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# Analytical Procedures in External Auditing: A Comprehensive Literature Survey and Framework for External Audit Analytics

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**Abstract:**
*There is an increasing recognition in the public audit profession that the emergence of big data as well as the growing use of business analytics by audit clients has brought new opportunities and challenges. That is, should more complex business analytics beyond the customary analytical procedures be used in the engagement and if so, where? Which techniques appear to be most promising? This paper starts the process of addressing these questions by examining extant external audit research. 301 papers are identified that discuss some use of analytical procedures in the public audit engagement. These papers are then categorized by technique, engagement phase, and other attributes to facilitate understanding. This analysis of the literature is categorized into an External Audit Analytics (EAA) framework, the objective of which is to identify gaps, to*

*provide motivation for new research, and to classify and outline the main topics addressed in this literature. Specifically, this synthesis organizes audit research, thereby offering guidelines regarding possible future research about approaches for more complex and data driven analytics in the engagement.*

## 1.0 Introduction

There is increasing recognition in the public audit profession that the emergence of big data as well as the growing use of analytics by audit clients has brought new opportunities and concerns (Appelbaum, Kogan, and Vasarhelyi 2017). That is, should more complex analytics be used in the engagement and if so, where? Which techniques appear to be most promising? It is said by many that the public auditing profession would be the last to adopt new technologies, that regulations mold the scope, breadth, and methodology of the engagement. However, the standards do not explicitly define the type of analytical approaches that should be undertaken by auditors to fulfill regulatory requirements, except that the auditor should develop an expectation from the appropriate analytics of reliable data from certain accounts, and then calculate the difference of these expectations and the recorded numbers (AS 2305, PCAOB, 2016). The standards require that analytical procedures be undertaken in addition to evidence collection at the preliminary review and final review stages (Daroca & Holder, 1985), but the decision about which analytical techniques to use is left to auditor judgment.

The opaqueness of this aspect of public auditing has led to numerous debates and discussion within the auditing academic community since 1958 (AICPA 1958). These debates have increased with the emergence of big data and automation of business financial reporting (Vasarhelyi, Kogan, and Tuttle 2015). These discussions and debates, as evidenced in academic publications, are indicative of the degree and breadth of analytical approaches available to the engagement. Therefore, it is only natural to investigate this vast body of audit academic research for insights regarding an expanded use of analytics. This research is relevant to:

- ✓ Audit academics and researchers who are interested in continuing with new research about analytics in the external audit engagement and who can refer to this paper for guidance as to which areas have previously been discussed in the literature and which could benefit from additional attention
- ✓ Practitioners or auditors who want to be aware of the degree of research and of innovative ideas about analytics and to possibly incorporate them in the engagement
- ✓ Regulators who are seeking to update the standards and suggest best practices regarding the use of analytical procedures in the audit engagement.

This paper represents an effort to identify and categorize academic publications referencing the use of analytics in the engagement. Accordingly, 301 papers are identified that discuss some aspect of analytical procedures in the external audit engagement. The large number of papers make it difficult for academics and practitioners to identify specific analytic techniques or gaps in the research. Therefore, these papers are first categorized by technique, engagement phase, and other attributes to facilitate an understanding. This preliminary analysis of the literature is subsequently categorized in an External Audit Analytics (EAA) framework, derived from Business Analytics (BA), and whose objective is to facilitate the identification of gaps, to provide motivation for new research, and to classify and outline the main topics addressed in this literature.

This paper organizes and synthesizes the previously uncategorized extant literature, thereby encouraging further research and exploration by academia, regulators, and practitioners. It systematically examines published literature regarding analytics in the external audit to understand central themes and status of this research, and provides an organizing framework which positions these findings in context with the modern business environment. The EAA framework provides a benchmark for expected research, against which to compare the available published research to date.

Following this Introduction, the Background section discusses Analytical Procedures as promulgated by the standards and typically practiced by the profession. The third section begins the Literature Review process by discussing the methodology for collecting these papers and how they are categorized by timeline, research methods, audit stage, technique, and orientation. The fourth section discusses the meaning of the results of the literature review, areas for future research, and gaps in the literature. An External Audit Analytics (EAA) conceptual framework is proposed in Section Four to facilitate an understanding of not only where research has been undertaken but also, given an understanding of business analytics practices by audit clients, where future research should concentrate. This EAA conceptual framework is derived from the synthesis of the literature in the context of business analytics. This paper then concludes with implications and discussions for future research regarding the broad potential for analytics in the external audit.

## 2. 0 Background

### 2.1 Analytical Procedures in the Standards and Typical Practice

AS 2305 (PCAOB 2016) defines Analytical Procedures (APs) as an "important part of the audit process that consists of evaluations of financial information made by a study of plausible relationships among both financial and nonfinancial data." AS 2305 states that APs may range from basic comparisons to the use of more complex models involving multiple relationships and elements in the data. APs are required in the planning/risk assessment phase and in the review phase of the engagement. APs utilized in the preliminary planning/risk assessment phase are

typically considered as reasonableness tests. At the review stage of the audit, they provide an overall review of the assessments and conclusions reached. APs may be used as a substantive test to obtain evidence about certain assertions related to account balances or types of transactions. In certain circumstances, APs may be more effective and efficient than substantive tests of details. When the data set is large and varied, APs may be more effective. When the risk of misstatement is minimal, APs may be more efficient and less costly.

The Cushing and Loebbecke (C-L) model (Figure 1) reflects the phase structure of the typical audit engagement by the Big 8 firms at that time and is the basis for the audit model in many textbooks (Louwers et al. 2016; Whittington and Pany 2014). In this model, auditors should conduct a preliminary analytical review in the planning activities, conduct analytical review procedures as well as substantive tests of transactions and tests of balances in the substantive testing phase. In the evaluation and review phases, this work requires revisiting and re-performing analytical tests (Cushing and Loebbecke 1986). Continuous Activities seemed to consist primarily of project management duties, light documentation, and follow-up procedures.

(Insert Figure 1 about here)

As described in AS 2305.05 (PCAOB 2016), analytical procedures "involve comparisons of recorded amounts, or ratios developed from recorded amounts to expectations developed by the auditor." For example, APs typically accomplish the following five tasks (Table 1):

(Insert Table 1 about here)

Based on this description of APs, it could be expected that the literature could easily be reviewed for relevant papers and organized to facilitate of understanding. However, as will be discussed in the following section, the literature about APs is not confined to the fundamental processes depicted in Table 1, but instead is much broader and varied in scope, thereby complicating this task. This complexity may require an expanded means for organization beyond that of the commonly understood analytical procedures.

