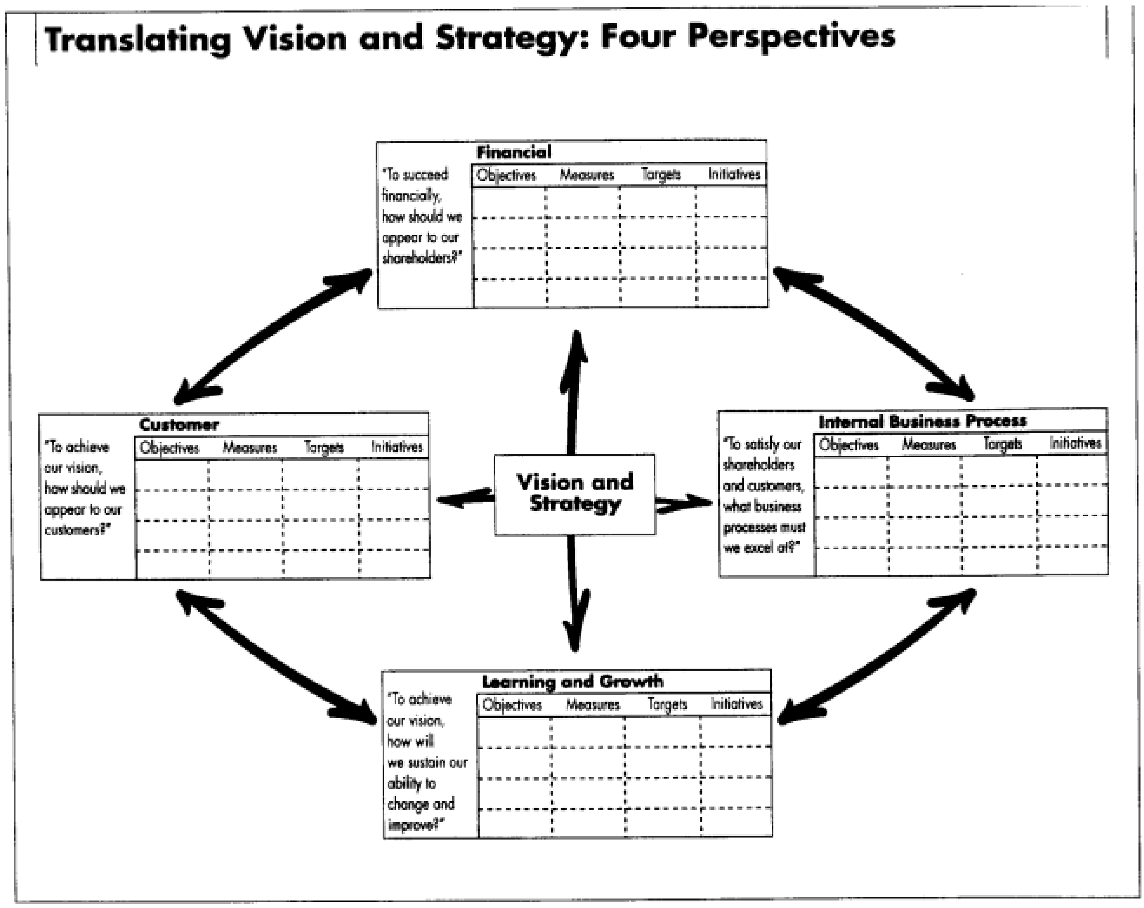

Figure 1.3 Balance Scorecard (Kaplan and Norton, 1996)

Real time audits are needed but not viable using manual methods and static measures. Vasarhelyi and Alles (2005) state "*A dynamic world cannot be well measured with static measurements and technology exists for a more dynamic method of measurement to evolve*." Auditors are not required to provide assurances in real-time but the usage of ex-post facto data is of limited value. CA decreases the time lag of assurance and allows auditors to provide an opinion in a more timely fashion, if not on an evergreen basis (CIA/AICPA, 1999). A continuous measurement system implemented simultaneously in multiple business cycles is needed to measure vibrant business processes. The predictive audit applies continuous measurements to business processes by measuring variables and applying analytic models. Measurements in the predictive audit can consist of both financial and non-financial metrics that truly reflect operating processes and audit objectives. For example, a measurement can be an inventory turnover ratio from financial statements or the number of defective products derived from KPIs.

1.3.3.4 Role of Automation in the Predictive Audit

Many traditional audit tasks are completed manually because some of the accounting documentation exists in paper form. This manual work is laborious and time consuming. In the contemporary audit, many of these tasks can be automated. Advanced technologies, cheap storage, sophisticated devices, and ERP systems facilitate the automation of audit procedures. In this context, auditors can automatically collect data by downloading it directly from a company's ERP system or an audit data warehouse. Then, various audit-aid tools and techniques can be used to analyze the data. Many organizations utilize automated tools for automatic sensing, such as radio frequency identification (RFID) chips and barcode readers in an inventory tracking system that send information to an ERP system. These technologies both facilitate automation and make implementation of CA more cost-effective (Vasarhelyi and Kogan, 1999). In addition, they substantially reduce latencies between events and associated data capture.

For all business and assurance processes, four types of latencies can be defined: intra-process latency, inter-process latency, decision latency, and outcome latency (Vasarhelyi et al., 2010a). Latency in an audit process may be reduced by electronizing

(Vasarhelyi and Greenstein, 2003) audit activities such as using electronic working papers, electronic communications, decision support systems, and real time feeds of evidence (Teeter et al., 2010). Figure 1.4 shows the audit process latencies and possible solutions via electronizing audit activities. The predictive audit could fully benefit from automation in several respects. First, automated systems reduce errors and time lags resulting from manual processes. Also, data in an automated system tend to have fewer errors than data residing in a manual context. Second, with electronization solutions, as soon as data are entered into a system, they may be automatically fed to a predictive model. The model could then immediately process and provide notification relative to exceptions.

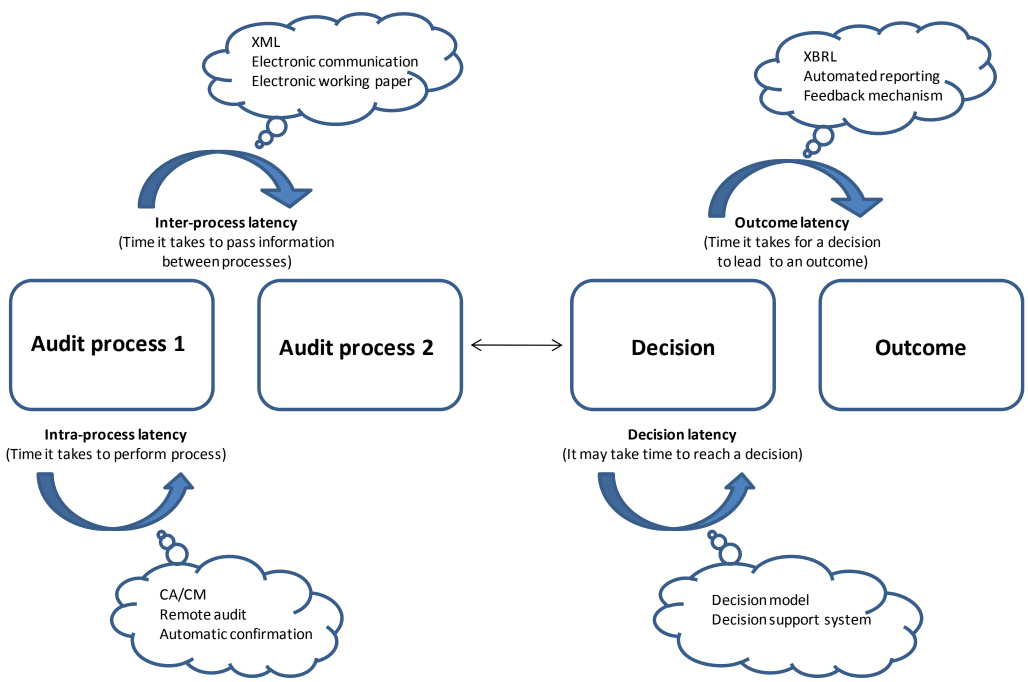

Figure 1.4 Audit Process Latency and Electronization Solutions (Adapted from Teeter et al., 2010)

1.3.3.5 Prevention

Forensic work often entails the usage of advanced analytics relying on historical data to screen transactions that may be faulty (Kim, 2011). These transactions are typically chosen because of specific characteristics and may be given discriminant scores based on the level of potential fault. A discriminant score can be created using various criteria depending on the available information and the nature of the business or process. It is typical that the score is calculated from multiple factors rather than a single factor. For example, ranking intervals of a transaction's frequency and amount can be summarized and calculated as suspicious scores. The larger transactions and holders of more suspicious scores are typically examined manually. The predictive audit uses similar advanced analytics to predict levels, flows, and parameters of transactions. The lack of confidence for the transaction is the result of a discriminant function. If discriminant functions can be derived and are reliable for screening past transactions, they also can be used to determine the reasonableness of future transactions. When problems emerge, the following question might arise:

> Why allow a transaction to be executed if it has a high probability of being faulty?

In fact, the predictive audit can use the weights in discriminant functions to prevent the processing of suspect transactions (Alfuraih et al., 2002; Cornish and Clarke, 2003; Sisalem et al., 2006). Hence, the preventive audit applies a forensic model to create filters to block anomalous transactions from being posted. Filtering rules are placed in the process and can flag transactions with a high potential for exceptions, prompting further review (Figure 1.5). This methodology enhances the audit by exception method (Vasarhelyi and Halper, 1991) and could be designed to have an interface to connect with the CM system for management purposes. This is especially true in internal audit.

Kim (2011) incorporates a forensic analysis routine into CA/CM to create an anomaly detection model for the wire transfer process of a bank. The model deploys an unsupervised method with a series of indicators to create a suspicion score. This score is assigned to each wire transfer payment transaction that passes through the model. The transactions with scores that are higher than an established threshold are labeled as potential anomalies and are forwarded to internal auditors for investigation. The filtering model is placed at the beginning of the process for early detection of possible exceptions, thus preventing them from further processing. The model screens data for patterns or faults under different scenarios. If exceptions are found, they are flagged and included in the exception report. Auditors then examine those errors on an interactive basis. Moving forward, the results of investigations are used to refine the model. As an example, Li et al. (2013) uses the Dempster-Shafer model in multiple interactions to fine tune a model.

It would be desirable if preventive models existed in all circumstances because this would substantially improve the quality of data. Unfortunately, there are many potential factors that make this infeasible. Such factors include a lack of reliable forensic models, largely manual processes, substantial level of investment needed for development, lack of tailoring of filters, etc. The predictive audit can be categorized as either a predictive audit with prevention (preventive audit) or a predictive audit without prevention. The key difference is that if transactions in a preventive approach are found to have a high threshold of risk, they are held prior to execution and submitted to a special audit review group that subsequently deals with the transactions. This places auditors in an operational mode and raises questions of independence from the traditional point of view. Elder-de-Aquino et al. (2013) implemented 18 filters to monitor bank branches relative to overnight transaction processing. The audit-monitoring group reviewed these transactions and when it was applicable, escalated them for review by higher management. Also, this process was performed in an ex-post-facto mode. If these transactions had been reviewed and vetted ex-ante, a “preventive audit” would have effectively been performed. From a traditional conceptual view, this may have been seen as a meta-control function and not considered auditing. With a discussion of key components in the predictive audit framework completed, the next section proposes ten steps for the creation of an actual predictive/preventive audit system.

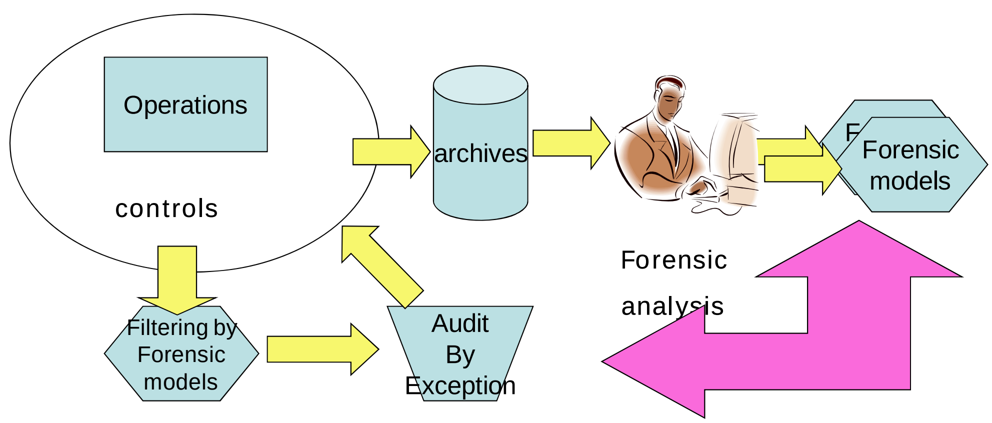

Figure 1.5 Incorporating Forensics into the CA/CM Philosophy

1.3.4 Predictive Modeling

Auditors have long been using analytical methods to identify relationships between sets of data (Tabor and Willis, 1985; Hirst and Koonce, 1996; Chen and Leitch, 1999; Cohen et al., 2000; Glover et al., 2000; Church et al., 2001; Green and Trotman, 2003; O'Donnell and Schultz, 2003). Analytical review usually applies to account balances in financial statements. Using this method, auditors could find trends, fluctuations, or irregularities that happened over time. In the past, auditors could analyze data only at the aggregate level because of limitations in data availability, resources, and technology. Furthermore, much of the audit work had to be performed manually. Data was scarce and audit staffing and timing was limited. Fortunately, current tools and technology allow a great deal of audit work to be automated. This changes the timing and extent of audit tasks. Due to substantial improvements in technology, data storage has become cheaper and contains far greater capacity relative to the past. This allows companies to tolerate the proliferation of data. In addition, both internal and external auditors have more access to data and are able to perform analyses at disaggregated levels and in expanded detail, especially via application of continuous auditing methods. The changing factors that affect auditing are illustrated in Table 1.2.

Table 1.2 Changing Factors that Affect Auditing

Factors	Past	Current
Data availability	- Scarce - Most of the data are in a paper format	- Abundant - Most of the data are in a digital format
Audit technology	- Moderate - Not many audit-aid technology	- Advanced technology - A number of audit automation
Access to data	- Limited	- Mostly unlimited - Audit data warehouse
Data storage	- Limited capacity (i.e. kilobyte, megabyte) - Expensive	- Large (i.e. terabyte, petabyte) - Cheaper

Using appropriate data analysis techniques, a predictive audit model can be constructed. In addition to computing the basic statistics and ratio analyses that are widely used in a traditional audit practice, the predictive audit uses sophisticated methods such as data mining and machine learning techniques. This allows auditors to gain more insight into data analytics at a detailed level. Also, trends and irregularities can be predicted and results of predictive models could direct auditors' attention to suspicious items. A predictive model formation is illustrated in Figure 1.6.

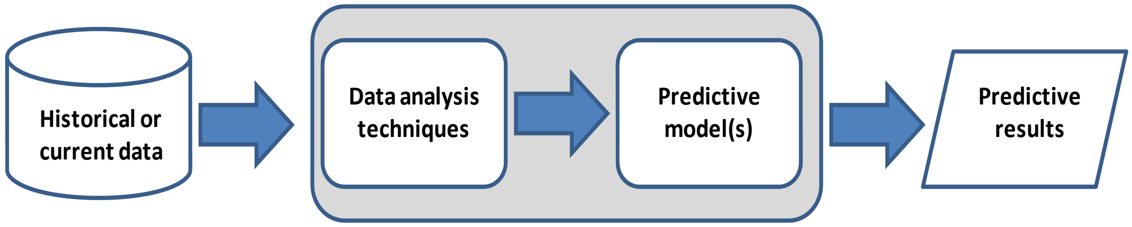

Figure 1.6 Predictive Model Formation

1.3.5 Steps in the Creation of a Predictive/preventive Audit Model

The steps in the continuous forensic and preventive audit process are as follows:

1. Determine a Profile of Risk

Each company has different risks. Some of them depend on the type of business and are known as inherent risks. Other risks are largely due to factors such as the state of the economy, competitors, and regulations. Management has to identify the types of risks it faces, potential impacts of those risks, tolerance level for risks, and possible palliative measures for these risks. When a risk profile is chosen, it can be used in many contexts such as to identify critical business processes or determine operational processes that have a high propensity of risk and need close monitoring. In addition, a risk profile can be used as a guideline for development of KPIs or a baseline in a forensic model. For example, an insurance business has high risks regarding customer claims. Specifically, the legitimacy of these claims is often in question. As a palliative measure, the company will invest in the claim verification process to reduce the risk of approving false claims.