## 3.0 Literature Review

### 3.1 Research Methodology

Keele (2007 p 3) states that "A systematic literature review…is a means of identifying, evaluating, and interpreting all available research relevant to a particular research questions, or topic area, or phenomenon of interest." Systematic research is conducted to:

- ✓ Summarize and organize the existing research
- ✓ Identify gaps in this research

- ✓ Provide a framework/background to understand the research and to appropriately direct new research activities

The main objective of this research is to explore and then categorize and synthesize the available academic research on analytical procedures in the external audit engagement. As discussed in the Introduction section, a primary concern of practice is whether business analytics should be used in the engagement, and if so, when and how often (Appelbaum, Kogan, and Vasarhelyi 2017)? And should these techniques be more complex? Could the focus of extant research help direct practice? However, it is not yet ascertained that these are concerns of academics historically.

The next objective is to organize these selected papers to assist in understanding this literature and identify existing gaps and areas for further investigation. The third objective is to apply the results to a structured framework that can appropriately direct future research activities.

Following the methodology of a systematic literature review as proposed by Keele (2007), this research comprises the following search procedures:

*Keywords Search:* Keywords and search strings are collected based on the research questions. This process entailed keyword searches for "*analytics", "analytical procedures", "analytical review", "audit planning", "risk assessment", "internal control assessment", "compliance testing", "statistical analysis", "statistical sampling", "substantive testing activities", "review", "fraud", "Going Concern",* and *"Fair Value Assessment".* Every technique type was also included in the search, as listed in Table 7 of Appendix A.

*Search strings:* These are constructed from the keywords in conjunction with the research questions. The string format is generic so that it may be used in most libraries. For example: (Management Fraud) OR (Earnings Misstatement).

*Sources:* To accomplish the task of initially identifying relevant papers, the database of auditing research compiled by a sub-committee of the AAA Auditing Section Research Committee (Trotman et al, 2009) is examined for academic papers likely to discuss audit analytics. The references of these papers are also examined for likely additions to the list and those subsequent papers are similarly reviewed and additional references tracked, in an iterative process. This entire process is then repeated in Google Scholar and SSRN.

*Filtering:* The papers selected for this study had to be published as full papers in academic journals or as completed dissertations or as completed working papers published online. After obtaining the results from the inclusion/exclusion lists that follow, all remaining studies were examined for the required additional textual analysis. Table 2 shows the selection steps for the literature review.

(Insert Table 2 about here)

The complete listing of all identified papers and major categorizations can be found in Table 9 of Appendix B. The inclusion criteria are as follows:

- ✓ Papers published in academic journals, completed dissertations available online, and working papers published online
- ✓ Papers mentioning external auditing, audit engagement, assurance services, engagement team, public accounting/auditing, financial auditing
- ✓ Papers discussing some aspect of analytical procedures/analytics/statistics/sampling/data mining/machine learning and/or one of those techniques
- ✓ Papers discussing at least one phase of the audit (see discussion that follows)
- ✓ Papers where analytics are not the primary focus but meet all other criteria (this is typical for many behavioral studies)

Papers are excluded based on the following criteria:

- ✓ Papers published in media that were practitioner journals at the time of publication
- ✓ Conference papers and workshop papers
- ✓ Incomplete papers and duplicate papers
- ✓ Papers that mention "auditing" or "auditor" but do not distinguish internal from external and do not describe or refer to a typical engagement responsibility or task
- ✓ Papers referring only to internal auditing/auditors
- ✓ Papers that do not discuss some aspect of analytics/statistics/sampling/data mining/machine learning and/or one of those techniques as either primary or secondary focus
- ✓ Papers that discuss some aspect of a technique but don't relate it at all to auditing (for example, papers on MU sampling never mention auditing or an audit phase or function)

In general, a paper is considered relevant if it mentions directly external auditing and discusses an aspect of analytics that typically belongs in at least one phase of the external audit model as developed by Cushing and Loebbecke (1986), see Figure 1 (Elliott, 1983). In the public company audit setting, analytics could be the primary focus of the paper or a secondary focus or part of another process/objective. For those papers where the use of analytics is not the primary focus, only those papers where analytics are essential to the process/argument/study are selected. For example, several behavioral studies are included that focus on professional judgement and utilize analytical procedures in the experiment or survey process (e.g. Arrington et al, 1984; Asare and Wright 1997). Furthermore, if an analytical procedure is discussed but the typical stage of the audit cycle for that procedure is not identified directly by the author(s) but is otherwise described, the audit cycle is not identified in the categorization table (Table 9) in Appendix B online.

## 3.2 Survey Results

This literature survey process encompasses a total of 572 papers across auditing, systems, accounting, economics, and finance literature, and after applying the selection process, results in 301 papers (Table 3).

(Insert Table 3 about here)

*Literature Evaluation:* A large majority of the papers (80%) discuss the effectiveness or efficiency of various APs as the primary topic. Fourteen papers mention the effectiveness and efficiency of the APs as topics for future research. The overwhelming thrust of each paper is the quality of the performance of APs as either a primary or secondary factor in some aspect of the external audit (Table 4).

(Insert Table 4 about here)

Most academic research about APs in the financial audit engagement appears to be accessible online for publications as of 1958. Although the publications were sparse for the first two decades, this changes in the 1980's and maintains that pace ever since for a total of 301 papers (Figure 2).

(insert Figure 2 here)

These papers are also classified by their research method into the following categories (Figure 3):

- ✓ Analytical (Simulation, Modeling, Design Science, Internal Logic (Vasarhelyi 1982 p 48-4)
- ✓ Behavioral (Case Study, Experimental, Field Study, Survey, Empirical/Behavioral)
- ✓ Archival (Empirical/Archival, Data Review/Analysis, Literature Review, Historical)
- ✓ Conceptual (Discussion, Theoretical, Normative)

(Insert Figure 3 about here)

Empirical methods are considered as both Behavioral and Archival since both approaches are based on research that can be verified through experimentation or verification (Vasarhelyi 1982 p 48-4; Coyne, Summers, Williams, and Wood, 2010 p 634) The research methods are described more precisely per paper in Appendix B, but are summarized in the body of this manuscript at the level of Analytical, Behavioral, Archival, and Conceptual, since these general approaches are predominant. For example, a paper may be classified as a survey in Appendix B but be represented in this figure as behavioral. These 301 papers vary in both research methods and in analytical techniques (see Figures 12, 13, 14, and 15 of Appendix A online). The most popular research methods are analytical, behavioral, archival, and conceptual.

The papers are published in thirty-three different journals, with *Auditing: A Journal of Practice and Theory* with the higher frequency, followed by the *Accounting Review*, the *Journal of*

*Accounting Research*, and *Contemporary Accounting Research*. Figure 15 in Appendix A displays the number of papers published by each journal. The earliest papers were published primarily in *The Journal of Accountancy* and *The Accounting Review*, both of which were considered the primary academic accounting publication venues at that time (Vasarhelyi, 1982). Prior to and changing in the 1950's, accounting academic literature emphasized individual expert opinion (most papers were single authorship) and internal logic (Vasarhelyi 1982; Vasarhelyi et al, 1988). Academic accounting research evolved during the late 50's and early 60's into more empirical thought and interdisciplinary approaches (Vasarhelyi 1982). Prior to the advent of the *Auditing: A Journal of Theory and Practice*, many papers referred to auditors as "outside accountants" or as "accountants and auditors" (Keenoy, 1958; Arkin, 1958; Hill, 1958). Auditing became more established as a field of its own, with unique issues of judgment and expertise that frequently were examined with behavioral methods (Felix and Kinney, 1982).

Specific areas of emphasis for analytical review procedures in the external audit are shown in this literature to be Financial Statement/Management Fraud (Hogan, Rezaee, Riley Jr & Velury, 2008; Trompeter, Carpenter, Desai, Jones & Riley Jr, 2013), Going Concern Opinion (Carson, Fargher, Geiger, Lennox, Raghunandan & Willekens, M., 2013), and Fair Value Measurement (Martin, Rich, & Wilks, 2006; Bratten, Gaynor, McDaniel, Montague & Sierra, 2013).

The papers mention analytical methods in the six audit phases with the frequency shown below in Figure 4, organized in sequence to the typical audit engagement process. Many papers discuss applying analytical methods in more than one phase, and each instance of analytical procedures in a phase is separately counted. Analytics are discussed in the papers as follows: 36 times for the Engagement phase, 228 times for the Planning/Risk Assessment Phase, 225 times for the Substantive Testing Phase, 167 times for the Review Phase, 46 times for the Reporting Phase, and not at all in the Continuous Activities Phase. Given the role of analytical procedures as prescribed in the standards, it is not surprising that research is primarily concentrated in the phases of planning, substantive testing, and review and minimally in the areas of engagement and reporting.

(Insert Figure 4 about here)

The analytical procedures are also examined for each step of the C-L model (Figure 1). Upon initial examination, it soon became obvious that this research is broader in scope than the AP processes detailed in Table 1. Accordingly, these techniques, detailed below as mentioned in the papers, are categorized[1] as follows:

- Audit Examination: Ratio Analysis, Transaction Tests, Sampling, Firm Developed Proprietary Software, Data Analytics, Data Modeling

[1] These are the techniques described in the papers that have been applied/discussed/debated as APs in the external audit engagement. The technique names were maintained, even if there is commonality across methods (for example, time series are linear and Box Jenkins and ARIMA are the same, yet are mentioned separately to maintain faithfulness to the literature). Short definitions and attributes for each technique may be found online in Appendix A, Table 7.

- Unsupervised[2]: Predictive Process Discovery, Clustering, Visualization, Simulation, Real Time Process Analysis, Text Mining
- Supervised[3]: Bayesian Theory/Bayesian Belief Networks (BBN), probability theory, Process Optimization, Bayesian Structural Time Series (BSTS), Naïve Bayes, Fuzzy Artificial Neural Networks (ANN), C4.5 Statistical Classifier, Random Forest, Bagging, Stacking, Majority Vote, Multilayer Feed Forward Neural Network (MLFF)
- Regression: Log, Linear, Time Series, Multivariate Regression Analysis, Univariate Regression Analysis, Step-Wise Logistic, Auto Regressive Integrated Moving Average (ARIMA), Martingale Model, Multivariate Distribution, Sub-Martingale Model, Box Jenkins (ARIMA), Discriminant Analysis, Seasonal Time Series X-11, Random Walk (ARIMA), Ordinary Least Squares (OLS), Double-Exponential Smoothing Model, Single-Exponential Smoothing Model, Random Walk Drift (ARIMA), Hypergeometric Distribution, Ordinal Regression Model, Probit Model
- Other Statistical Methods: Descriptive Statistics, Benfords Law, Monte Carlo Study/Simulations, Complementary Hypothesis Evaluation, Analytic Heirarchy Process (AHP)

The Audit Examination, Unsupervised, Supervised, Regression, and Other Statistical techniques are considered appropriate if they had been applied in the context of the Cushing-Loebbecke model (Figure 1), which may also be referred to as the "traditional" external audit model. A complete listing of the literature with audit phases and analytical techniques identified may be found online in Appendix B.

The percentage of papers using specific analytical techniques is shown below in Figure 5. Many papers mention more than one analytical technique. In the realm of audit analytic techniques, the most frequently used techniques are those of Audit Examinations followed by Regressions. Audit Examinations were discussed 459 times; Unsupervised Methods, 43 times; Supervised Methods, 171 times; Regression, 251 times; and Other Statistical Methods, 77 times.

(Insert Figure 5 about here)

Many of the techniques are applied to the different phases of the external audit, albeit sporadically in the case of unsupervised and supervised methods and frequently in the case of Audit Examination techniques and Regression techniques. Each of the audit phases of Engagement, Planning/Risk Assessment, Substantive & Compliance Testing, Review, Opinion

[2] Unsupervised approaches are those techniques that draw inferences from unlabeled datasets in which instances either have no output specified or the value of the output is unknown (such as whether a transaction is fraudulent or not) (Han, Kamber and Pei 2012, p 330).

[3] Supervised approaches are those techniques that draw inferences from labeled datasets, otherwise known as training data (Han et al, 2012, p 330).