2. Identify and Understand the System

Management needs to identify business processes and systems for which they want to implement the preventive audit. A clear scope of the target systems will ease a project team's work. The project team must understand the system's structure and features, as each system has different characteristics. The more understanding there is about the system, the more successful the project will be.

3. Capture and Clean Relevant Data

One of the key processes in data analysis is to capture relevant data. A company may have a large amount of data but not all is relevant to the target analysis. After data is extracted, it must be scrubbed because it may not be in a format suitable for analysis. In particular, there may be errors such as missing data, duplicate data, or wrong data types (e.g. text in a numeric field, numeric data in a date field, etc.). Also, the data may have an unreasonable range or order. For instance, in an employee database, an employee may have a birth date after a hire date. All these errors have to be cleaned before that data can be used in analyses. Otherwise, results may be unreliable.

4. Create KPI and Extraction Models

After data has been prepared for analysis, a predictive model can be created using several techniques such as descriptive statistics or sophisticated analytical methods. A complex method is not necessarily better than a simple one. Often, a complex model requires too many resources and effort, making it less useful than anticipated. Usually, a model is based on the characteristics or behavior of a target business process. Thus, the understanding of data and business routines is very important.

Each result from the model must be compared to a predefined baseline. Therefore, the company needs to define a baseline or benchmark for each measurement. This baseline can be generated from existing KPIs or newly established criteria with acceptable or expected levels. If the analysis result deviates from the baseline, it may be a signal of an anomaly. For example, if a KPI indicates that money transfers should be cleared within one business day, clearing transactions that take more than one business day may need further investigation.

5. Run Models under Different Scenarios

Different processes or activities can cause various types of errors and irregularities. In some instances, similar errors may originate from different sources. Although it is difficult to identify all possible business scenarios that may cause problems, especially in terms of irregularity or fraud, it is desirable to create business cases that cover as many circumstances as feasible. Additionally, the model may behave differently in different scenarios. Thus, the model has to be run under various conditions to ensure that it is robust and working as expected. For example, in the case of a loan, a customer may pay equal installments each month until the end of the contract or he/she may make a balloon payment before the contract matures. While building the model, these two scenarios must be included and the model has to be tested using these differing conditions to ensure that it works properly for both cases.

6. Place Filters at the Beginning of Processes

The purpose of filtering models in the preventive audit is to impede undesired anomalies in the system. Instead of placing the model at the middle or end of the processes, it will be placed at the very beginning of the processes in order to screen potential anomalies as soon as possible. In addition, this will also prevent them from execution or passing through to the next process. A common example occurs when a customer buys a product via credit card. In this case, the seller first needs the transaction to be authorized by the credit card company before the seller can process the payment and issue the corresponding transaction receipt. If the credit card has a problem, the credit card sale will not be processed.

7. Examine Interactively and Audit by Exception

Any transaction that exceeds a predefined threshold is flagged and sent to internal auditors for further investigation. The system can generate an alarm in real time. Therefore, internal auditors can examine exceptions found on an interactive basis. The preventive audit helps create an “audit by exception” mechanism within an internal audit organization. Consequently, internal auditors can pay more attention to the transactions that are identified as exceptions by the system.

8. Create Interfaces to Continuous Monitoring

A company can create a link between an internal audit system and a management's continuous monitoring system. This fully integrated system will allow management to monitor activity and examine any exceptions so that it can respond to potential problems in a timely fashion.

9. Continue the Forensic Model Development Process Based on Filtering Results

A preventive audit model filters transactions and generates real time results, which allow either internal auditors or management to investigate exceptions on an interactive basis. To enhance the efficiency and effectiveness of the preventive audit system, the results of exception investigations can be used to improve and update the forensic model.

10. Rely, as an external auditor, on Internal Audit Work

Statement on Auditing Standard 65[1] allows an external auditor to rely on internal auditors' work to a certain degree if that work meets the required standards.

> *The auditor considers many factors in determining the nature, timing, and extent of auditing procedures to be performed in an audit of an entity's financial statements. One of the factors is the existence of an internal audit function. This section provides the auditor with guidance on considering the work of internal auditors and on using internal auditors to provide direct assistance to the auditor in an audit performed in accordance with generally accepted auditing standards (AICPA, 1991).*

[1] The Auditor's Consideration of the Internal Audit Function in an Audit of Financial Statements

An automated and systematic forensic model for a preventive audit can properly support an external audit. A systematic and disciplined approach of internal audit work will encourage external auditors to rely on internal audit work (Wood, 2004). External auditors can reduce time and resources for an audit and obtain information from an inside view of internal auditors.

Figure 1.7 demonstrates the 10 steps in the creation of a predictive/preventive audit model. If desired, an established discriminant function in a screening model could be used in a preventive capacity to block questionable activity. This mechanism is similar to a control system but associated with an audit process. Therefore, it is considered a meta-control. A well-designed internal control system with this meta-control structure could detect and prevent anomalies and/or fraud on a timely basis. This allows management to correct problems prior to execution. Also, management could use preventive mechanisms in continuous monitoring to monitor and manage key controls. In general, the three types of predictions (risks, control trends, and levels and flows) can be used complementarily.

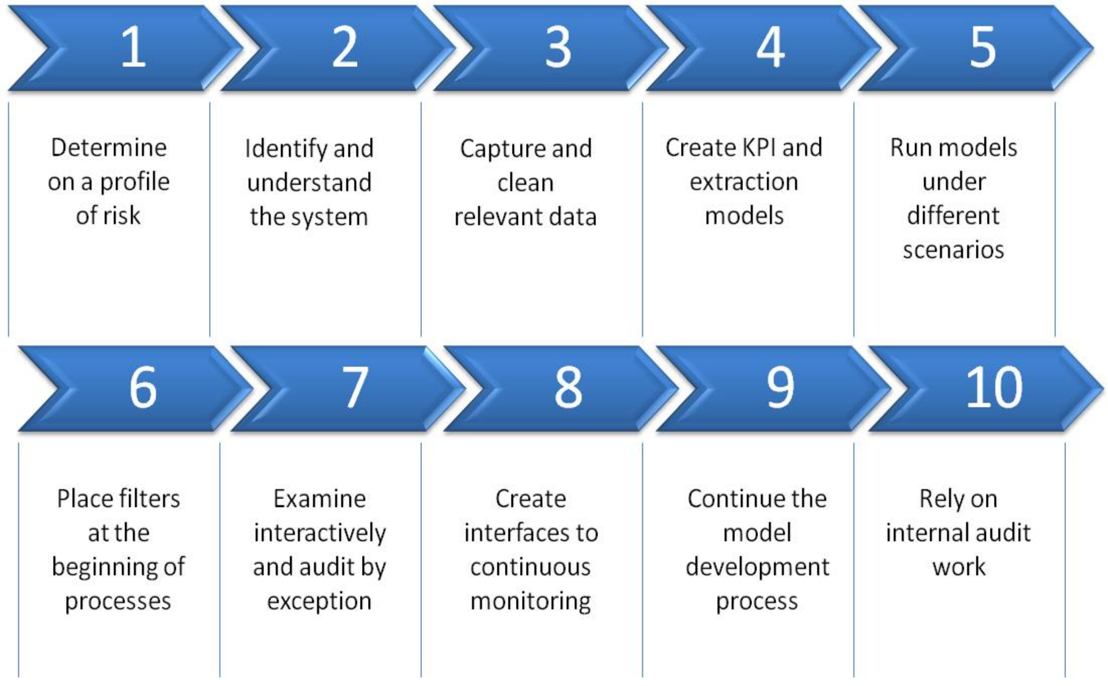

Figure 1.7 Steps in the Creation of a Predictive/preventive Audit Model

1.4 Methodological Issues

As discussed earlier, most accounting and auditing standards were set prior to the advancements in information technology. Bringing the audit close to the event, having it occur on a frequent basis, and automating many of its processes raise a series of methodological questions that will eventually affect the economics, practice, and standards of auditing.

1.4.1 Quality of Prediction

Organizations and processes vary widely in data consistency and the distributional nature of data. Factors such as cyclicality, periodicity, nature of the product, and other items have a significant impact on the usefulness of associated predictions. There is no sufficient empirical evidence to support the creation of a contingency model that would provide specific guidance concerning what models should be implemented, as well as where and how these models should be used. Initial intuition indicates that if historical processes are better predictors, they would be better suited for use in model development.

1.4.2 Auditor Independence

Earlier in this paper, the nature of the preventive audit was described: "*Transactions are potentially not executed if found to have a high threshold of risk in the preventive mode and submitted to a special audit review group that subsequently deals with the transactions. This places auditors in an operational mode and raises questions of independence from the traditional point of view*." Due to the manual intensity of processes, the traditional audit required that auditors be very independent on a formal basis. This was limited by the fact that auditees paid the external auditor and internal auditors reported to financial management. As systems become more automated and audit processes have to be inbuilt and automatic, an exception review function becomes important. This review function needs to be defined formally and maintain a large degree of objectivity. However, it does not necessarily require a strictly defined state of independence.

1.4.3 Materiality

Materiality is a concept of acceptable relative error in transactions. The fuzzy definition of materiality in audit standards represents a tradeoff between the benefits of review and costs of manually performing such an examination. With modern automation and full population testing, the tradeoffs focus more on the benefits of data quality and the costs of meta-review. In this new setting, likely relative error thresholds will be contingent on actual corporate circumstances, the type of predictive model being used, and the cost of review of data in the "audit by exception" approach (Vasarhelyi and Halper, 1991).

1.4.4 Level of Scrutiny

The economics of audit review has been changed by automation, thus affecting materiality. Consequently, rather than relying on a generic audit standard, the level of scrutiny of business transactions is probably more related to the business needs of the auditee. This scrutiny will depend on the power of analytical procedures and the economic value of these procedures to the corporation relative to the degree of scrutiny. For instance, as analytic processes become more automated, these capabilities will eventually become integral components of packaged software such as ERPs and audit tools. In these systems, after the costs of acquisitions, the variable cost will be minimal but the cost of human selection and review will be substantial (Issa, 2013). Thus, auditors will have to be cognizant of this in deciding the level of scrutiny that suits a company's needs.

1.4.5 Timing

Vasarhelyi et al. (2010a) discuss the timing of the continuous audit:

> *Even more importantly, the word 'continuous' undoubtedly would not be used today, because it implies a frequency of auditing that is both difficult to achieve technically without impacting the operations of the entity's IT systems, and probably beyond the needs of most users. The different elements of a corporate information system have different pulses and natural rhythms. The assurance process must be coherent with these rhythms to be useful and effective.*

The CICA/AICPA (1999) illustrates a continuous audit example with an "evergreen opinion" that is always unqualified until an exception occurs that changes its nature. Such an exception now must be generated by predictive analytic procedures, weighted a–priori, and qualified for human review.

1.4.6 Nature of Procedures

Organizations and processes vary widely and this affects the way auditors can investigate and analyze each procedure. Analytical methods in auditing range from basic financial ratios (Kinney, 1987) to more complicated methods such as statistical analysis

(Kinney and Salamon, 1982; Wilson and Hudson, 1989, Chen and Leith, 1999) and data mining techniques (Kogan et al., 2010). Auditors have to understand a target process that they want to review and carefully select analytical methods and relevant variables that are most suitable for that process. The predictive audit could readily utilize data mining and machine learning techniques that are able to predict the outcome of a future observation (Tan et al., 2005). To determine an algorithm to be used, data type must be taken into consideration. If information about the classification of an outcome (e.g. fraud or not fraud) is available, a supervised learning algorithm can be used. Conversely, if class label information is not obtainable, an unsupervised learning algorithm is appropriate.

1.5 Conclusions

The traditional audit is retrospective and does not respond to current business needs in a timely manner. An audit is periodically conducted according to audit cycles. If identified, anomalies (errors and frauds) are often detected long after the associated events. For a variety of reasons, businesses still benefit from retroactive audits but modern analytics and computer technologies have allowed the performance of more than just backward assurance. They can obtain meaningful warnings concerning possible errors or irregularities. As such, the nature and timing of an audit should evolve to become more proactive.

Continuous auditing and continuous control monitoring create a contemporary audit that responds well to the real time economy. In order to incorporate a timely response mode within the traditional audit, it must be progressively automated. The three major methods for audit automation and a forward-looking audit are characterized as the following: the progressive audit, the predictive audit, and the preventive audit. The progressive audit is a way to initiate audit automation. Audit processes are formalized and automated where possible. Although these audits require a higher degree of automation, the progressive audit provides a good foundation for future instantiation of predictive and/or preventive audits. The predictive audit integrates a forward-looking analytical methodology into the traditional audit and allows auditors to estimate the possible outcome of transactions and accounts in advance. It can help management and auditors better plan their tasks and facilitate resource allocation. Nevertheless, there are controversial issues with the implementation of the PA that need to be considered. They are the following: quality of the prediction, auditor independence, materiality, level of scrutiny, and timing.

This chapter proposes a conceptual framework of the predictive audit with an implication that it can be applied in a number of business areas to improve performance and maintain competitive advantages. The next chapter illustrates an application of the predictive audit to a real business data set, specifically in a revenue cycle.

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Chapter 2: The Predictive Audit and the Application to a Transaction Status Prediction

2.1 Introduction

Auditing methods must change with business information processing technologies. Manual information processing (MIP) led to a set of accounting rules (Vasarhelyi, 2012) and auditing standards that minimized manual processing and record access resources. Methods such as FIFO and LIFO inventory recording, sampling, mail based confirmations, and historical costing of most assets made sense in the manual information processing environment. Vasarhelyi (2012) argues for a revamped model of reporting:

> *Disclosure at a substantially more disaggregate level (with transactions as atoms) requires a paradigm shift in accounting philosophy, yet in line with the discussion in this paper, it must be said that standards as we now know them are becoming progressively inadequate. Companies do not use them often to make decisions; they force one model onto diverse users with varying needs; they promote consolidated results in a way that obfuscates more meaningful sectorial results; and the information often arrives quite some time after it was needed for decision making*.

The advent of computers and the subsequent exponential decrease of the cost of storage and processing cycles have totally changed the framework for business measurement, assurance, and reporting. However, the natural tendency to resist change and the inflexibility in the standard setting process has created an anachronistic accounting and auditing environment. Prodded by the need to maintain competitive advantage, businesses have changed their approach by adopting computers, real-time customer interfaces, databases, OLAP (online analytical processing) cubes, and other technological support.

2.1.1 Real Time Economy Audit

Auditing is an essential part of the public market mechanisms. It is considered backwards oriented (retroactive audit) in a manual information-processing environment. Auditing focuses an “after-the-event” examination to verify the accuracy of the business measurement process within the concept of “fair representation.” This implies reporting without material error. Materiality is also an imprecise concept related to the decision-making framework of the investor. A new set of conceptualizations and their operationalization into accounting and assurance rules and procedures must be developed to cope with the real time economy (Economist, 2002; Vasarhelyi and Alles, 2005). In this environment, businesses operate continuously and companies extensively adopt integrated software and modern technologies (Vasarhelyi et al. 2010). Internal and external auditors have to adapt accordingly. The nature, timing, and extent of audit procedures are bound to change. In the traditional audit, auditors use sampling for data analyses or substantive tests and generalize results to a population. This is due to limited access, resources, and technology. Nevertheless, the role of auditors has changed over time. In addition to the financial statement audit, auditors have to evaluate internal controls, the viability of the company’s core business activities, and its operational processes. For example, this must be done to fulfill Sarbanes-Oxley (SOX) requirements or to issue a going concern opinion. As businesses become more complex, auditors face entirely different configurations of data (big data and cloud resident data) to be processed and analyzed. The emergence of continuous auditing (CA) and continuous control monitoring (CM) are direct responses to an increasingly rapid pace of business (Vasarhelyi et al., 2010). Auditors can perform audit testing more frequently and can recalculate and monitor an entire population in a more timely manner. CA is able to process and analyze an entire data set as opposed to only a subset or sample of that data. Transaction verification components in CA are able to filter exceptional transactions and bring them to the auditors' and managements' attention (Kogan et al, 2010).