Formulation and Reporting, and Continuous Activities exhibits academic research as follows (please see Table 8 in Appendix A and Appendix B for more detailed analysis per publication):

1. Engagement: The papers from this phase primarily discuss ratio analysis, regression, descriptive statistics, and expert systems, with only a few papers handling visualization, text mining, expert systems, multi-criteria decision aids and structural models.
2. Planning/Risk Assessment: Most of the papers in this phase deal with all types of audit examination, all of the regression techniques, and descriptive statistics, with some discussion of expert systems, Bayesian Belief Networks (BBN), and probability models, and slightly less of clustering, text mining, visualization, multi-criteria decision aids, and structural models.
3. Substantive Testing & Compliance Testing: Audit examination techniques are enormously popular here as were all of the regression techniques, descriptive statistics, expert systems, BBN, and probability models. Less popular were the unsupervised methods and other supervised techniques such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), genetic algorithms, bagging/boosting, and multi-criteria decision aids.
4. Review: Ratio analysis and Computer Assisted Audit Techniques (CAATS) are discussed frequently as were linear and time series regression and expert systems, with BBN, probability models, and descriptive statistics used occasionally.
5. Opinion Formulation and Reporting: In the opinion phase, the main techniques mentioned are ratio analysis, visualization, expert systems, log and linear regression, descriptive statistics and multi-criteria decision aids.
6. Continuous Activities: None of the papers discuss analytics in the context of ongoing/continuous activities.

All the techniques observed even once in the literature are marked in Table 5 below as to which audit phase they occur. For example, although all instances for sampling total 164 mentions, some variations of sampling occur more than once in some papers, resulting in total of 145 papers in Table 5. Additionally, Table 8 in Appendix A online contains a listing of the papers for each technique per audit phase that have been identified in the external audit literature.

(Insert Table 5 about here)

Based on the analysis of which techniques are used in the various audit phases in the literature, a preliminary mapping (Table 5) has been created, based entirely on the discussions in the 301 papers. The predominant techniques for all phases belong to the Audit Examination and Regression approaches, with some use of BBN, probability models, descriptive statistics, and expert systems. Although it may appear in the framework that many other more complex techniques are analyzed by audit academics, their deployment in the literature is inconsistent and sporadic. Some techniques are discussed only a couple of times, as is the case with text mining, visualizations, process mining, SVM, ANN, Genetic Algorithm, C4.5 Classifiers, AHP, and hypothesis evaluation.

In the task of Audit Examination, techniques such as sampling, ratio and trend analysis, CAATS usage, and general ledger tests are clear favorites. Sampling techniques and ratio and/or trend analysis are discussed more frequently than any other method, at 37.8% and 43.5% respectively. CAATS are included in this category as many of the tests conducted by external auditors in the papers were general ledger tests and basic calculations (Figure 6).

(Insert Figure 6 about here)

Additionally, Bayesian statistics are applied extensively in the area of sampling (Ijiri & Kaplan, 1971; Corless, 1972; Elliott & Rogers, 1972; Hoogduin, Hall, & Tsay 2010) and in auditor judgment and planning (Felix, 1976; Chang, Bailey, & Whinston, 1993; Dusenbury, Reimers, & Wheeler, 2000; Krishnamoorthy, Mock, & Washington, 1999).

Regression techniques are second in popularity, discussed 251 times in the audit literature. Log Regression was mentioned 81 times, with Linear Regression at 62 times, Time Series Regression at 34 times, ARIMA at 20, and Univariate and Multivariate at 54 (Figure 7).

(Insert Figure 7 about here)

Most popular of the supervised techniques is the application of Bayes Learners/Bayesian Belief Networks at 46 times, followed by Expert Systems at 41, Probability Models at 30, and Artificial Neural Networks at 24 times (Figure 8).

(Insert Figure 8 about here)

Unsupervised Methods are discussed minimally, with Process Mining being the most popular (Figure 9).

(Insert Figure 9 about here)

Other Statistical Methods are slightly more popular with coverage in 77 papers, with Descriptive Statistics receiving the most attention in 31 papers (Figure 10).

(Insert Figure 10 about here)

## 4.0 Evolution of the External Audit Analytics Framework

The sheer number of academic papers still presents a challenge for researchers even after many features have been described. The available academic research on analytical procedures goes well beyond developing expectation models and testing actual results, which is the definition for Analytical Procedures as described in the standards. The systematic research method (Keele 2007) suggests that an organizing conceptual framework should be developed to facilitate understanding.

The aim of this structured research is not just to aggregate the evidence but to also provide guidelines for future academic research and practitioner applications in a specific context.

A conceptual framework may be defined as "the way ideas are organized to achieve a research project's purpose" (Shields and Rangarjan 2013, p 24). The purpose of a framework is to organize the literature to best understand how academic researchers apply analytical procedures to the audit engagement. Since the typical engagement proceeds with the format of the audit phases, it seems logical to organize the literature first by audit phase and then these phases are subsequently divided by AP type. Table 5 summarizes this information which is also available in more detail with paper numbers, see Table 8 of Appendix A online. However, Table 8 may still appear overwhelming. Therefore, it may be appropriate to organize this literature within another view of APs, that of Business Analytics (BA).

## 4.1. Business Analytics

Since auditors examine business financial data, much of which may be generated with applications and analytics embedded in management enterprise systems, gaining knowledge of and perhaps adapting concepts of business analytics as discussed in academic literature (Holsapple et al, 2014) could be beneficial. Business analytics is 'the use of data, information technology, statistical analysis, quantitative methods, and mathematical or computer-based models to help managers gain improved insight about their operations, and make better, fact-based decisions' (Davenport and Harris, 2007).

The recently proposed three dimensions of Business Analytics (BA), domain, orientation, and techniques (Holsapple et al 2014), are useful for understanding the scope of business analytics. Domain refers to the context or environment in which the analytics are being applied. Orientation describes the outlook of the analytics – descriptive, predictive, or prescriptive, while techniques refer to the analytical processes of the domain and orientation (Holsapple et al 2014). The feasibility of the application of a technique is dictated not only by its orientation, but also by the available data.

In the environment that the audit team operates, the domain dimension of the client is business enterprise and management. The three dimensions of orientation (descriptive, predictive, and prescriptive), as discussed by Holsapple et al (2014), should be clarified to gain an understanding of their potential roles in the business domain. The differing orientations of these dimensions are partly due to the availability of different types of data in conjunction with various techniques and the capabilities of the client enterprise systems.

*Descriptive Analytics*

Descriptive analytics answers the question as to what happened. It is the most common type of analytics used by businesses (IBM, 2013) and is typically characterized by descriptive statistics, Key Performance Indicators (KPIs), dashboards, or other types of visualizations (Dilla, Janvrin, and Raschke 2010). Descriptive analytics also forms the basis of many continuous monitoring alert

systems, where transactions are compared to data based analytics (Vasarhelyi and Halper 1991) and thresholds are established from ratio and trend analysis of historical data.

*Predictive Analytics*

Predictive Analytics is the next step taken with the knowledge acquisition from descriptive analytics (Bertsimas and Kallus, 2014) and answers the question of what could happen (IBM, 2013). It is characterized by predictive and probability models, forecasts, statistical analysis and scoring models. Predictive models use historical data accumulated over time to make calculations of probable future events. Most businesses use predominantly descriptive analytics and are just beginning to use predictive analytics (IBM, 2013).

*Prescriptive Analytics*

Prescriptive Analytics (Bertsimas and Kallus, 2014; Holsapple et al, 2014; IBM, 2013; Ayata, 2012) answers the question of what should be done given the descriptive and predictive analytics results. Prescriptive analytics may be described as the optimization approach. Prescriptive analytics go beyond descriptive and predictive by recommending one or more solutions and showing the likely outcome of each.

The techniques for predictive and prescriptive analytics may appear similar, but their orientation and ability to prescribe or predict depends on the type and amount of data available for analysis. The bigger the data and more varied the data types, the more likely the solution may be prescriptive. Prescriptive techniques may pull upon quantitative and qualitative data from internal and external sources. Analytics based on quantitative financial data alone are utilizing only a fraction of all available data, since most data is qualitative (Basu, 2013). Based on business rules, constraints, and thresholds, in a prescriptive orientation, mathematical simulation models or operational optimization models are built that identify uncertainties and offer solutions to mitigate the accompanying risks or adverse forecasts (Appelbaum et al 2016).

The techniques of business analytics can be considered as either qualitative or quantitative, or as deterministic or statistical, or based on unstructured, semi-structured, or structured data (Table 7, App. A). The most traditionally used accounting techniques are those that are quantitative, statistical, and based on structured data. While in the past most advanced business analytics techniques came from statistical data analysis, more recently research has begun incorporating techniques that originate in machine learning, artificial intelligence (AI), deep learning, text mining, and data mining. Some of these recently popular techniques do not make any statistical assumptions about underlying data, and consequently generate models that are not statistical in nature. The techniques found in business analytics are classified in Table 7 of online Appendix A.[4] Given the attributes of audit engagement APs as discussed in the literature, the next challenge is to obtain an understanding of how these APs can be considered as Business Analytics. This process

[4] Due to space concerns, Appendix A, Appendix B (Table 9), and the Table 9 Reference List (all papers listed in Table 9) are available online. The references in Section 6 pertain only to those citations in the body of the text.

starts by first understanding this literature to date, by undertaking the next steps of the literature review process.

## 4.2 Given its attributes, how can this literature be presented to direct future academic research?

One of the more common reasons for performing a literature review is to provide a framework or context to appropriately position new research activities, having identified the extant research (Keele 2007, p 3). Within this scope of a review lies the opportunity to provide an overview of the literature with the intent to influence the direction of future research. This paper began by describing the dilemma of the current audit profession, that the emergence of big data as well as the growing use of analytics by audit clients has brought new concerns. That is, audit clients are progressively using more complex Business Analytics (BA) and auditors are concerned that APs as typically and historically applied may not be relevant or effective. Since auditors examine business financial and BA data, ideally a literature review based framework should be directed towards these new concerns.

This section will discuss the evolution of a conceptual External Audit Analytics (EAA) framework, where this examination of extant audit academic research regarding Analytical Procedures is applied to the more general context of Business Analytics (BA). Although there have been many applications of Analytical Procedures in the external audit practice[5], there should be a framework providing guidance for academic research of the more complex analytical techniques.

External Audit Analytics (EAA) is defined as: *the utilization of various analytical procedures, methods, and models to facilitate the transformation of data into external audit evidence and subsequently into audit decisions.* EAA may be considered as a special sub-area of the wider area of Business Analytics (BA) since public auditors examine business financial data.

Business Analytics in academic research is discussed in the previous section and its dimensions (domain, orientation, context) are subsequently applied to the Analytical Procedures function of the audit engagement. In this context, APs as practiced to date (Table 1) are but one component of EAA. APs in the context of EAA provide a greater scope and variation than the APs as conventionally understood.

The conventional Analytical Procedures (APs) process, when regarded under the view of Business Analytics, can now be conceptually regarded as one component of External Audit Analytics (EAA). EAA provides the generalization needed to encourage further research and use of this expanded view of APs. For example, in Table 1 APs are limited to basic comparisons and ratio analysis using both financial and nonfinancial data – however, EAA pertains to all BA techniques that lend themselves to the engagement process. In this context, EAA in an audit

[5] Li et al. (2016) surveyed users of an audit analytics software and found very limited use of advanced analytics.

engagement could comprise of ratio analysis, text mining, and network mapping – a combination of quantitative and qualitative data sources and a varied range of techniques.

Accordingly, the three BA dimensions are useful for defining EAA. The initial findings of this literature review will be categorized by these three BA dimensions of domain, orientation, and technique. These dimensions, particularly that of orientation, are a new way of understanding analytics in the external audit. The process of categorizing each paper in the context of EAA involves the following three steps:

- Determine the audit phase as described in the paper
- Determine the orientation of the research task (descriptive, predictive, prescriptive)
- Determine the type of analytical technique deployed in the publication

Parts of the following Figure 11 are a high level graphic illustration of the results of this three-step process. It illustrates a literature-based framework which identifies the APs that the papers discuss and what type of EAA orientation and techniques were examined:

(Insert Figure 11 about here)

Figure 11 categorizes the literature at a high summary level and could be regarded as the literature based framework for APs in the external audit domain.[6] Checkmarks indicate where a paper has been identified, based on the process for that phase/orientation/technique type. All the unchecked blank or shaded spaces theoretically represent areas where literature has not been found to date, yet could be potential areas of research

4.2.1 Domain of EAA

The domain of EAA is naturally associated with the stages of the audit cycle where BA methods and models may be applied. When applying the properties and techniques of BA to APs in the process of developing EAA, issues which may emerge during this process could be as follows:

- How different are the objectives of Internal and External Audit Analytics in the current context (Li et al, 2016)?
- Isn't there a substantive overlap between business monitoring and real-time assurance?

[6] It is recommended that interested researchers follow these procedures:

- ✓ First, identify the area(s) of interest in Figure 11 here;
- ✓ Secondly, look at those phases and their more detailed AP type in Table 7 to obtain more insight about the techniques;
- ✓ Thirdly, look at Table 8**Error! Reference source not found.** in Appendix A under the specific AP technique(s) and phase(s) (from Table 7) to gather all relevant paper numbers;
- ✓ Finally, find these paper numbers in Table 9 (Appendix B) for research and analysis.