Instead of a conventional audit with large amounts of paper documents, numerous manual testing procedures, and periodic reviews only, internal auditors now often utilize technology to support their work. Automated audit testing began in the 1970s with a few tailored audit procedures that accessed computer records. In 1980s, computer assisted audit techniques (CAATs) were deployed by auditors to complete substantive testing on large electronic data sets (Coderre, 2006). Vasarhelyi and Halper (1991) developed a continuous auditing and continuous control monitoring system to monitor a large paperless real-time billing system at AT&T Bell Laboratories. In 2000, Glover et al. (2000) surveyed software usage trends by internal auditors worldwide with 2,700 members of Institute of Internal Auditors (IIA). They found that the usage of software to extract and import data was rapidly increasing from the prior 1998 survey. Almost half of the respondents used software to find trends, create exception reports, detect fraud, and locate duplicate transactions. CA and CM changed the audit paradigm to more frequent reviews and automated audits. They also allow auditors to produce timelier reporting to support management decision-making. According to the audit maturity model

(Vasarhelyi et al., 2012), at a mature continuous audit stage, an audit organization will have benchmarking and a critical meta-control structure allowing auditors to perform audit by exception (Vasarhelyi and Halper, 1991). The system will provide alerts to auditors and management and ultimately may suspend processes when anomalies are found.

Applying technology to audit work will assist internal auditors in the modern age data rich information environments. Appropriately analyzing data can uncover interesting patterns, trends, and weaknesses in the data and underlying processes. The nature of auditing is changing from retroactive to predictive, moving to newly evolving audit dimensions. Teeter (2013) discusses three dimensions applicable to the audit:

- Level of Automation -> manual to automated
- Timing -> discrete vs continuous
- Location -> local vs remote

To which we add focus and procedure:

- Focus -> retroactive vs predictive
- Procedure -> the process the auditor may use

These dimensions are displayed in Figure 2.1 and provide a framework to understand the evolution of the audit. For example, ABC company’s traditional audit is purely manual, discrete (performed once a year), retroactive, local (always performed at the client location), and incorporates traditional processes such as confirmation, physical verification, and cutoffs.

On the other hand, by using the traditional audit approach and incorporating modern technology, the audit of the XYZ company is 80% automated and includes some continuous audit modules. In addition, auditors are primarily in contact with auditees remotely most of the year. The audit adapts the traditional (retroactive) focus and encompasses a hybrid set of audit procedures. Some of these procedures are required by Generally Accepted Auditing Standards (GAAS) and others are enabled by new information technology and analytic technologies.

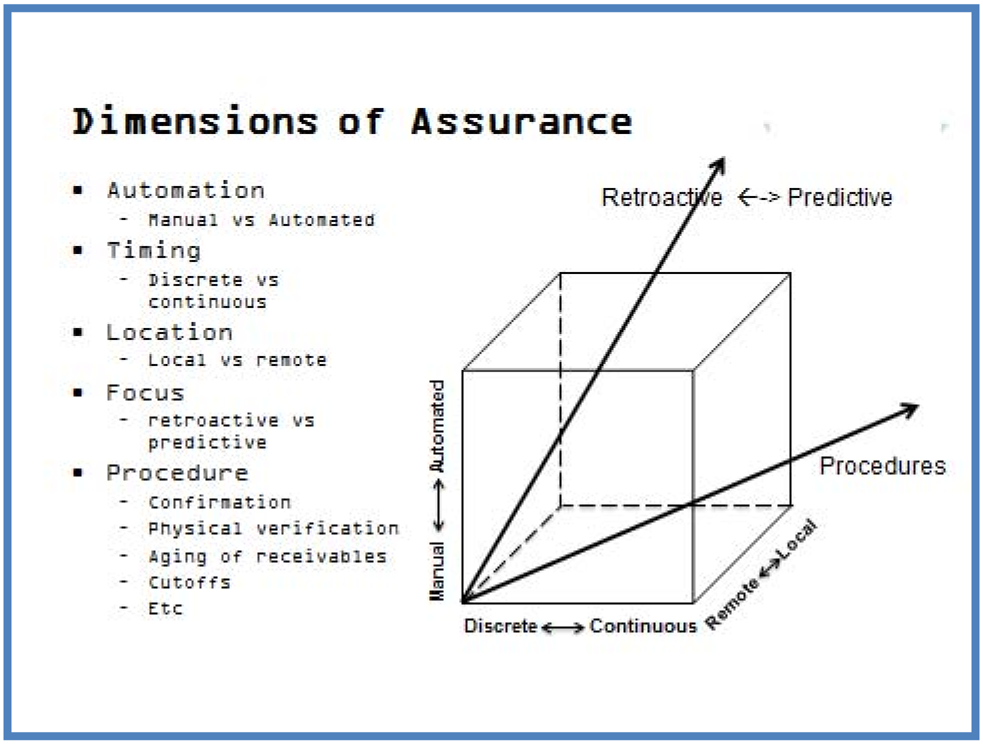

Figure 2.1 Dimensions of the Evolving Assurance Process

2.1.2 Predictive Audit

The focus dimension has been added as new analytical capabilities have emerged in business, such as forecasting (Engle and Yoo, 1987; West and Harrison, 1997), analytical decomposition (Serrano, 1998; Chen et al., 2006), data mining (Fayyad et al., 1996; Keim, 2002), modeling (Duffie, 2005; Chelley-Steeley, 2005), and continuity equations (Kogan et al., 2010). This allows for a closer to the event assurance function and the use of analytical prediction to simplify and improve the capabilities of the assurance function. The use of analytical methods to predict corporate reporting levels (balance sheet) and flows (income statement, funds flow) enhances and adds new dimensions to the assurance function. The actual quality of the predictions is contingent on a set of process and environmental variables among which we consider: the stability of the process, the number of related variables, the predictive methodology used, changes in the environment, etc.

Figure 2.2 illustrates the concept of audit focus. Traditional auditing inevitably has a backward focus and therefore exerts any reaction ex-post-facto. Although this provides numerous benefits, it is progressively losing its value with businesses and the economy becoming more real time. The ability to forecast (predict) measurement levels brings new capabilities to the assurance domain. For example, at the account or sub-account level, with the need to accelerate and simplify audit findings and to focus on higher risk areas, auditors can use analytical methods to predict account activity and allowable tolerance levels. If the corporate systems find “actuals” (Vasarhelyi and Halper, 1991) that are within the range of tolerable differences, auditors can deem the account as having acceptable risk and focus on more risky account prospects. This would be called a “predictive” audit.

Assuming more frequent assurance, the predictive audit is a look-forward process that could initially identify potential problems and incorporate a prevention mechanism. Kuenkaikaew and Vasarhelyi (2013) defined the predictive audit as:

> *The predictive audit (PA) is a methodology that incorporates the traditional audit (backward) with the forward looking audit procedure, so that auditors not only examine the past events and create adjustments based on changes or errors that have already occurred, but also perform the audit that could rapidly detect (predictive) or prevent (preventive) irregularities and anomalies or create adjustments in an ex-ante manner.*

2.1.3 Preventive Audit

At a transaction level, if screening models can be developed to identify faulty transactions (with a reasonable degree of confidence), why not block these transactions prior to their execution? Prevention is economically preferable to correction (Hwang and Aspinwall, 1996; King, 1999). Field and Swift (2012) mentioned that “Prevention is better than detection because detection is a waste – it costs money and doesn’t add value.”

Kim (2011) worked with an insurance company developing a forensic model to identify wire transfer payments that had a high probability of being defective and then provided this information to the internal audit staff for review. The variables used in the selection were all existing parameters of the actual transaction. If such a reliable fault prediction model can be developed, it may be highly desirable to block transactions with high fault characteristics from indiscriminant loading and have them examined prior to execution. This is very different from the traditional role of auditing and may be construed as reducing auditor independence. However, the benefits for data quality are obvious. This would be called a “preventive” audit that can be defined as a predictive audit with selective filtering.

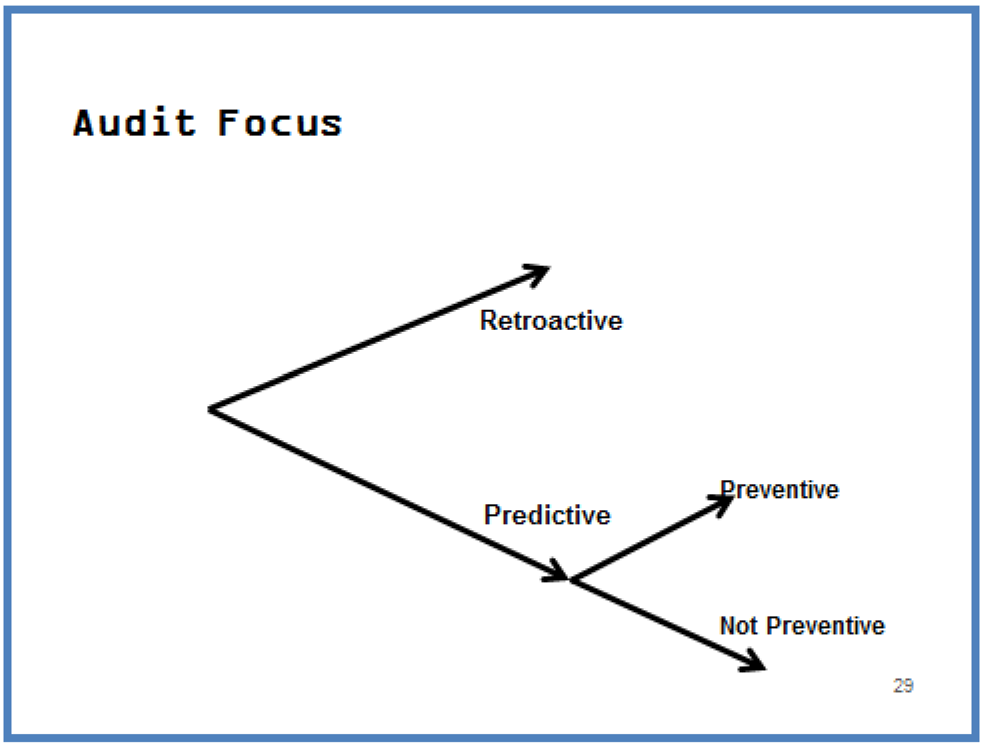

Figure 2.2 Audit Focus

The predictive audit, as discussed above, can help auditors and management to identify and suspend a problem before it spreads. It is better to look forward to identify a potential problem rather than to look back at historical data or past transactions. In this paper, several constructs are developed as indicators for predictive models to illustrate the application of a predictive audit. In addition, machine-learning techniques are used to predict sales transactions status and determine whether the transaction will be canceled. At the time of the sale, these indicators can identify expected outcomes of a particular sales transaction as it has the potential to be either a normal transaction or a problematic one.

2.1.4 Background

Timely auditing and monitoring can help a company to detect and resolve errors or anomalies before they cause problems. Kogan et al (2010) proposed a methodology of automatic error correction. This methodology can be used as a form of the preventive audit and minimize the delays incurred in operational processes while awaiting auditor review. If auditors and management are warned of suspicious activities in a timely manner, they can minimize consequent losses. Continuous auditing and monitoring processes will generate alerts of different types that can be distributed to stakeholders (such as internal auditors, managers, fraud managers, or regulatory authorities) when a significant deviation from the predicted baseline occurs. Vasarhelyi and Halper (1991) rated alarms at 4 levels, from insignificant to process stopping alarms. An alarm and warning system can be implemented in many business processes to assist auditors and management in monitoring the systems. Real-time alerts are a new form of audit evidence for the continuous audit. This paper illustrates the application of this feature in a front office operation-the sales function in a revenue cycle.

2.1.4.1 The Savings Product Setup

The ABC bank[1] has a savings product that requires a monthly payment. Customers can select their monthly payment and the number of payments. The denominations range from 5 to 50 USD. A customer accumulates the value of the monthly payments, collects interest, and is part of a lottery with cash prizes and other rewards. This money cannot be withdrawn before the contract ends. If this occurs, the bank will return money to the customer with a penalty. However, a customer can cancel, suspend, or reimburse a purchase if he is not satisfied with the product.

Sales are an important business process and one of the processes that have a high risk of fraud. Sales incentive programs are widespread in banks. Thus, employees may try to increase their sales as much as possible to get additional compensation or rewards. In this case, sales transactions can be canceled if customers are not satisfied with the product. These cancellations may be illegitimate if sales employees try to unethically boost sales with methods such as channel stuffing. Sales employees in this study get compensation based on their total number of sale transactions. Therefore, they may try to increase the number of sales transactions in several ways. For example, they may sell several low value monthly payments to the same customer to increase the number of sales performed in their performance plan and then allow customers to cancel those transactions.

The predictive audit is applied to predict a sales transaction status at the time of customer purchase. As soon as a customer purchases a product and the information is

[1] This example illustrates the analytic work performed at a multinational bank.

entered into the system, a model could predict the future status of that sales transaction (canceled or not canceled). Each sales transaction has different properties such as seller characteristics, buyer qualifications, and product information. Accordingly, by examining all relevant factors together, the system may issue an alarm to notify potential problematic transactions. Several machine learning classification techniques are used to create prediction models relative to their sale transaction.

2.1.5 Research Question Development

"Audit by exception" (Vasarhelyi and Halper, 1991) allows planning and execution of the assurance function based on continuous audit procedures and auditors can focus on specific areas that need attention. Generally, a system is considered to be functioning satisfactorily until an alarm arises (Vasarhelyi et al. 2004). AT&T Bell Laboratories implemented a continuous assurance system to monitor its billing system. If anomalies were detected (when the transaction exceeded a predefined acceptable threshold of performance), it triggers alarms that were delivered selectively to auditors and/or management (Vasarhelyi and Halper, 1991).

Fraud is a growing concern for companies and regulators. SAS 99[2] (AICPA, 2002) emphasizes its importance by requiring auditors to assess the risk of material misstatement due to fraud. The Enron case showed that untimely and opaque accounting fraud discovery mechanisms can cause the company and their external auditors to fail (Chaney and Philipich, 2002; Thomas, 2003; Lu, 2005; Alles et al., 2006). Vasarhelyi et

[2] Consideration of Fraud in a Financial Statement Audit

al. (2002) suggested that continuous auditing would have been able to detect the abnormal nature of Enron's special purpose entities and could have alerted auditors and management in a timelier more beneficial manner.

The ability to predict or estimate conditions or identify areas that are prone to fraud facilitates management's decision and auditors' work. Management and auditors can operate business, implement internal controls, and provide assurance on their systems in a preventive manner. Several studies (Eining et al., 1997, Bell et al., 2002, Dowling and Leech, 2007) examined how decision support systems facilitate audit work such as client risk assessment (Bedard and Graham, 2002), internal controls evaluation (Murphy and Yetma, 1996), and analytical review explanation (Mueller and Anderson, 2002). For example, Bell et al. (2002) used a procedure to evaluate client risk based on several factors to aid on client acceptance. Management and auditors can use the predicted results to consider appropriate action (e.g. not accept the client). Most of these papers examined data in an aggregate view. However, most papers do not study data at a transaction level. As such, in this paper, predictive models are created and used to forecast business outcomes at a transaction level. Considering a number of transaction attributes, the model will predict a potential result of a transaction. The result of the predictive models could warn management to pay attention to those transactions that have negative results. This leads to the research question:

Research question: Which prediction model(s) will more accurately forecast business sales transaction cancellations?

Prediction models using machine-learning techniques are proposed. Each model has advantages and disadvantages that have to be weighed. The accuracy of the prediction result is one of the most important factors in considering the integrity of the model, as precise forecasts benefit both auditor and management decisions.

2.2 Literature Review

2.2.1 Sales Forecast Studies

Sales forecasting is critical for business planning, strategy, supply chain, and many other business processes. A number of prior studies examined various perspectives about sales forecasting using alternate approaches. The classic sales forecast model proposed by Winters (1960) introduce the moving average exponential model with a seasonal and trend smoothing technique and specified the desired characteristics of the forecast to be quick, cheap, and easy. Thus, the model includes only past sales history and does not include any external factors.

Current research tends to concentrate on developing new models and finding more efficient algorithms for a sales forecast. Morwitz and Schmittlein (1992) use segmentation methods to improve the accuracy of sales forecasting based on purchase intention theory. They segment heterogeneous individual groups into homogeneous subgroups. This assumes that consumers are heterogeneous in purchase intention. The segmentation methods used are a priori, CART, discriminant analysis, and k-mean cluster analysis. The results show that after segmenting consumers into similar groups, the average forecast errors are reduced and more accurate sales forecasts are obtained. When using discriminant analysis as a segmentation method, the average percentage in forecast error is most reduced.

Cadez et al. (2001) propose probabilistic modeling to make inferences about individual behavior (profile) given transaction data from a large data set of individuals over a period of time. The behavior is focused on the likelihood that an individual would purchase a particular item and a model-based approach is applied to the profiling problem. A flexible probabilistic mixture model for transactions is proposed and compared with baseline models based on raw or adjusted histogram techniques. The data are separated into two time periods for training and testing. The log-probability (logp score) of the transactions is used to evaluate the predictive power of the models. Finally, customers with relatively high logp scores per item are found to be the most predictable ones. This score can also be used to identify interesting and unusual customer purchasing behavior.

Chang and Wang (2006) employ a fuzzy back-propagation network (FBPN) to forecast monthly sales in the Printed Circuit Board (PCB) industry. FBPN is the integration of fuzzy logic and artificial neural network algorithms. A stepwise regression analysis and fuzzy Delphi method are applied to select variables related to the sales forecast from three domains: market demand, macroeconomics, and industrial production. The authors found that both stepwise regression and fuzzy Delphi methods provide better performance when they include a tendency factor and the fuzzy Delphi technique outperforms the stepwise method. Finally, FBPN is compared with three other methods, which are Grey forecasting, multiple regression analysis, and Back-propagation network. They conclude that among these four models, FBPN is the best model with 97.61% prediction accuracy.

Typically, forecasting is based on a time-series or historical data, where it is expected that new observations will behave similarly. Likewise, this study uses historical (Fisher and Raman, 1996) sales information of employees for the prediction and the results are used to redefine (Lee et al, 2003) the analytical model. Fisher and Raman (1996) use historical data of previous products combined with expert opinions to perform sales predictions. They propose a new model to estimate demand densities of fashion skiwear. New and unique products like songs, movies, and books usually do not have past sales information. In this case, the data of diverse prior products could be used for preliminary sales forecasting and then update the forecast later when data for these products becomes available. Lee et al (2003) use a hierarchical Bayesian model of the logistic diffusion model to forecast prelaunch weekly sales of individual song albums and updated post launch when sales data became available using the sampling/importance Bayesian resampling algorithm. In the hierarchy, the first level of a sales prediction model is at the album level and the second level prediction is at the underlying characteristics of artists and albums. The study illustrates that the prelaunch of the album forecast with album characteristics has a better result than the one without album characteristics and the forecast result is significantly improved after the first week of sales with the updating data applied to the model.

2.2.2 Sales Forecast with Machine Learning Techniques

Machine learning is a computerized analytic technique used to learn from sample data or historical information and utilizes discovered patterns to predict new data. With its instrumental features, this technique is widely used in sales forecast studies. Three machine learning algorithms are used in this study. They are logistic regression (Garber et al., 2004), decision tree (Thomassey and Fiordaliso, 2006), and support vector machine (Bruhl et al., 2009).

Garber et al. (2004) study the success and failure of newly launched products. While it was difficult to obtain enough sales data for a new product to enable reliable sales prediction, the authors include spatial data to render a better prediction. This spatial information was available since the product was launched and sold. The cross entropy is calculated as a measure and logistic regression is run to classify the cases. When plotting the graphs of entropy, a successful product and a failed one have different patterns. As a result, the model successfully predicts success or failure in 14 out of 16 products. Fashion product demand is challenging because of short product lifetimes, long lead times, fluctuating demand, and lack of historical demand information.

Thomassey and Fiordaliso (2006) develop a hybrid model based on clustering and decision trees to forecast mid-term sales for a textile industry. The prediction is processed in two stages. First, clustering is applied to produce sales profiles. Next, each new product is assigned to a sales profile by decision tree algorithm. This methodology uses sales behaviors of past products to identify a possible pattern of a new product, which has no historical data. Using k-means clustering, a number of clusters are set between 2 and

20. Then, a decision tree (C4.5) is applied to each different set of cluster results and the absolute error is computed to select the number of clusters that produce the most accurate classification.

Data representing newly registered automobiles in Germany from 1992-2007 are used to test the sales forecast model by Bruhl et al. (2009). Yearly, monthly, and quarterly data are compared using multiple linear regression (MLR) for the linear trend estimation, while support vector machine (SVM) is used for the non-linear trend estimation. The results show that a non-linear (SVM) model outperforms the linear model and quarterly data have the lowest prediction error. However, there are some difficulties for the yearly and monthly models. The problems in the yearly model are a very small data set and information content. The problems for the monthly model are that most of the exogenous variables used in the model are not collected monthly. As a result, substitute or average values have to be used.

A number of studies have been performed in the area of sales forecasting. However, in the auditing field, no studies appear to exist that predict the status of the sale, especially at the transaction level. Moreover, the main objective of the current study is not to predict the future income of a company but to predict the sales transaction status and use the result as an alarm for internal auditors to further investigate the irregularity of the sales transactions and employee performance.

2.3 Data

The data is from one of the largest banks in the world consisting of sales related information, which includes sales and cancellation transactions for a special savings product and employee sales records. The data sets include transactions occurring during November 2009 to April 2010. These transactions are from all branches country-wide. The sales transaction table has 607,189 records. There are 40,463 canceled transactions, which are considered to be 6.66 percent of total sales transactions. There are also 566,753 non-canceled transactions, which are considered to be 93.34 percent of the total transactions. The number of canceled transactions is very small compared to the total number of sales transactions. This is challenging for model development, as it is analogous to fraud detection and fraud transactions are very rare and difficult to identify.

Even though the total value of special savings account cancellation transactions during the 6 month period are only 6.66% of total transactions, the preliminary analysis of the cancellation summary by date shows that they are increasing over the period from approximately 110 transactions per day at the beginning of the period to 470 transactions per day at the end of the period (Figure 2.3).

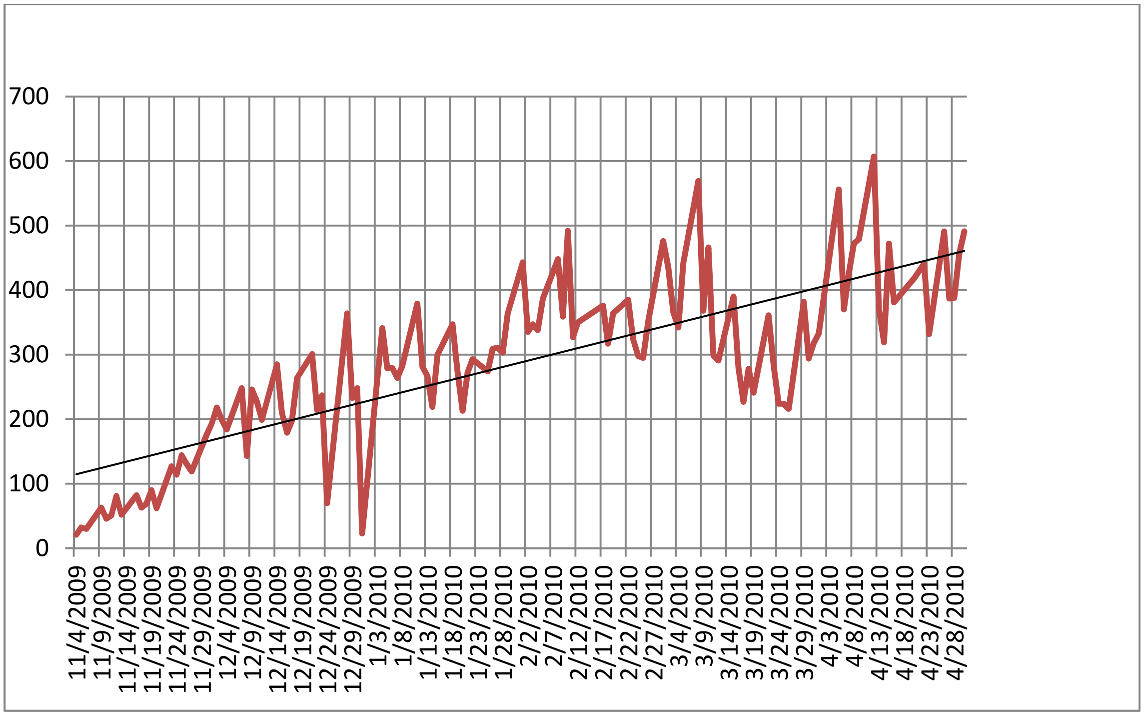

Figure 2.3 Special Saving Account Cancellation Transaction Summary by Date

2.4 Model Development

Channel stuffing is a practice of inflating the sales by distributing products to the distributors above their demand. This inflates sales and accounts receivable. Normally, the company will offer long-term credit or long return periods to the distributors to make them accept the large quantity of goods. Analogously, in this study, employees push sales to increase the number of transactions and allow customers to later cancel and get reimbursed for those sales.

While building the model, the important criterion to selecting attributes is that they all have to be known at the time of prediction. For example, a status of the current sales transaction is not known at the time a customer makes a purchase. This is the outcome that will be predicted by the model. Thus, the current sales transaction and its status cannot be included in the prediction variables. This is unlike the value and number of installments of the current transaction, which are known at the time of sale. Other attributes that are available at the time of purchase are past performance of the sales employees (e.g. total sales transactions sold in the past and the total sales transactions with complaint for each sales staff). The attributes selected as variables for prediction follow the criterion mentioned above and they are attributes that available in the data set. The variables are as follows:

1. Number of sales cancellations by employee
2. Number of reimbursements by employee
3. Number of matched sales by employee
4. Number of sales to inactive accounts by employee
5. Number of sales with complaints by employee
6. Number of sales to another employee
7. Number of sales transactions by employee

Most of the variables are related to the historical sales information (Fisher and Raman, 1996) of each employee. In the data preprocessing, these variables are normalized as a ratio to avoid bias and to make data comparable. Several algorithms are applied to the data set to predict the status of each sales transaction. Only algorithms suitable for nominal or categorical outcome are selected. These include classification trees (Chan and Stolfo, 1998; Shen et al., 2007), logistic regression (Yeh and Lien, 2009; Shen et al., 2007), and support vector machines (Joachims 1998; Tong and Koller, 2002). The data are split into training and testing sets for model validation. The training set is the first 4 months of data, while the testing set is the last 2 months of data. The model is a time-dependent measure, which means that the order, date, and time of the transactions matter. Past performance of an employee affects the outcome of the transaction. Value of a new transaction's variables is calculated based on the previous transactions.

2.5 Results and Analysis

To compare the results among algorithms, several measurements are considered. They are an accuracy rate, a true positive rate, and a false positive rate (Junker et al., 1999; Alpaydin, 2004; Davis and Goadrich, 2006). A true positive rate (TP) indicates that the algorithm predicts the right class. This study is interested in predicting canceled transactions, which is analogous to suspicious transactions. As such, a true positive rate here is to measuring how well the algorithm correctly classified canceled transactions. A false positive rate (FP) specifies that the algorithm predicts a normal transaction as a suspicious transaction. In this case, it will be considered an additional task for auditors to investigate these transactions. Figure 2.4 shows an illustration of the true positive rate and false positive rate from the predictive results for canceled transactions.

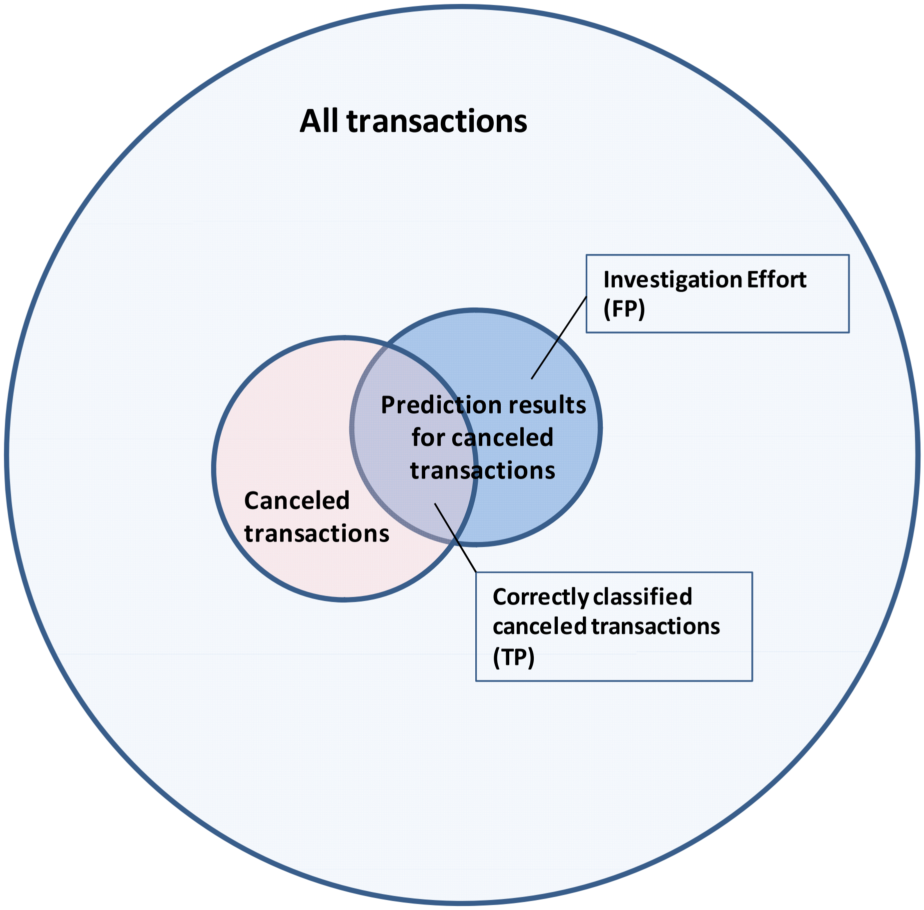

Figure 2.4 The Illustration of True Positive Rate and False Positive Rate (Adapted from Nyce, 2007)

Additionally, the results of the models are expected to assist auditors' decision for examination, investigation, or audi planning on the level of scrutiny (Kuenkaikaew and Vasarhelyi, 2013). Among the others, a cost-benefit approach is a widely accepted criterion. Chan and Stolfo (1998) study the affect of the overhead cost[3] and data distribution to the classification of illegitimate credit card transactions. Four machine - learning algorithms [C4.5 (Thomassey and Fiordaliso, 2006), CART (Withrow et al., 2009), RIPPER (Cohen, 1995), and BAYES (Clark and Niblett, 1989)] are used in the

[3] Unit cost of investigation

experiments. There is an overhead or cost for each potential fraudulent investigation. When the overhead is small, the company prefers to investigate more transactions. They could tolerate more false alarms. However, if the overhead is large, the company tends to accept a higher false negative rate (misses) to reduce the cost of investigation. In addition, the authors create different data combinations, which have diverse fraud distributions such as 20:80, 30:70, 40:60, and 50:50. They find that the 50:50 distribution generates the best cost saving result for any of the overhead amount.

In terms of the accuracy of the models, the first run of the analysis gave a very high percentage of correctly classified instances at more than 90 percent for all algorithms. This is a signal of abnormality because the results are too good for all algorithms. Thus, the data was re-evaluated and found that it suffered from the imbalanced data problem. From a total of 607,189 records, 93.34 percent of the total records are non-canceled sales transactions, while 6.66 percent of the total records are canceled sales transactions. The data set has voluminous non-canceled records compared to canceled records.

Generally, there are two approaches to deal with the imbalanced data problem. They are a cost-sensitive approach and a sampling approach. A cost-sensitive approach is used to modify the relative cost of the data by making both canceled and non-canceled transactions more reasonably weighted by adding a penalty for incorrectly classifying the result (Japkowicz and Stephen, 2002; Chawla et al., 2004; Tan et al., 2005). Another approach is to select a balanced sample by selecting the same amount of canceled and non-canceled transactions. In this case, both approaches with different results were attempted.

2.5.1 Cost Sensitive Approach

In a cost-sensitive approach, a relative cost is assigned to a smaller portion of the data. This represents canceled sales transactions, as these are transactions of interest. This means that the cost of misclassifying a canceled transaction will be more than that of misclassifying a non-canceled one (Japkowicz and Stephen, 2002). There is no specific method to calculate the correct weight or cost assigned to the data but several numbers could be attempted to find the best result. The first weighted value attempted is 1:10. As stated above, a 1:10 ratio implies that misclassifying a canceled transaction will cost 10 times more than that of misclassifying a non-canceled one.

With a cost sensitive approach, the result of the classification tree (J48) is 67.69 percent correctly classified instances. After adjusting the cost, the logistic regression algorithm result is 76.67 percent correctly classified instances. This is better than the J48 algorithm result. The support vector machine algorithm presents the best accuracy among all three algorithms. The model correctly classifies instances for 89.17 percent. Other important measurements are a true positive rate and a false positive rate. True positive rates and false positive rates for each algorithm are as follows: True positive rates are J48 (0.41), logistic regression (0.40), and support vector machine (0.21) and false positive rates are J48 (0.31), logistic regression (0.22), and support vector machine (0.09).