- Considering that there is substantive overlap in data analytic needs, are the traditional three lines of defense (Freeman, 2015; Chambers, 2014)) still relevant?

4.2.2 Orientation of EAA

A distinction can be drawn regarding descriptive, predictive, and prescriptive orientations of EAA.

*Descriptive EAA* answers the question as to what happened. It is the most common type of analytics used by auditors and is typically characterized by descriptive statistics, Key Performance Indicators (KPIs), dashboards, or other types of visualizations. It is expected that the focus of discussion in the academic literature would be predominant in this orientation of the audit.

*Predictive EAA* is the next step taken with the knowledge acquisition from descriptive analytics (Bertsimas and Kallus, 2014) and answers the question of what could happen (IBM, 2013) and is characterized by predictive and probability models, forecasts, statistical analysis and scoring models. Most audit clients use predominantly descriptive analytics and are just beginning to use predictive analytics (IBM, 2013). The following issues perhaps should be considered by audit researchers in this evolving analytic environment:

- Traditional auditing has a retrospective approach, as traditional technologies did not allow for other approaches - can the current environment allow for a prospective look?
- What parts / procedures of the audit are fully or partially automatable?
- Will it allow a disruptive change (Christensen, 2013)?

*Prescriptive EAA* (Bertsimas and Kallus, 2014; Holsapple et al, 2014; IBM, 2013; Ayata, 2012) goes beyond descriptive and predictive by recommending one or more solutions and showing the likely outcome of each approach. It is a type of predictive EAA in that it prescribes a solution requiring a predictive model with two components: actionable big and varied (hybrid) data and a validation/feedback system. A prescriptive EAA model will have a decision function that chooses among alternatives – an optimization model. Interesting questions emerge from attempting to prescribe:

- Can the key contingencies in the audit be formalized?
- Will these be allowed to evolve under the current audit standards?
- Are they so disruptive (Christensen, 2013) that these advanced analytics will be ignored by current leading audit firms?

4.2.3 Techniques of EAA

EAA undertaken in an engagement where big data is available may result in a prescriptive analytics approach where a set of techniques computationally identifies several alternative actions to be taken by the auditor, given the audit's complex objectives and limitations, with the goal of reducing audit risk. For example, EAA techniques utilizing varied sources of big data could be

used to arrive at a quantitative score for the audit opinion, as opposed to the current pass/fail opinion.

The currently mandated pass/fail opinion format [7] does not reflect the nuances and details of the auditor's work - the culmination of much laborious examination and careful judgement by the auditor. With more advanced EAA techniques and reliable evidence, it is probable that this process and resulting opinion could be quantified with prescriptive analytics. Prescriptive analytics may allow for a graduated scale or ranking of audit opinion and audit risk. In an ideal scenario, auditors should be prolific in their use of analytic techniques of all three orientations, as analytics should be dominant in industries that are very data-rich and where one of the major improvements from analytics usage is risk reduction (Banerjee et al, 2013).

4.2.4 The Integration of the Literature Framework with EAA

Many of the techniques observed in the external audit literature are quantitative in nature. This dominance of quantitative techniques in APs may be because the main objective of external audit has been to provide assurance on the accounting numbers. Therefore, the accounting numbers traditionally were the focus of APs. However, with the availability of internal textual data, social media, and big data, the scope of APs could be expanded to that of EAA. This greater variety of available data creates the opportunity for more advanced analytics research.

Accounting numbers are derived by manipulating (aggregating, adjusting, etc.) quantitative descriptions of business transactions and are obviously well structured. This structured data leads typically to analysis which is quantitative and descriptive, and can be categorized as Audit Examination techniques. Audit Examination entails, among many procedures, basic transaction tests, three-way matching, ratio analysis, sampling, re-confirmation, and re-performance. These tests are applied in every external audit engagement, and are regarded as fundamental EAA.

4.2.5 Expectation Models and EAA

To obtain context for how the EAA framework could fit in an audit engagement, a review of expectation models in the audit should be presented. The most common types of techniques utilized in EAA, in addition to those of the afore-mentioned audit examination, are expectation models. The standards prescribe that auditors should develop expectations of accounts in the risk assessment phase (PCAOB AS2110.48, 2016). A typical expectation model is an empirical relationship among several accounting numbers or some other important quantitative measures of business operations.

[7] There is ongoing discussion regarding Critical Audit Matters within the profession and the PCAOB. The PCAOB Release No. 2013-005, August 13, 2013, Docket Matter No. 034, The Auditor's Report on an audit of Financial Statements When the Auditor expresses an Unqualified Opinion, discusses the auditor's responsibilities regarding certain other information in certain documents containing audited financial statements and the related auditor's reports and related amendments to the PCAOB standards. See also Lynne Turner's comments (https://pcaobus.org//Rulemaking/Docket034/ps_Turner.pdf).

An expectation model is inferred from the archive of historical records. If it turns out to be possible to infer a stable empirical relationship that fits the historical records well, then it is reasonable to expect this relationship to hold for the near future, assuming no significant changes take place in the business. Therefore, this relationship provides an expectation model for the accounting numbers and other important business metrics of the near future. The accuracy of this future relationship provides important audit evidence about the veracity of the quantities involved.

It is common to focus on a certain accounting number (e.g., revenue), and represent an expectation model as an equation for this accounting number. Then, for a given confidence level, this equation can be used to derive a prediction interval for the future value of the accounting number. If the actual future value turns out to be inside the prediction interval, this can be interpreted as strong evidence that the accounting number is properly represented. Otherwise, if the actual future value lies outside the prediction model, the auditor will need to conduct further investigation to determine if there is indeed a problem with this accounting number. The expectation model forms the basis of audit examination in the engagement and determines the direction and degree of evidence collection and audit scrutiny.

The EAA usage described above has predictive orientation, and the amount of audit evidence provided is based on the level of agreement between the observed business reality and the predictions. This is utilized not only to verify accounting numbers, but also to provide assurance on controls by comparing the observed business process workflow with the expectations derived either from the existing business rules, or from the past observations of business processes. As an example of the former, a business rule stating that "purchase orders exceeding $1,000 require management authorization" creates an expectation with which all future purchase order transactions would be compared. As for the latter option, if the analysis of past purchase orders shows that 99% used vendors that were pre-approved, then it would be reasonable for the auditors to expect that every future purchase order would use a pre-approved vendor, and those that do not would warrant investigation.