The ROC area is another measurement for model evaluation. The model that performs better than a random guess would have the ROC area higher than 0.5 (Tan et al, 2005). In Table 2.1, all three models have the ROC area higher than 0.5. The logistic regression algorithm has the highest ROC area rate of 0.63, while J48 and support vector machine algorithms have ROC area rates of 0.55 and 0.56 respectively. The summary results of the cost sensitive approach for all algorithms with 1:10 ratio are shown in Table 2.1.

Table 2.1 Models Comparison of Cost Sensitive Approach with 1:10 Ratio

Algorithm/ Measurement	**Accuracy Rate (%)**	**Correctly Classify Canceled Transaction (TP Rate)**	**Investigation Effort (FP Rate)**	**ROC Area**
J48	67.69	0.41	0.31	0.55
Logistic	76.67	0.40	0.22	0.63
Support vector machine	89.17	0.21	0.09	0.56

Practically, a logistic regression is the simplest algorithm among the three algorithms and is less time and resource consuming compared to the other two algorithms. On the contrary, a support vector machine algorithm is the most complex algorithm and requires a large amount of computational resources. Therefore, machine - learning methods that are selected for additional ratio analyses are logistic regression and classification tree (J48) algorithms. According to Table 2.1, the performance of each algorithm in this study is compared and shown in Table 2.2.

Table 2.2 Comparison of Algorithms' Performance

Performance	**Decision tree (J48)**	**Logistic regression**	**Support vector machine**
Computationally intensive	Average	Lowest	Highest
Accuracy rate	Lowest	Average	Highest
Correctly classify canceled transaction	Highest	Average	Lowest
Investigation effort	Highest	Average	Lowest
ROC area	Average	Highest	Average

In addition to a 1:10 ratio, several different cost sensitive ratios are attempted for a comparison purpose. Those ratios are 1:8, 1:9, 1:11 and 1:12. Table 2.3 shows a logistic regression algorithm with different ratios. A classification tree (J48) algorithm with different ratios is shown in Table 2.4.

The accuracy rates of the logistic regression algorithm are as follows: 90.80 (1:8), 85.55 (1:9), 76.67 (1:10), 63.24 (1:11), and 47.55 (1:12). True positive rates are as follows: 0.18 (1:8), 0.27 (1:9), 0.40 (1:10), 0.55 (1:11), and 0.70 (1:12). False positive rates are as follows: 0.07 (1:8), 0.12 (1:9) 0.22 (1:10), 0.36 (1:11), and 0.53 (1:12). All ratios have the same ROC area of 0.63.

The accuracy rates of the classification tree are: 76.36 (1:8), 75.56 (1:9), 67.69 (1:10), 57.76 (1:11), and 54.16 (1:12). True positive rates are as follows: 0.30 (1:8), 0.32

(1:9), 0.41 (1:10), 0.53 (1:11), and 0.57 (1:12). False positive rates are as follows: 0.22 (1:8), 0.23 (1:9), 0.31 (1:10), 0.42 (1:11), and 0.46 (1:12). All ratios have the same ROC area of 0.55.

Table 2.3 A Cost Sensitive Approach Using Logistic Regression Algorithm with Different Ratios

Ratio/ Measurement	Accuracy Rate (%)	Correctly Classify Canceled Transaction (TP Rate)	Investigation Effort (FP Rate)	ROC Area
1:8	90.80	0.18	0.07	0.63
1:9	85.55	0.27	0.12	0.63
1:10	76.67	0.40	0.22	0.63
1:11	63.24	0.55	0.36	0.63
1:12	47.55	0.70	0.53	0.63

Table 2.4 A Cost Sensitive Approach Using Classification Tree (J48) Algorithm with Different Ratios

Ratio/ Measurement	**Accuracy Rate (%)**	**Correctly Classify Canceled Transaction (TP Rate)**	**Investigation Effort (FP Rate)**	**ROC Area**
1:8	76.36	0.30	0.22	0.55
1:9	75.56	0.32	0.23	0.55
1:10	67.69	0.41	0.31	0.55
1:11	57.76	0.53	0.42	0.55
1:12	54.16	0.57	0.46	0.55

The predictive results in Table 2.3 and Table 2.4 show different outcomes for each ratio and algorithm. However, they are in a similar pattern. While a ratio is increased, an accuracy rate is decreased and a true positive rate and a false positive rate are increased. The accuracy rate is decreased because more non-canceled transactions are predicted as canceled transactions. In addition, the cost for wrongly predicted canceled transactions as non-canceled transactions is higher when a ratio is increased. Even though the accuracy rates are decreased, the model performs better in predicting canceled transactions, which is the objective of this study. However, there must be a trade off with a lower true positive rate. This means that more non-canceled transactions were predicted as canceled transactions.

2.5.2 Sampling Approach

Another approach to deal with the imbalanced data problem is to select a balanced sample from the data set. There are two sampling methods that can be used for this approach. They are the oversampling and undersampling methods. In an oversampling method, minority transactions (such as suspicious transactions) will be repeated until they result in the same number as majority transactions (such as normal transactions). This sampling method is usually preferred when the dataset is very small. For an under-sampling method, some majority transactions will be omitted until they have the same number as minority transactions (Tan et al, 2005). In this study, an under-sampling method is selected because the dataset is considerably large.

The canceled and non-canceled sales transactions are randomly selected from the population in the same volume. Machine learning algorithms are applied with a 2-fold cross-validation. In the first run, a classification tree (J48) algorithm correctly classifies instances at 63.34 percent. A logistic regression algorithm correctly classifies instances at 69.92 percent. A support vector machine correctly classifies instances at 79.17 percent. True positive rates are as follows: J48 (0.64), logistic regression (0.71), and support vector machine (0.82). False positive rates are as follows: J48 (0.43), logistic regression (0.53), and support vector machine (0.65). The ROC area rates are as follows: J48 (0.63), logistic regression (0.64), and support vector machine (0.58). The summary results of the first run of a sampling data approach of all algorithms are shown in Table 2.5.

Table 2.5 Model Comparison of Sampling Approach: First Run

Algorithm/ Measurement	**Accuracy Rate (%)**	**Correctly Classify Canceled Transaction (TP Rate)**	**Investigation Effort (FP Rate)**	**ROC Area**
J48	63.34	0.64	0.43	0.63
Logistic	69.92	0.71	0.53	0.64
Support vector machine	79.17	0.82	0.65	0.58

In the second run, a classification tree (J48) algorithm correctly classifies instances at 59.72 percent. A logistic regression algorithm correctly classifies instances at 69.84 percent. A support vector machine correctly classifies instances at 79.65 percent. True positive rates are as follows: J48 (0.59), logistic regression (0.71), and support vector machine (0.83). False positive rates are as follows: J48 (0.37), logistic regression (0.49), and support vector machine (0.63). The ROC area rates are as follows: J48 (0.66), logistic regression (0.66), and support vector machine (0.60). The summary results of the second run of a sampling data approach of all algorithms are shown in Table 2.6.

Table 2.6 Model Comparison of Sampling Approach: Second Run

Algorithm/ Measurement	**Accuracy Rate (%)**	**Correctly Classify Canceled Transaction (TP Rate)**	**Investigation Effort (FP Rate)**	**ROC Area**
J48	59.72	0.59	0.37	0.66
Logistic	69.84	0.71	0.49	0.66
Support vector machine	79.65	0.83	0.63	0.60

Finally, the averages of the first and the second runs are calculated to find the final result of a sampling approach. The result shows that a classification tree (J48) algorithm correctly classifies instances at 61.53 percent. A logistic regression algorithm correctly classifies instances at 69.88 percent. A support vector machine correctly classifies instances at 79.41 percent. True positive rates are as follows: J48 (0.61), logistic regression (0.71), and support vector machine (0.82). False positive rates are as follows: J48 (0.40), logistic regression (0.51), and support vector machine (0.64). The ROC area rates are as follows: J48 (0.64), logistic regression (0.65), and support vector machine (0.59). The summary results of sampling data approach of all algorithms are shown in Table 2.7.

Table 2.7 Model Comparison of Sampling Approach: Results

Algorithm/ Measurement	**Accuracy Rate (%)**	**Correctly Classify Canceled Transaction (TP Rate)**	**Investigation Effort (FP Rate)**	**ROC Area**
J48	61.53	0.61	0.40	0.64
Logistic	69.88	0.71	0.51	0.65
Support vector machine	79.41	0.82	0.64	0.59

This study aims to predict the status of each sales transaction and whether it has a high probability of being canceled. While prior studies use aggregate data, such as monthly data in Garber et al. (2004) and yearly, quarterly, and monthly data in Bruhl et al. (2009), the sales data used here is disaggregate data at the transaction level. The main variables of the forecasting models are past performance of sales employees (Fisher and Raman, 1996), and the models automatically update when new sales information arrives (Lee et al, 2003). However, none of the prior literature explores sales forecast in the auditing area. Hence, this study contributes to the auditing and continuous auditing literature by illustrating the application of the predictive audit, using machine-learning techniques, to sales forecast for internal auditors.

The results show that each machine learning technique has both pros and cons (Table 2.2). For example, from Table 2.1, a support vector machine algorithm has the highest accuracy rate, the lowest true positive, and the lowest false positive rate. The low true positive rate indicates that the model does not perform well in predicting canceled transactions. However, the low false positive rate means that there are a small number of normal transactions that were predicted as canceled transactions. As such, auditors do not have to spend too much effort to investigate flagged transactions. Nevertheless, there is a higher chance to miss suspicious transactions. A logistic regression algorithm has lower accuracy rate, higher true positive rate, and higher false positive rate compared with those of a support vector machine algorithm. Thus, a logistic regression algorithm predicts canceled transactions better than a support vector machine algorithm. However, auditors may have to spend more effort examining those transactions. There is a tradeoff between the costs and benefits of the investigation of flagged transactions. This is consistent with the literature (Chan and Stolfo, 1998) asserting that the company would rather investigate more transactions when the cost of examination low. If auditors prefer not to investigate too many transactions to avoid process interruption or want to control the budget, they can select the prediction method that has a lower false positive rate. However, if auditors are more concerned with the problematic transaction, they can choose the model that has a higher true positive rate.

2.5.3 Additional Variables

In the second phase of the study, the main sales transaction table is merged with an additional table that provides information about sales characteristics. After the tables are merged, the data set has more meaningful attributes that could be used in the analysis. Consequently, more variables are selected and added to the models with the anticipation that they will improve the predictability of the models. All of the additional variables are nominal variables. Therefore, they have to be coded into a format that can be used in the models. Table 2.8 shows a list of additional variables that could be used in the analysis.

Table 2.8 List of Additional Variables

Variable	**Definition**	**Possible Values**
C1-4	Contract Status	0, 1, 21, 30, 31
V1-5	Unit value of the product	20, 35, 50, 60, 500, 1000
VP1-5	Unit value of the product x total units purchase	500, 1000, 1200, 2100, 3000, 3600
Day1-4	Day of the week	Monday, Tuesday, Wednesday, Thursday, Friday
D1-6	Branch area	2, 3, 4, 5, 6, 43, 99
S1-2	Product segment	3, 4, L
z_TIP_CLI	Type of customer	J= company, F= person
P1-5	Product description	PIC, mini PIC, PIC Ano Novo, PIC Da Selecao, Super PIC, Super PIC Ano N

At this stage, the candidate variables for the analysis are additional variables in Table 2.8 and the seven original variables that were used in the previous analyses. To consider which variables should be included in the model, a stepwise regression is employed. Table 2.9 shows the result of a stepwise regression selection. A total of 14 variables are selected at the 99.99 percent confidence level.

Table 2.9 A Summary of Stepwise Selection Result

Summary of Stepwise Selection							
Step	**Effect**		**DF**	**Number In**	**Score Chi-Square**	**Wald Chi-Square**	**Pr > ChiSq**
	Entered	**Removed**					
1	**C2**		1	1	156490.506		<.0001
2	**C3**		1	2	68111.3648		<.0001
3	**C4**		1	3	16541.4478		<.0001
4	**V2**		1	4	9383.2596		<.0001
5	**D_CANC_RA**		1	5	6033.4828		<.0001
6	**P1**		1	6	485.5239		<.0001
7	**C1**		1	7	470.3410		<.0001
8	**V1**		1	8	374.6816		<.0001
9	**D_CASA_RA**		1	9	252.6947		<.0001
10	**D4**		1	10	238.7115		<.0001
11	**z_TIP_CLI**		1	11	80.4279		<.0001
12	**P5**		1	12	69.9915		<.0001
13	**D3**		1	13	44.7385		<.0001
14	**P2**		1	14	25.6783		<.0001
15	**D1**		1	15	11.8549		0.0006

Summary of Stepwise Selection							
Step	**Effect Entered**	**Removed**	**DF**	**Number In**	**Score Chi-Square**	**Wald Chi-Square**	**Pr > ChiSq**
16	**D2**		1	16	14.1727		0.0002
17	**S2**		1	17	7.0731		0.0078
18	**D5**		1	18	6.1156		0.0134
19	**D_FUNC_RA**		1	19	1.9388		0.1638
20	**Day1**		1	20	1.6018		0.2056
21	**S1**		1	21	1.2989		0.2544

Variables that are selected by a stepwise regression are as follows:

1. Contract status (C1-4)
2. Unit value of the product (V1-5)
3. Number of sales cancellations by employee (D_CANC_RA)
4. Product description (P1-5)
5. Number of sales to another employee (D_CASA_RA)
6. Branch area (D1-6)
7. Type of customer (z_TIP_CLI)

Using the above variables, predictive models are created. Machine learning algorithms used to create predictive models in this stage are a logistic regression algorithm and a decision tree (J48) algorithm. These two models were chosen because their performances were reasonable in the previous analyses. A cost-sensitive approach is selected to deal with imbalanced data. Different ratios are attempted to determine the possible results for each algorithm. The ratios are 1:10, 1:12, 1:14, 1:16, and 1:18. The results of a cost sensitive approach using a logistic regression algorithm are shown in Table 2.10 and the results of a cost sensitive approach using decision tree algorithm are shown in Table 2.11.

The accuracy rates of the logistic regression algorithm are as follows: 96.61 (1:8), 96.05 (1:9), 95.21 (1:10), 94.00 (1:11), and 92.31 (1:12). The true positive rates are as follows: 0.63 (1:8), 0.63 (1:9), 0.64 (1:10), 0.65 (1:11), and 0.67 (1:12). The false positive rates are as follows: 0.02 (1:8), 0.03 (1:9), 0.04 (1:10), 0.05 (1:11), and 0.07 (1:12). All ratios have the same ROC area at 0.90.

The accuracy rates of the classification trees are as follows: 90.41 (1:8), 89.04 (1:9), 84.06 (1:10), 82.15 (1:11), and 77.85(1:12). The true positive rates are as follows: 0.65 (1:8), 0.66 (1:9), 0.69 (1:10), 0.70 (1:11), and 0.72 (1:12). The false positive rates are as follows: 0.09 (1:8), 0.10 (1:9), 0.15 (1:10), 0.17 (1:11), and 0.22 (1:12). All ratios have the same ROC area at 0.84.

Table 2.10 Cost Sensitive Approach Using Logistic Regression Algorithm with Additional Variables

Ratio/ Measurement	Accuracy Rate (%)	Correctly Classify Canceled Transaction (TP Rate)	Investigation Effort (FP Rate)	ROC Area
1:8	96.61	0.63	0.02	0.90
1:9	96.05	0.63	0.03	0.90
1:10	95.21	0.64	0.04	0.90
1:11	94.00	0.65	0.05	0.90
1:12	92.31	0.67	0.07	0.90

Table 2.11 Cost Sensitive Approach Using Decision Tree (J48) Algorithm with Additional Variables

Ratio/ Measurement	Accuracy Rate (%)	Correctly Classify Canceled Transaction (TP Rate)	Investigation Effort (FP Rate)	ROC Area
1:8	90.41	0.65	0.09	0.84
1:9	89.04	0.66	0.10	0.84
1:10	84.06	0.69	0.15	0.84
1:11	82.15	0.70	0.17	0.84
1:12	77.85	0.72	0.22	0.84

The results of the models with additional variables are significantly improved from the original models with seven variables in the previous analysis. Using the logistic regression algorithm with 1:10 ratio, an accuracy rate is increased from 76.67 percent (Table 2.1) to 95.21 percent (Table 2.9). Other measurements are as follows: a true positive rate is increased from 0.40 to 0.64, a false positive rate is decreased from 0.22 to 0.04, and an ROC area is increased from 0.63 to 0.90. It could be concluded that additional variables considerably improve the performance of the predictive models.

With the seven available variables in the first analysis, a status of sales transactions by employee can be predicted before a customer actually cancels the transaction. To consider whether there is a fake sale, internal auditors could further investigate transactions that were flagged as having a high potential to be canceled using past performance or historical information of an employee who sells that transaction. Then the compensation for that transaction can be blocked or suspended.

When additional relevant information becomes available, it can be included in the model to improve predictability. In this analysis, additional attributes relate to transaction characteristics. With all information, a sales transaction status can be estimated before an employee makes a sale. Therefore, management will avoid approval of suspicious transactions.

2.6 Conclusion

Continuous auditing and continuous monitoring are direct responses to real time business needs. Timely review and notification could call the attention of auditors and management to a problem. The ideal situation is that a problem is identified and automatically resolved as soon as possible, preventing it from permeating into other processes. The predictive audit, based on CA, allows auditors to look forward to estimate possible results of account activities and possible anomalies.

This paper illustrates the application of the predictive audit that could monitor controls and detail transactions on an ex-ante basis. The sales activities and the compensation of sales employees, which is based on the sales transactions, are front office processes that have inherent risk. The volume of sales is large and continuous by nature. Prediction models using machine-learning techniques are created to predict the status of each sales transaction. The results could alert auditors for possible fraud or irregularities of transactions. Nonetheless, the outcomes of the predictive audit may vary depending on the analytic techniques and weighted ratios used in the models. Auditors can select a method that suits their needs, whether they are more concerned with exceptional transactions or the budget. There is a trade-off between the costs and benefits of investigating the results. Furthermore, assuming that there is high accuracy of prediction and the economic tradeoffs of the situation are conclusive, the firm may use the model to block the execution of the transaction. This is known as a preventive audit.

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Chapter 3: The Predictive Audit and the Preventive Audit for Credit Card Sales Transactions

3.1 Introduction

Technology in auditing and accounting accelerates and vastly facilitates a number of auditing tasks. Information is being processed instantly or close to real time. Unfortunately, accounting rules and auditing standards are not keeping pace with these changes. Most audit work relies on manual procedures and auditors must verify evidence subsequent to the occurrence of transactions. The traditional audit perspective is backwards and audit reports are not issued in time for important decision making (Vasarhelyi, 2012). For that reason, companies and audit firms are moving towards an audit which occurs closer to the event. Continuous auditing (CA) has the capability to capture transactions and analyze them at a disaggregate level on a real-time basis (Alles et al., 2006). It incorporates technology to support audit tasks and enables auditors to provide assurance simultaneously with or soon after the occurrence of events (CICA/AICPA 1999).

In a data rich environment, continuous auditing and advanced analytic technologies allow auditors to perform data analytics to uncover interesting patterns, trends, and exceptions. Big data is now allowing a whole new set of analytic methods. The audit scope can be expanded to cover the whole population as opposed to only the sample data. In addition, auditing occurs close to the event or even on a real-time basis. All these evolutions could affect traditional audit perspectives. The nature of the traditional audit is backwards or retroactive, while a new audit focus is forward looking or predictive (Kuenkaikaew and Vasarhelyi, 2013). In response to these changes, the predictive audit arises from continuous auditing and incorporates intense predictive analytics. The predictive audit allows auditors to identify, in advance, possible exceptions or high-risk transactions that may occur. This allows auditors to plan and adjust their audit schedule accordingly. This paper applies predictive analytics in auditing, to a real business data set to identify irregular transactions which are infrequent. This is known as the predictive audit. The results of the predictive audit can be used to construct filtering rules for a preventive audit.

3.1.1 Predictive Analytics

Predictive analytics are widely used in practice. For example, they can be used to assess risks in operation processes, optimize business decisions, predict default loans, and to anticipate security breaches (SAS, 2012). Predictive analytics is now becoming an interesting topic in academia. Internal auditors can be more proactive in investigating transactions using data analytics. The International Standards for the Professional Practice of Internal Auditing suggested that "*internal auditors must consider the use of technology-based audit and other data analysis techniques* (IIA, 2010)." Generally, auditors use data analytics in their fieldwork. For example, such analytics can be used for a trend analysis at the account level. In addition to using data analytics in an audit execution procedure, auditors can utilize data analytics as an effective tool for an audit planning (Hoesing, 2010). For example, IT incidents data could be loaded into audit analytic tools to evaluate their severity and frequency and the results can be incorporated in risk assessment and audit planning processes. In addition, auditors have to use their professional skepticism to identify irregularities or anomalies occurring from normal transactions because these could be a sign of fraud (Singleton, 2010). Therefore, auditors could use data mining and data analysis techniques for fraud detection.

The advance of technology and the availability of data are important factors that support the utilization of predictive analytics (Nyce, 2007). Most of the analyses in predictive analytics are computationally intensive. They involve a significant number of calculations and require more processing time when data is larger. There are various sources of data that can be used in the analysis such as proprietary data, third-party data, and public data. These data have to be cleaned and converted into usable and compatible formats because missing data or incomplete data affect the accuracy of the predictive models. This step is called data preprocessing, which is crucial in any data analysis techniques, especially for data from a legacy system.

3.1.2 The Predictive Audit and the Preventive Audit

The predictive audit can be defined as the following:

> *"The predictive audit (PA) is a methodology that incorporates the traditional audit (backward) with the forward looking audit procedure, so that auditors not only examine the past events and create adjustments based on changes or errors that have already occurred, but also perform the audit that could rapidly detect (predictive) or prevent (preventive) irregularities and anomalies or create adjustments in an ex-ante manner." (Kuenkaikaew and Vasarhelyi, 2013)*

In the traditional audit, most of audit work is performed manually and auditors periodically review accounting information in an ex-post basis. Many exceptions or irregularities may have occurred for weeks or months before they are discovered. In the predictive audit, auditors do not have to wait until the end of the accounting period to do the verification, evaluation, or adjustments. Auditors can use data analysis techniques to explore trends, possible exceptions, and predict potential results of the audit. As such, auditors can use predictive results to identify risky audit areas for further verification or prepare for the solutions when the predicted exceptions occur.

The prediction models and results could be used to develop more robust models, which will consistently predict faulty transactions. Additionally, these can later be implemented in the system as a preventive screening. The predictive audit that includes filters to block highly problematic transactions before execution is called the preventive audit. Even though the preventive screening has some characteristics of continuous monitoring, it could be used in continuous auditing, especially for an internal audit. This would identify potentially highly suspicious transactions that will be audited in a proactive manner. This study examines the application of the predictive audit and the preventive audit with a real business data set. The predictive models and the preventive audit mechanisms are created to identify irregular transactions for credit card sales' activities.

3.1.3 Audit Concern

The company in this study is a large international bank. One of the major sources of revenue for this company is generated from offering financial products to customers. Credit cards are one of the main products of this company and constitute a very large number of sales transactions. Sales employees can sell several products, including credit card, to customers and get compensation based on a total number of sales transactions. However, if customers are not satisfied with the product, they can later cancel the sales transaction. Therefore, sales employees may try to increase their compensation by overstating their number of their sales transactions. For example, sales employees can sell a credit card as a bundle with other products that a customer may not want. Additionally, they may convince a customer who needs a loan to apply for a credit card. The sales employees will then help the customer expedite a loan approval.

Internal auditors are concerned with misbehavior by sales employees. Unethical sales can affect the company's reputation and employee benefit systems. In addition, inappropriate approval of credit cards can lead to more serious consequences such as customer credit card fraud and uncollectable credit card debt. Both instances can tremendously cost the company tremendously. Therefore, internal auditors want to create a system that can identify those suspicious transactions in advance, allowing them to promptly investigate the issue. Ultimately, the results could be used to evaluate a sales employee's performance or re-evaluate the compensation scheme.

3.2 Literature Review

3.2.1 Predictive Analytics

Predictive analytics has been used in a number of disciplines such as medical science, supply chain management, information technology, marketing, and business. Predictive analytics have six important roles in scientific research (Shmueli and Koppius, 2011). It can be used to 1) generate new theory, 2) develop measures, 3) compare competing theories, 4) improve existing models, 5) assess relevance between theory and practice, and 6) asses predictability. Insurance is one of the businesses that relies heavily on forecasting (Nyce, 2007). The basic analysis is done primarily using univariate analysis. Then more complicated analyses are able to be employed with the advantage of advanced technology. Such analyses include multivariate analysis and today's methodology, predictive analytics. Predictive analytics can be applied to several areas in the insurance business. For example, marketing agents could increase a hit ratio by using predictive analytics to identify purchasing patterns and contact potential customers. They can also create marketing schemes that could retain existing customers to increase a customer retention ratio. Underwriters could use predictive analytics to create a score to filter out applications that do not meet the criteria. Another common usage of predictive analytics in the insurance business is to identify fraudulent claims and prioritize claims.

Predictive analysis has been widely used in medical literature. Sanchez et al. (2008) analyze the possibility that a novel resistance determinant of bacterial genes could emerge. They used existing information of bacterial genomes, bioinformatics, and functional tools to predict antibiotic resistance before it emerges at a clinical setting.

Grimwade et al. (2001) study acute myeloid leukemia (AML) in 1,065 patients from the United Kingdom Medical Research Council. AML is fundamentally predictable in younger patients and is based upon diagnostic karyotype. Thus, this prognostic factor is used to consider whether it can be use to predict AML in older adults.

The electric power demand and supply in China are forecasted using predictive analysis by Huang et al., 2007. The electric power consumption rate in China fluctuates and drastically increases due to several reasons such as high economic growth and the rapid increase of factories. Hence, China faces a lack of electricity and needs a prediction of the electric power demand and supply for proper power planning. The historical electric power consumption data show large fluctuations. As a result, the GM (1,1) Grey forecasting model and the Markov-chain forecasting model, which are suitable for unstable time series data, are used to calculate a trend of historical data. Then, these two algorithms are combined to estimate the forecast value of electric power consumption for the year 2003 to 2013.

Anderson et al. (2007) identify several tools that retail companies use to create customer relationship management (CRM). One of these tools is predictive analytics. The technique is used to determine direct mail responses from customers and to predict a customer’s future purchases based on past purchasing behavior. Wang et al. (2013) study the relationship between security risk factor disclosures in annual reports and future security breach announcements. They anticipate that information security risk factors released at time t would indicate the possibility of security incidents that may occur in the future (time t+1). Text mining is used to cluster the contents of disclosed security risk factors. Then, a decision tree algorithm in SAS Enterprise Miner is applied to the clusters to predict breach announcements. The result shows that the model accurately predicts breach announcements about 77 percent of the time.

Due to the dynamic nature of an online auction, it is very challenging to predict the price of an ongoing auction. To deal with this problem, a dynamic forecasting model based on a functional regression analysis is proposed by Wang et al. (2008). This dynamic forecasting model is unique from existing forecasting models because it can update the prediction with newly arriving information and predict the price of an in-progress auction. The authors use the auction's price velocity, acceleration, and other auction-related variables to predict the auction price. By comparison, the proposed model has lower prediction errors and outperforms standard forecasting models such as a double exponential smoothing model.

Predictive analytics can be used in business process analytics in order to support management decision making (zur Muehlen and Shapiro, 2009). In Business Process Management System (BPMS), components in business processes are collected and analyzed to determine efficiency and effectiveness of the processes. Samples of BPMS are process dashboards and process information cockpits. There are three focus areas of analyses in the BPMS: process controlling, business activity monitoring, and process intelligence. While process controlling is an analysis of business processes in the past, business activity monitoring is a real time monitoring of the current processes. Process intelligence uses the data to forecast future behavior of business processes. The predictive process analysis is used to determine the performance of a newly design process or the compatibility between a new and existing process. Techniques for a predictive process analysis are simulation, data mining, and optimization. Figure 3.1 shows flows and integration of different stages and IT infrastructure of zur Muehlen and Shapiro (2009)'s business process analytics.

This business management system can be applied to the area of auditing by creating similar modules to support auditors' work and decision making. Particularly, information are collected by CA and CM and fed to the predictive audit to forecast future behavior of accounting transactions.

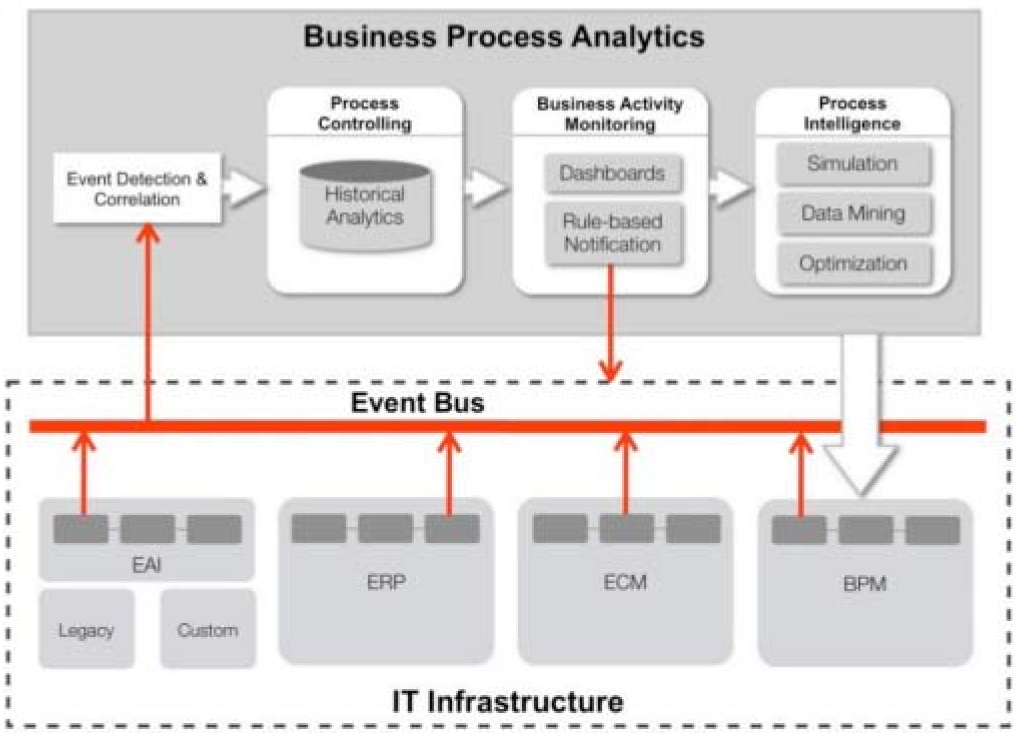

Figure 3.1 Business Process Analysis (zur Muehlen and Shapiro, 2009)

3.2.2 Credit Card

As opposed to looking at consumer use of credit cards, this essay will focus on the vendor. The behavior of sales employees who sell credit card products is investigated and the outcomes of credit card sales transactions are predicted. While a number of academic research studies are about fraud detection in consumer use of credit cards or finding irregular spending patterns of customers, there are a very limited number of studies which focus on fraud or irregularities by the credit card issuer, particularly in auditing.

Credit card fraud detection methodologies evolve over the time. More sophisticated techniques are developed, especially those based on complicated statistics and data mining. Lee et al. (2002) use a backpropagation neural network (BPN) and a traditional discriminant analysis approach together to explore the performance of credit scoring. This is used to determine whether the bank will grant credit cards to customers. Variables used in the model are gender, age, marriage status, educational level, occupation, job position, annual income, residential status, and credit limits. Three prediction methods are employed and compared. They are discriminant analysis, logistic regression, and BPN. The results show that BPN outperforms other methods. It has an average correct classification rate of 73.70 percent. Furthermore, the hybrid prediction model is created using discriminant analysis to reduce a number of input variables and BPN is executed to classify the credit scoring results. This hybrid model has the highest average correct classification rate at 77.00 percent.

Logistic regression and classification trees are machine learning techniques that are extensively used in credit card fraud detection. A logistic regression is similar to a simple regression, but it is suitable when the predicted result is dichotomous (Shen et al., 2007). A decision tree divides problems into small and simple IF-THEN rules. It is a quite flexible and interpretable method (Alpaydin, 2004). These two algorithms are employed in this study.

Yeh and Lien (2009) deploy data mining techniques to predict the probability of customer credit card payment defaults. The six data mining techniques used are K-nearest neighbor, logistic regression, discriminant analysis, Naïve Bayesian, neural networks, and classification trees. A new approach called Sorting Smoothing Method (SSM), is proposed to estimate the probability of the default. This extends beyond the binary yes or no result. In the SSM, the binary results of prediction models are placed in the order of validation data and are smoothed by the number (2n+1) of data. Then, the results of each data mining technique are plotted on the graphs and linear regression is created. Among the six algorithms, neural networks have the highest explanatory ability for a real probability of the default.