#### 4.2.6 EAA Expanded

While the uses of EAA expectation models that have been derived from formalized business rules are usually essential in the current engagement process, they are not as methodologically difficult, and this manuscript focuses on other EAA expectation models obtained from more advanced techniques.

The most basic dichotomy of the EAA techniques distinguishes between structural and quantitative methods. Structural techniques look for various structural properties in the historical records. A recent example is process mining (Jans et al, 2013). It provides techniques for analyzing enterprise system logs and identifying the most common paths of enterprise business workflow to be used as expectation models. If the observed workflow of a particular process deviates significantly from the expected path, it should warrant an investigation.

It is appropriate to make a distinction between univariate and multivariate methods. Univariate techniques usually infer various distribution properties of individual quantities, and can be as familiar as estimating the median, mean, skewness and kurtosis, or more complex as applying Benford's Law to auditing.

There is a great variety of EAA multivariate techniques, and no generally accepted agreement on their taxonomy[8]. It could be useful to differentiate multivariate techniques by considering whether a particular EAA technique explicitly assumes the presence of latent[9] features. For example, common classification and regression techniques do not work explicitly with any latent features, while common clustering techniques do (with the latent feature being the cluster ID). Often, the utilization of latent features techniques is necessitated by the lack of critical information in the historical records. For example, while it is commonly assumed that managerial or financial statement fraud is a routine occurrence in most enterprises, very few confirmed and documented cases of such fraudulent transactions exist. For this reason, most audit engagement teams face the challenge of creating expectation models for what is fraudulent versus normal, given that the historical records do not identify past transactions in this way. In this situation, it would be ideal for an auditor to examine transactions with a different perspective that is more exploratory in nature.

Another important technique dimension to consider is the scale of variables utilized in the expectation models, with the categorical and continuous ones being the two most commonly used. The two important measurement scales of categorical variables are nominal and ordinal, while the two important measurement scales of continuous variables are interval and ratio.

It is often the case that a technique assumes that all the variables are measured on one type of the scale, and adaptations are required for those measured on a different one. For example, multiple linear regression models are developed for the case of continuous variables, while the categorical scales of independent variables are accommodated by using dummy variables. Sophisticated generalizations of multiple linear regression models such as ordinal regression models are utilized to deal with the case of categorical dependent variables. On the other hand, decision trees are

[8] The primary objective of multivariate techniques is to develop relationships between or among variables/features under study. In this view, the universe of multivariate techniques is wider than what is usually considered to be the domain of multivariate statistics, where joint distributional properties of more than one variable are studied. If only a single variable is viewed as the outcome or dependent variable, and its univariate distribution is studied given the values of some the other variables, such as case in multiple linear regression, then we view it as a multivariate technique even though it is traditionally not considered to be multivariate statistics.

[9] Latent features are attributes or qualities that are not directly observed. For example, a concept such as trust is measured in terms of multiple indirect observations that have shown correlation with it, thereby deriving a value for this attribute which cannot be directly measured.

developed for nominal variables, while the continuous ones are accommodated by introducing their comparisons with threshold values.

An important subset of continuous EAA models consists of the time series models, where the time variable is afforded special treatment. Note that univariate time series models are based on two variables (including time). Also, commonly used time series models study relationships between variable values at discrete moments in time. Those much more complicated models where time is continuous belong to the realm of stochastic processes, and such models have not so far found applications in audit analytics.

#### 4.2.7 The EAA Framework

Combining knowledge of the EAA with the literature, a summary conceptual framework of EAA for academic research in the external audit domain is proposed (Figure 11). By grounding the EAA framework with analytics based on prevalent business and external audit practices, future academic research maintains its relevance to the profession.

This framework identifies with shading those areas of APs (now considered as EAA) that have been covered by extant literature yet require additional study, in addition to those areas of research that exhibit gaps in the EAA domain. Audit Examination techniques form the foundation of each step in the proposed EAA framework. Since Audit Examination techniques may be descriptive, exploratory, and confirmatory (Liu 2014), they provide a level of domain and transaction knowledge that are essential to the auditor. In EAA, it is expected that data preparation procedures such as data verification, data cleaning, and data harmonizing contribute to “client knowledge” or “client data expertise” and are similarly time-consuming and laborious to obtain.

The framework in Figure 11 illustrates with shading the general type of technique (Audit Examinations, Unsupervised, Supervised, Regression, and Other Statistics) that potentially could be deployed by auditors and the orientation of these techniques (Descriptive, Predictive, and Prescriptive). This framework may serve as a foundation for additional detailed research by practitioners, standard setters, and academia regarding the use of the various suggested techniques for each audit phase. The framework provides guidance as follows:

- Checked areas: the audit phase where published research has been found with that description and technique type
- Checked without shading: The areas that are checked without shading are areas exhibiting high volume of research (Figure 11).
- Shaded areas, checked/not checked: The phases where research appears to be scant or missing to date are shaded.
- The shaded cells shown in Figure 11 are identified now as research-sparse EAA.

For example, clustering as an unsupervised descriptive method has been found to be missing in the engagement phase literature and is suggested here for future analysis. Additionally,

visualization as an unsupervised method has been examined for many audit phases in some research; however, this does not mean that there isn't room for additional research contributions. In general, the phases of Engagement, Opinion, and Continuous Activities are particularly sparse, most likely because the standards do not require analytical procedures at these phases, and therefore could benefit from additional research.

The proposed EAA framework is based on the assumptions that the auditor has few technical constraints and has access to a significant amount of client and other external data. Figure 11 combines the discussion of the potential approaches for possible technique types in each audit phase (see beginning of this section) with that of the literature findings.

In Figure 11 there are research gaps/sparse research in visualization, process mining, and all prescriptive methods for every audit phase. For example, an unsupervised technique such as Visualization, which is already predominant in BA (Holsapple et al, 2014), might be readily accepted to supplement audit examination techniques in each phase. A different view of the proposed EAA Framework is provided in Table 6, where areas suggested for future research are checked:

(Insert table 6 about here)

It is anticipated that techniques that are of descriptive orientation (audit examination, unsupervised, and other statistics) would be employed first for EAA as these are most similar to the audit examination process in that they are descriptive. Techniques that are of predictive orientation (unsupervised, supervised, regression, and other) would be next, followed last by prescriptive oriented techniques (unsupervised, supervised, regression and other).