Classification models are used in Shen et al. (2007) to identify fraudulent transactions in the credit card dataset. The classification methods employed are decision trees, neural networks, and logistic regression. Some of the variables used in this study are POS terminal numbers, transaction date and time, the amount of the credit card transactions, card type, total amount of transactions of the card in the same day, and transaction characteristics within five days. The results show that neural networks and a logistic regression outperform a decision tree. Furthermore, credit card variables in Shen et al. (2007) are similar to some characteristics of past sales performance of employees in this study. For example, the total number of sales by employee and matched sales (sales within a close period of time) are similar to the variables in Shen et al.

Stolfo et al. (1997) evaluate the performance of the following four machine learning algorithms: decision trees (ID3 and CART), BAYES, and RIPPER. These algorithms are used for credit card fraud detection. The data set includes 500,000 records of credit card transactions with 30 attributes and 20 percent of the records are fraudulent. Due to the large number of data, only data within 12 months period are selected as a sample in the experiment and redundant variables are removed. The most important criteria to evaluate the results are true positive (fraud catching) and false positive (false alarm) rates. As a result, the best classifier is the BAYES learning algorithm with a modified fraud distribution of 50:50. The model has a true positive rate of 0.8 and a false positive rate of 0.13.

In this chapter, the entire population is used in the analysis without sampling and the distribution of fraud (4.10 percent) is not modified. The same model evaluation criteria (true positive and false positive rates) are used but the ROC area is added as another measure.

3.3 Data

The data set in this study is from a banking business. It contains the records of 1,081,857 credit card sales transactions during November 2009 to April 2010. The data set has information about customer reimbursements and contains indicators of sales to employees within the company, bundle sales, sale cancellations, sales to inactive customers, and sales with complaints. This information will be used to predict the status of status of each sales transaction. Details of each indicator are as follows:

1. Reimbursements: When customers are not satisfied with the product, they can ask the bank to cancel those purchases. In some cases, the company may give them a reimbursement for their purchases.
2. Bundle sales: If a customer buys more than one product at a time, it is considered a bundle sale. For example, a customer may buy a credit card and life insurance from the company at the same time or in a very close period of time. This sale will be classified as a bundle sale.
3. Sales to employees: It is common that customers can be employees within the bank. In some cases, a sales employee may ask another employee, who is a client of the bank, to buy his products to increase sales performance.
4. Inactive customers: A customer that does not have any activity with the bank for a certain period of time is considered an inactive customer.

3.4 Model Development

A general rule for prediction is that only the past or current information can be used to predict the future event. Therefore, all related attributes that are included in the predictive models have to be known at the time of sale, except for the status of the current transaction. Thus, the unknown or dependent variable in the model is the status of the current sale transaction. Independent variables in the model are the following:

1. Number of sales cancellations by employee (IND_CANC)

2. Number of reimbursements by employee (IND_RESS)

3. Number of bundle sales by employee (IND_CASA)

4. Number of sales to employees by employee (IND_FUNC)

5. Number of sales to inactive accounts by employee (IND_INAT)

6. Number of sales with complaints by employee (IND_RECL)

7. Number of sales transactions by employee (C_A_SALE)

These variables are normalized as ratios to avoid bias and make data comparable. Machine learning techniques are applied to the data set to create prediction models. The techniques used are logistic regression and decision tree algorithms. The data are split into training and testing sets for model validation. The training set is the first 4 months of data, while the testing set is the last 2 months of data. The model is a time-dependent measure, meaning that the order, date, and time of the transactions matter. Past performance of an employee affects the outcome of the transaction. Value of a new transaction's variables is calculated based on the previous transactions. In addition to the predictive model's creation, the filtering rules are formulated as an additional screening to the predictive audit results. These rules are derived from the predictive models and will be constructed as a discriminant set for the preventive audit.

3.5 Results and Analysis

Typically, anomaly transactions are very difficult to distinguish from regular transactions. When this occurs, it can cause an immensely negative effect and identifying irregularities is challenging. A predictive model that has the highest accuracy rate may not be the best model for abnormality prediction. A good model should have a reasonably high true positive rate on classifying canceled transactions and a relatively low false positive rate for misidentifying normal transactions as canceled ones (Stolfo et al., 1997).

In a credit card data set, the total sales transactions are equal to 1,081,857 records, where 1,037,536 (95.90%) records are normal sales transactions and 44,321 (4.10%) records are canceled sales transactions. The dataset has a very large number of normal transactions and a small number of canceled sales transactions. This characteristic is not uncommon in most of the irregularity or fraud detection datasets because these anomalies are rare and difficult to discover. However, the small number of canceled transactions and the large number of normal transactions cause a problem known as imbalanced data (He and Garcia, 2009; Kuenkaikaew and Vasarhelyi, 2013). This means that the irregularity or an object of interest is not easy to identify. Without a proper technique, the predictive model may not generate an accurate result for an imbalanced dataset.

The result of the first run of the logistic regression algorithm shows the model accuracy at 97.46 percent. The true positive rate and the false positive rate are 0.00 and 0.00 respectively. The model has difficulty identifying canceled transactions. This is the result of an imbalanced dataset. To solve this problem, a cost sensitive function is added to the model (Tan et al, 2005). A cost sensitive function will assign a relative cost to the model if it wrongly predicts the result of a canceled sale transaction. The cost of misclassifying a canceled transaction is greater than that of misclassifying a non-canceled one (Japkowicz and Stephen, 2002). Different cost sensitive ratios are attempted in order to find the model that performs well on identifying canceled transactions (high true positive rate) and requires less investigation effort from auditors (low false positive rate).

3.5.1 The Predictive Audit

3.5.1.1 Logistic Regression

The first cost sensitive ratio used in the predictive model creation is 1:24, which is a proportion between canceled and non-canceled transactions in the data set. The result of the logistic regression algorithm shows a 74.91 percent accuracy rate. The model correctly classifies canceled transactions (true positive rate) at 0.38 and classifies non-canceled transactions as canceled ones (false positive rate) at 0.24. A false positive rate means that auditors have to spend more effort investigating flagged transactions. The ROC area measurement of 0.61 indicates that the model performs better than a random guess (Tan et al, 2005).

Another four ratios are attempted to examine the predictability of the models. The ratios are 1:20, 1:22, 1:26, and 1:28. The accuracy rates of each cost matrix model are 1:20 (88.04), 1:22 (82.48), 1:26 (64.62), and 1:28 (52.61). Even though the 1:20 ratio model has the highest accuracy, the model does not perform well compared to the other models on classifying canceled sales transactions. The true positive rates of each cost matrix model are 1:20 (0.19), 1:22 (0.28), 1:26 (0.51), and 1:28 (0.64). The 1:28 ratio model outperforms other models in correctly classifying canceled transactions. However, it has the highest false positive rate. The false positive rates of each cost matrix model are 1:20 (0.10), 1:22 (0.16), 1:26 (0.35), and 1:28 (0.37). All cost matrix ratios have the same ROC area of 0.61. The summary results are shown in Table 3.1.

Table 3.1 Cost Sensitive Approach Using Logistic a Regression Algorithm

Ratio/ Measurement	**Accuracy Rate (%)**	**Correctly Classify Canceled Transaction (TP Rate)**	**Investigation Effort (FP Rate)**	**ROC Area**
1:20	88.04	0.19	0.10	0.61
1:22	82.48	0.28	0.16	0.61
1:24	74.91	0.38	0.24	0.61
1:26	64.62	0.51	0.35	0.61
1:28	52.61	0.64	0.37	0.61

3.5.1.2 Decision Tree (J48)

Another machine learning algorithm used in a predictive model creation is a decision tree (J48). Similarly to a logistic regression algorithm, several cost matrix ratios are applied to the models. They are 1:20, 1:22, 1:24, 1:26, and 1:28. When the ratio is increased, the accuracy rate is decreasing. The accuracy rates of each cost matrix ratio are as follows: 1:20 (81.33), 1:22 (81.24), 1:24 (79.99), 1:26 (79.03), and 1:28 (78.33). Even though the accuracy rates are decreased while the ratios are increased, the true positive rate is increased. The model classifies canceled transactions better when the ratio is increasing. The true positive rates of each cost matrix are as follows: 1:20 (0.20), 1:22 (0.20), 1:24 (0.21), 1:26 (0.21), and 1:28 (0.22). More investigation effort is needed due to the increasing false positive rate. The false positive rates of each cost matrix are as follows: 1:20 (0.17), 1:22 (0.17), 1:24 (0.18), 1:26 (0.19), and 1:28 (0.20). The ROC area of all ratios is 0.51, which is lower than that of the logistic regression algorithm. The summary results of a decision tree (J48) algorithm with different ratios are shown in Table 3.2.

Table 3.2 Cost Sensitive Approach Using a Decision Tree Algorithm

Ratio/ Measurement	**Accuracy Rate (%)**	**Correctly Classify Canceled Transaction (TP Rate)**	**Investigation Effort (FP Rate)**	**ROC Area**
1:20	81.33	0.20	0.17	0.51
1:22	81.24	0.20	0.17	0.51
1:24	79.99	0.21	0.18	0.51
1:26	79.03	0.21	0.19	0.51
1:28	78.33	0.22	0.20	0.51

3.5.2 Filtering Rules

Kuenkaikaew and Vasarhelyi (2013) suggested that the result of the predictive audit could be used to construct precautionary rules for the preventive audit. In this analysis, combinations of indicators are created and analyzed to uncover rules that could be used together with the predictive audit. In this instance, the filtering rules are the indicators that were used to create prediction models for the predictive audit and they are available in the data set. From the previous section, the predictive audit results show that these indicators could indicate potential problems. Thus, they can be developed to create preventive rules that could filter or block transactions that have high fault characteristics before they are processed.

The hypothesis here is that each indicator contributes differently to the outcome (canceled or not-canceled) of the transactions. Therefore, all indicators are analyzed individually and jointly in different combinations to examine how they contribute to the canceled and non-canceled transactions. All possible combinations are built and the contribution ratios of each condition are calculated. These ratios are also compared to determine whether they are significantly different and could be used to pre-identify potentially problematic transactions. For example, there are 2,434 canceled transactions and 21,109 non-canceled transactions that have the indicator IND_RECL, which is a sale with complaints. These numbers are calculated as a ratio of 0.05 per total canceled transaction and 0.02 per total non-canceled transaction. Thus, it is hypothesized that a transaction that has an IND_RECL indicator has a high likelihood to be a canceled transaction. The summary of all possible indictors and the contribution ratios are shown in Table 3.3.

Table 3.3 The Combinations of Indicators for the Preventive Audit

Indicators	Number of Canceled Transactions	Ratio per total canceled transactions (44,321 transactions)	Number of Non-canceled Transactions	Ratio per total non-canceled transactions (1,037,536 transactions)
IND_RECL	2,434	0.05	21,109	0.02
IND_CASA AND IND_FUNC	55	0.0012	632	0.0006
IND_CASA AND IND_RECL	296	0.0067	3,727	0.0036

The ratio for each condition may be very small but it is not uncommon. In general, most of the sales transactions are normal transactions without any indicator. Therefore, transactions with indicators for irregularities are in the minority. Examining each combination of indicators and its contribution ratio reveals there are 3 combinations where the ratios between canceled transactions and non-canceled transactions are highly different. The ratio of each condition is as follows:

IND_RECL (0.05 and 0.02)

IND_CASA AND IND_FUNC (0.0012 and 0.0006)

IND_CASA AND IND_RECL (0.0067 and 0.0036)

To compare whether each pair of ratios for each condition are statistically significant difference, a t-test statistic is applied to the data set. The t-test results confirm that a canceled transaction ratio and a non-canceled transaction ratio of each condition are statistically significant difference. Table 3.4, 3.5, and 3.6 show the t-test results of IND_RECL indicator, IND_CASA AND IND_FUNC indicator, and IND_CASA AND IND_RECL indicator respectively.

Table 3.4 The t-test Result of IND_RECL Indicator

The TTEST Procedure

Variable: IND_RECL

z_ind_canc	N	Mean	Std Dev	Std Err	Minimum	Maximum
C	44321	0.0549	0.2278	0.00108	0	1.0000
N	1037536	0.0203	0.1412	0.000139	0	1.0000
Diff (1-2)		0.0346	0.1457	0.000707		

z_ind_canc	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
C		0.0549	0.0528	0.0570	0.2278	0.2263	0.2293
N		0.0203	0.0201	0.0206	0.1412	0.1410	0.1414
Diff (1-2)	Pooled	0.0346	0.0332	0.0360	0.1457	0.1455	0.1459
Diff (1-2)	Satterthwaite	0.0346	0.0324	0.0367			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	1.08E6	48.91	<.0001
Satterthwaite	Unequal	45785	31.69	<.0001

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	44320	1.04E6	2.60	<.0001

Table 3.5 The t-test Result of IND_CASA AND IND_FUNC Indicator

The TTEST Procedure

Variable: z_casa_func

z_ind_canc	N	Mean	Std Dev	Std Err	Minimum	Maximum
C	44321	0.00124	0.0352	0.000167	0	1.0000
N	1037536	0.000609	0.0247	0.000024	0	1.0000
Diff (1-2)		0.000632	0.0252	0.000122		

z_ind_canc	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
C		0.00124	0.000913	0.00157	0.0352	0.0350	0.0354
N		0.000609	0.000562	0.000657	0.0247	0.0246	0.0247
Diff (1-2)	Pooled	0.000632	0.000392	0.000871	0.0252	0.0252	0.0252
Diff (1-2)	Satterthwaite	0.000632	0.000301	0.000963			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	1.08E6	5.17	<.0001
Satterthwaite	Unequal	46198	3.74	0.0002

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	44320	1.04E6	2.04	<.0001

Table 3.6 The t-test Result of IND_CASA AND IND_RECL Indicator

The TTEST Procedure

Variable: z_casa_recl

z_ind_canc	N	Mean	Std Dev	Std Err	Minimum	Maximum
C	44321	0.00668	0.0814	0.000387	0	1.0000
N	1037536	0.00359	0.0598	0.000059	0	1.0000
Diff (1-2)		0.00309	0.0609	0.000295		

z_ind_canc	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
C		0.00668	0.00592	0.00744	0.0814	0.0809	0.0820
N		0.00359	0.00348	0.00371	0.0598	0.0597	0.0599
Diff (1-2)	Pooled	0.00309	0.00251	0.00366	0.0609	0.0608	0.0609
Diff (1-2)	Satterthwaite	0.00309	0.00232	0.00385			

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	1.08E6	10.45	<.0001
Satterthwaite	Unequal	46385	7.89	<.0001

Equality of Variances				
Method	Num DF	Den DF	F Value	Pr > F
Folded F	44320	1.04E6	1.85	<.0001

3.5.2.1 The Preventive Audit (Ex-Ante)

These filtering rules can be applied to the data set either ex-ante (preventive) or ex-post. If the filtering rules are placed at the beginning of the process, transactions that have these indicators will be flagged for investigation before they are processed. This can be called the preventive audit. If a system operates on a real-time basis, any incoming transactions that meet the conditions in the filtering rules will be flagged and sent to auditors.

After applying these filtering rules to the credit card data set, there are 24,193 transactions that have at least one of these conditions (IND_RECL, IND_CASA AND IND_FUNC, and IND_CASA AND IND_RECL). The number of canceled transactions contains 2,489 (10.29%) records and the number of non-canceled transactions contains 21,704 (89.71%) records. With filtering rules, a chance to identify irregularities or canceled transactions in this study is increased and auditors could target a more specific group of transactions that have a high probability of anomaly. From the total population, canceled transactions are 4.10 percent. With the screening rules in the preventive audit, the percentage of canceled transactions is significantly increased to 10.29 percent. A comparison of a chance to identify canceled transactions with and without the implementation of the preventive audit is shown in Table 3.7.

Table 3.7 A Comparison between Analyses With and Without the Preventive Audit

Preventive Audit	Canceled Transactions		Non-canceled Transactions		Total Transactions
	Number of transactions	%	Number of transactions	%	
Without	44,321	4.10	1,037,536	95.90	1,081,857
With	2,489	10.29	21,704	89.71	24,193

3.5.2.2 The Predictive Audit with Screening (Ex-post)

Another way to use filtering rules is applying them to the predictive audit results. After running the predictive models, auditors may get a number of transactions that are flagged as problematic or canceled transactions. However, not all of them are truly problematic. Reviewing all flagged transactions will require a considerable amount of time and resources from auditors (Issa, 2013). In general, some of the characteristics may cause more serious problems than the others. If auditors could find filtering rules that can identify those characteristics, they can use them to select or to prioritize flagged transactions to review.

With the credit card sales transactions data set, the predictive audit model predicts 365,426 canceled transactions but 24,535 (6.71%) transactions are actually canceled. This is a fairly large number of transactions for auditors to verify. The filtering rules are applied to assist auditors in selecting transactions to review. After applying the filtering rules to the results of the predictive audit, there are 9,754 transactions that have at least one of these indicators (IND_RECL, IND_CASA AND IND_FUNC, and IND_CASA AND IND_RECL). Among this number, 1,473 (15.10%) transactions are the actual canceled transactions. In this case, the filtering rules considerably increase a chance for auditors to find problematic transactions from 6.71 to 15.10 percent. Table 3.8 shows the summary results.

Table 3.8 A Comparison of the Predictive Audit With and Without the Filtering Rules

Filtering Rules	Total Flagged Transactions	Canceled Transactions	Percent of Total Flagged transactions
Without	365,426	24,535	6.71
With	9,754	1,473	15.10

3.6 Conclusion

In the competitive and real time environment, it is vital for companies to maintain their ability to compete and achieve their desired goals. Companies not only want to know the past, they want to be able to predict the future. Predictive analytics could be a critical asset for a company to retain and increase it’s competitive advantage. In this study, the predictive analytics are applied to the audit function, specifically the internal audit function. The predictive audit can help internal auditors identify the possible outcome of the audit area of interest. In this case, the credit card sale status can be predicted so that auditors could plan ahead for their tasks. The predictive audit can improve the control environment and ensure that all applicable controls are in place and followed.

Two machine learning algorithms, a logistic regression and decision tree, are used to create the predictive models. The predictability of the logistic regression is slightly better than that of the decision tree. Nevertheless, auditors must consider the tradeoff between the cost and benefit of the investigation. Additionally, the filtering rules are created from the results of the predictive audit. The rules can be applied to the data set either ex-ante or ex-post. If they are applied before the data is executed to identify and possibly block highly problematic transactions, this will be called the preventive audit. Alternatively, the rules can be applied after the transactions were already processed. It could help reduce the number of flagged transactions that auditors have to further investigate and could increase a hit ratio for auditors to find actual irregularities out of all flagged transactions. The preventive audit and the filtering rules could reduce audit work and allow auditors to better allocate their time and utilize their resources.

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Appendix

The Possible Combinations of Indicators for the Preventive Audit

Indicators	Number of Canceled Transactions	Ratio per total canceled transactions (44,321 transactions)	Number of Non-canceled Transactions	Ratio per total non-canceled transactions (1,037,536 transactions)
IND_CASA	5,909	0.13	177,724	0.17
IND_FUNC	888	0.02	9,479	0.01
IND_INAT	1,008	0.02	30,995	0.03
IND_RECL	2,434	0.05	21,109	0.02
IND_RESS	612	0.01	0	0
IND_CASA AND IND_FUNC	55	0.0012	632	0.0006
IND_CASA AND IND_INAT	184	0.0042	6,205	0.0060
IND_CASA AND IND_RECL	296	0.0067	3,727	0.0036
IND_CASA AND IND_RESS	98	0.0022	0	0
IND_CASA AND IND_FUNC AND IND_INAT	0	0	33	0
IND_CASA AND IND_INAT AND IND_RECL	1	0	183	0
IND_CASA AND IND_RECL AND IND_RESS	16	0.0003	0	0
IND_CASA AND	0	0	1	0

Indicators	Number of Canceled Transactions	Ratio per total canceled transactions (44,321 transactions)	Number of Non-canceled Transactions	Ratio per total non-canceled transactions (1,037,536 transactions)
IND_FUNC AND IND_INAT AND IND_RECL				
IND_CASA AND IND_INAT AND IND_RECL AND IND_RESS	0	0	0	0
IND_CASA AND IND_FUNC AND IND_INAT AND IND_RECL AND IND_RESS	0	0	0	0
IND_CASA AND IND_INAT AND IND_RESS	1	0	0	0
IND_CASA AND IND_FUNC AND IND_RECL	0	0	37	0
IND_CASA AND IND_FUNC AND IND_RECL AND IND_RESS	0	0	0	0
IND_CASA AND IND_FUNC AND IND_RESS	3	0	0	0
IND_CASA AND IND_FUNC AND IND_INAT AND IND_RESS	0	0	0	0
IND_FUNC AND IND_INAT	15	0.0003	236	0.0002

Indicators	Number of Canceled Transactions	Ratio per total canceled transactions (44,321 transactions)	Number of Non-canceled Transactions	Ratio per total non-canceled transactions (1,037,536 transactions)
IND_FUNC AND IND_RECL	17	0.0004	173	0.0002
IND_FUNC AND IND_RESS	3	0	0	0
IND_FUNC AND IND_INAT AND IND_RECL	0	0	1	0
IND_FUNC AND IND_RECL AND IND_RESS	0	0	0	0
IND_FUNC AND IND_INAT AND IND_RECL AND IND_RESS	0	0	0	0
IND_FUNC AND IND_INAT AND IND_RESS	0	0	0	0
IND_INAT AND IND_RECL	27	0.0006	611	0.0006
IND_INAT AND IND_RESS	5	0	0	0
IND_INAT AND IND_RECL AND IND_RESS	0	0	0	0
IND_RECL AND IND_RESS	112	0.002	0	0

Chapter 4: Conclusion

4.1 Summary

Traditional audit provides retroactive assurance and may not well serve current business needs. Continuous auditing utilizes audit automation to facilitate audit work, shorten the audit timeframe and occasionally to provide the means to undertake an audit that otherwise could not be justified. Consequently, auditors may try to accelerate the cycle of audit processes where possible to provide frequent or continuous assurance. This dissertation contributes to auditing and continuous auditing literature by proposing the predictive audit framework, and illustrates its application to actual business data sets.

The predictive audit (PA) utilizes continuous auditing and data analytics to predict the possible outcome of processes at either detail or aggregate levels. With this forward looking examination technique, auditors can better plan their time, resources and their use of appropriate audit methodologies. The traditional audit is still needed as a foundation for PA. When audit methodologies are progressing, the audit vision is more similar to management's vision, and some management philosophies could be applied to auditing. There may be overlap between audit and management activities. Traditional audit models are changing. Traditionally, auditing entails review or investigative processes performed after the fact. However, in the PA, audit activities could be performed before the business event occurs. Auditors could pre-identify possible accounts or transaction values, and examine if the actual results are largely different. For example, accounting estimations in financial statements are the responsibility of management[1] (AICPA, 1988), and auditors have to evaluate the reasonableness of those estimations at year-end. However, auditors can now predict the level of estimation in advance, without having to wait until year-end, and compare this result with management's numbers, when that information is available. If there are significant deviations or if actual estimations exceed allowable values, additional investigation will be required.

PA profoundly relies on technology and audit automation, which could be achieved with incorporation of the progressive audit. Audit processes are formalized and automated where possible. Results from the progressive audit can lead to new guidelines and a rule book that can be used in subsequent reviews. Major changing factors in auditing that enhance the development of PA are data availability, audit technology, access to data, and data storage. There are several types of future estimates for PA such as risks, control trends, and level and flow. Furthermore, a robust predictive model and results could later be used to construct a preventive audit in order to avoid possibly incorrect transactions from being executed. Ten steps to create a predictive/preventive audit model are as follows.

1. Determine a profile of risk
2. Identify and understand the system
3. Capture and clean relevant data
4. Create KPI and extraction models
5. Run models under different scenarios
6. Place filters at the beginning of processes

[1] SAS 57 Auditing Accounting Estimates

7. Examine interactively and audit by exception
8. Create interfaces to continuous monitoring
9. Continue the forensic model development process based on filtering results
10. Rely, as an external auditor, on internal audit work

In the second chapter of this dissertation the predictive audit is applied to a revenue cycle, specifically savings account sales transactions, to identify whether the transactions were generated with the intention of being canceled by unethical employees trying to increase their compensation. The predictive models are constructed using three machine learning techniques, which are logistic regression, a decision tree and support vector machines. Most of the variables are derived from the past sales performance of the employees.

Generally, irregularities or abnormalities are rare and difficult to identify. Similarly, within the data set only 6.66 percent of the data represents canceled transactions, which leads to an imbalanced data problem for prediction. To deal with this problem, two approaches are deployed, which are the cost-sensitive approach and the sub-sample approach. The results from chapter 2 show that a cost-sensitive approach performs slightly better than a sub-sample approach. In the cost-sensitive approach, a logistic regression algorithm outperforms other algorithms, and is the simplest and least resource consuming algorithm in terms of implementation and performance. Different cost-ratios are assigned to the data set and the results are evaluated to identify the ratio that suits the auditor's requirements. This cost-ratio is a penalty if the model misclassifies a canceled transaction. The logistic regression with a 1:8 ratio shows the highest accuracy rate at 90.80 percent, correctly classifying canceled transaction (true positive rate) at 0.18, a false positive rate (investigation effort) at 0.07, and an ROC area at 0.63.

Later, more information about sales characteristics is provided; therefore, they are added to the models to improve the predictability. Those additional variables are, for example, the unit value of the product, a product description, and type of customer. Using a stepwise regression, seven out of fifteen variables are selected. The results of new the predictive models are significantly improved from the original model. The logistic regression with a 1:8 ratio shows the highest accuracy rate at 96.61 percent, correctly classifying canceled transaction (true positive rate) at 0.63, a false positive rate (investigation effort) at 0.02, and an ROC area at 0.90. It is implied that variable selection is one of the most important factors to the predictive model formation.

In the third chapter, the predictive audit is applied to credit card sales data to predict the status of sales transactions. In this data set, the number of total canceled sales transactions is very small at 4.10 percent. The selected algorithms for the predictive models are a logistic regression and a decision tree as they perform better and consume less computational resources than a support vector machine does. An approach to handle an imbalanced data problem is the cost sensitive approach. The results of this analysis show that a logistic regression algorithm outperforms a decision tree algorithm. This is similar to the predictive results of the study in chapter 2. The logistic regression with a 1:20 ratio shows the accuracy rate at 88.04 percent, correctly classifying canceled transactions (true positive rate) at 0.19, a false positive rate (investigation effort) at 0.10, and an ROC area at 0.61.

The results of the predictive audit are then analyzed and used to create structural rules for the preventive audit and applied to the data set. All variables in the predictive model are explored for their contribution to identifying the possible statuses of transactions. As a result, three sets of indicators show that they affect the ratios between canceled and non-canceled transactions. The three sets of indicators are IND_RECL (number of sales with complaint) condition, IND_CASA AND IND_FUNC (number of bundle sales and number of sales to another employee) condition, and IND_CASA AND IND_RECL (number of bundle sales and number of sales with complaint) condition. In the preventive audit, these rules are placed at the beginning of the process to filter, flag or block highly faulty transactions before they are further executed. If auditors knew this in advance, they could prepare for an investigation or intervention if necessary. With the implementation of the predictive audit, auditors have a greater likelihood to identify canceled transactions resulting in an increase in detection from 4.10 to 10.29 percent.

On the other hand, these rules can be executed after PA. The predictive models will identify transactions that have a high probability of cancellation, which could consist of a number of transactions. However, not all of the flagged transactions are truly problematic. As such, the filtering rules can be applied to the predictive results to narrow down the number of flagged transactions, which will reduce audit work and increase the chance of auditors finding problematic transactions. In this study, the chance of identification increases from 6.71 to 15.10 percent. The preventive audit and filtering rules results are summarized in Table 4.1.

Table 4.1 Preventive Audit and Filtering Rules Results

Approach	Without			With		
	Canceled Transactions	**Percent of Total Transactions**	**Total transactions**	**Canceled Transactions**	**Percent of Total Transactions**	**Total transactions**
Preventive audit	44,321	4.10	1,081,857	2,489	10.29	24,193
Filtering Rules	24,535	6.71	365,426	1,473	15.10	9,754

In conclusion, the predictive audit is a forward looking audit that uses analytic methods to proactively identify possible exceptions at either detail or aggregate levels. The framework is based on both the traditional audit and continuous auditing. The results of the predictive audit can be developed and provide the structure (parameters) of the preventive audit. PA can support both internal and external auditors, with their differing objectives. Internal auditors may use PA as their monitoring tools and review only exceptions, while external auditors could use PA to undertake the planning, identify risk areas, and predict the account balances. It will change the audit perspective from backward, after the fact analysis to forward and proactive, and speed up audit tasks so that exceptions can be discovered sooner. Ultimately, audit methodologies will move toward a predictive stance, and will influence management internal controls. Preventive controls will become more advanced and will be preferable options to detective controls that lag in timing and provide less value.

4.2 Limitations

There are some limitations and concerns that should be considered for the predictive audit application. The predictive model requires a substantial number of transactions to be tested, especially exception transactions, in the data set for accurate prediction. Insufficient amounts of transactions and very small samples of irregularities may result in inaccurate or low predictability.

Variable selection is also an important process. Only variables that are known at the time of the prediction can be used in the model, and using more informative variables could provide better predictability. As presented in chapter 2, adding relevant attributes drastically improve the performance of the models. The predictive models for credit card data set in chapter 3 generated moderate results due to two primary reasons. The first is that the data contained a limited numbers of variables, and the second is that there were few canceled transactions in the data set.

Another limitation of this study is that it restrains the prediction of sales transaction status because of the availability of data. To build a robust model and be able to verify its performance, the results of the model need verification either by using the labeled data (data with pre-identified outcomes) or by a domain expert. As such, the property of the data is one of the considerations. The exploration and application in different areas would make a case for the predictive audit.

PA is appropriate for certain industries considering the aforementioned limitations. It is adaptive to new transactions, but if new variables are available, the model needs to be adjusted. Businesses that are changing, such as by mergers, new product launches or other major changes that could affect the nature of the firm's processes, may have provide difficulty in implementing PA due to a lack of identified process profiles.

4.3 Future Research

As discussed earlier, organizations, processes, analytic methods, and techniques for the treatment of data vary widely. Companies are constantly changing and looking for methods that could provide more reliable information. The one solution for all approaches methodology (one consolidated financial statement, one audit standard, one opinion) may be replaced by a set of template-based measurements, and, consequently, a set of assurance circumstances and approaches to the examination. Most likely, the basically bimodal opinion will give way to some form of rating per segment, per account, or per process, and relative to the disclosure (probably disguised) of the nature of the anomalies found in risks, controls, and levels and flows.

External and internal auditors have to carefully scrutinize the implementation of the predictive and preventive audits. Even though the predictive audit is defined as an audit, it can be applied to both continuous auditing and continuous monitoring. As mentioned earlier, continuous auditing and continuous monitoring techniques are interchangeable/ complementary where appropriate. Evolving to a predictive audit methodology raises a series of methodological questions that must be addressed. They involve the quality of prediction, auditor independence, level of scrutiny, materiality, timing, the nature of the procedures, and many other issues.

The predictive audit is a new way of auditing, and could bring about substantive changes in auditing. Also, some of the key extant research studies raise the following questions:

1) What is the level of scrutiny auditors could employ to maintain an acceptable degree of objectivity? There is a dilemma for internal auditors when the predictive audit or the preventive audit flag transactions for verification. Should auditors intervene if they know that there is a high possibility of anomaly, which may cause a massive negative effect to the business? To what extent could auditors examine the alert while adequately maintaining their independence?

2) How can the three levels of controls in business (risks, control trends, and levels and flows) be predicted? Some types of controls are easier to estimate than the others. For example, a variety of business components, at the micro and macro levels, have to be included to determine the level of risks. Some of the components include a subjective evaluation, which makes a risk assessment difficult and complicated. On the contrary, predicting the number of finished goods from a production process is more straightforward. Thus, there is much work to be done, such as what is a proper method for each level of controls, which controls are critical and which will benefit from prediction.

3) What is the recommended model or methodology for prediction? Each business has its own characteristics such as banks, manufacturing, service industries, and retail. Even companies in the same industry are not alike. Therefore, it is difficult to have a

standard model that could fit all businesses/processes. However, if common attributes can be identified, they can be used as a guideline to create generic models for particular industries or processes.

Furthermore, research on the methodological design and implementation of the predictive audit are needed. The research might entail qualitative surveys of auditing firms as well as studies of emerging practices in the insurance and banking industries. Future research in these areas will provide additional insight and better clarify the path to deployment of the predictive audit.

4.4 References

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