As it stands now, auditors typically face significant challenges to obtain sufficient and reliable client evidence, quantitative and qualitative. Looking forward, it is believed that these assumptions regarding the EAA framework will not be unrealistic – many clients today process dozens of terabytes of internal data, not to mention acquiring additional external sources of data, which is more than 1000 times the data available just ten years previously (Banerjee et al, 2013). Over time, clients may expect deeper insights from their external auditors, to maximize the potential benefits of their investment in internal IT infrastructure and big data collection. Other client stakeholders may also expect deeper levels of analysis from the external auditor in this big data technology driven business environment.

By and large most advanced analytical procedures are of value for predictive methods but not necessarily prescriptive. Descriptive methods complement these approaches. Traditional descriptive methods can also be supplemented by other statistical methods. This huge potential usage of predictive and prescriptive methods also raises the issue of the adequacy of the traditional organization of the audit in an assurance process that is close to real time, mainly automated, subject to deep human decision making, and complemented by analytic technology.

## 5.0 Concluding Comments

This research is motivated by the current demands of academia, regulators, and the profession for guidance regarding the increased use of analytics in external auditing. Upon exploration of the academic audit literature for such guidance, it appears that a comprehensive and updated synthesis is not available. Accordingly, the vast body of audit literature is searched for those papers that discuss the use of analytical procedures in at least one phase of the external engagement. This literature is then examined and categorized by audit phase, analytic technique, research technique, and other details.

This preliminary understanding is then expanded with the concepts of business analytics (Holsapple et al. 2014), applications which capture the potential information made possible with big data. Considering audit analytics with the concepts of business analytics(BA) is appropriate since auditors examine business processes and decisions. This combination of literature findings and BA, now called the External Audit Analytics (EAA) framework, is organized around descriptive, predictive, and prescriptive orientations of BA. Although predominantly literature based, the EAA framework contains recommendations for the utilization of prescriptive techniques.

This paper organizes and synthesizes the previously uncategorized extant literature, thereby encouraging further research and exploration by academia, regulators, and practitioners. Due to the very large number of publications discussing data analytics in the external audit, the process of organizing and understanding this research is just beginning. The breadth and scope of approaches in the literature is astonishing, given the somewhat limited and narrow applications of analytics in assurance practice. The fact that 301 papers discuss analytics in the audit engagement is significant. The expanse of extant research is apparent and challenges the assumption that the profession has always been focused only on ratio analysis, sampling, and scanning. This literature review provides a significant contribution to the audit literature in that it:

- Summarizes and organizes the existing research about analytics and big data in the audit engagement;
- Provides a framework/background – the EAA Framework – with which to understand this extant relevant research and to appropriately direct new research activities, practice, and regulations;
- Identifies gaps in this extant research by means of the EAA Framework.

This paper details and organizes all the relevant research for any approach that occurs in a phase of the audit engagement. Academics, practitioners, and regulators may readily identify previous research for many techniques in the audit phases. For example, the PCAOB is re-assessing the feasibility of a more quantitative reporting format for the Audit Opinion and CAMs – and this paper provides an organized reference guide that directs attention to the papers that discuss various analytics and reporting techniques for that phase of the engagement. The PCAOB may see that 46 papers discuss analytics in the reporting phase, and these papers are identified.

Essentially, this paper may assist in directing the research process for the audit profession and exposes the degree of thought and analysis that has already occurred, thereby offering a significant contribution to the field.

However, when considering these papers in light of EAA, more research could be applied in the engagement phases as follows:

1. Engagement: The auditors have access to the audited financial statements and other public information as well as other external sources of data, not dissimilar to investment/financial analysts. Expectation models could be developed at this time, derived from quantitative and qualitative data. At this stage, researchers should focus on performing the following techniques: ratio analysis of audited statements, text mining, visualization, regression, and descriptive statistics.
2. Planning/Risk Assessment: Similar to the Engagement Phase, but the researchers can assume that auditors would have access to the current unaudited financial statements and could develop models of what could and should happen. Clustering, visualization, regression, belief networks, expert systems, and descriptive statistics may be used in addition to ratio and trend analysis.
3. Substantive Testing & Compliance Testing: Research in this phase could compare sampling to testing 100% of the transactions, depending on the client environment. Transactions could be tested against benchmarks and expectation models. Results that are flags or indicative of further investigation could be subject to further testing and evidence collection. However, initially research for this phase most likely would include all audit examination techniques, Audit by Exception (ABE) if appropriate, clustering, text mining, process mining, visualization, SVM, ANN, expert systems, decision trees, probability models, belief networks, regression, Benford's Law, descriptive statistics, structural models, and hypothesis evaluation.
4. Review: Research of this phase could entail cross-validation tests and analysis of exceptional results using different techniques. It would tend towards prescriptive testing, since what should have happened will serve as the benchmark of what happened. All the techniques outlined in Substantive Testing could be applied here, with more emphasis on expert systems, probability models, belief networks, SVM, ANN, genetic algorithms, multi-criteria decision aids, regression, and hypothesis testing.
5. Opinion Formulation and Reporting: This phase is open for much research given that the PCAOB has promised to improve the quality and transparency of the audit opinion format. It is anticipated that there may be a more nuanced measurement of risk than the current unqualified/qualified opinion. Potentially the audit opinion could be a more informative, graduated opinion derived from prescriptive analytics of reliable evidence. This phase could feasibly benefit from the same approaches mentioned in earlier phases, with more emphasis on time series regression, probability models, belief networks, expert systems, and Monte Carlo simulation studies. The topic of the application of analytical techniques

to arrive at a more quantitative audit opinion, away from the current mainly dichotomous outcome, is a very important area for future research.

6. Continuous Activities: The researcher and/or auditor may run continuous or interim tests using many different models to generate predictive and prescriptive expectations of the ongoing client's activities and how they may impact the upcoming financial statements. This phase would involve the use of many audit examination techniques as a foundation for the use of regression, descriptive statistics, belief networks, probability models, expert systems, decision trees, process mining, visualization, text mining, and clustering. Prescriptive models would be continuously updated with new data, improving the models' accuracy over time. Although not mentioned by Cushing and Loebbecke (1986), Continuous Auditing (CA) (Vasarhelyi and Halper 1991) with its real-time feed of relevant information could be considered as an interim continuous activity.

Although there exists a vast body of academic analysis providing an expanded view of APs, this view of available research to date has many gaps. As can be seen, much additional analysis needs to occur in every audit phase with most techniques, despite the broad expanse of extant research in this domain. It is hoped that regarding these APs in a slightly different light will encourage additional discussion. Academia has already conducted extensive research regarding the use of expanded analytics in the external audit, yet even more is required. The application of these papers towards an EAA framework maintains their relevance in the modern economy and in the modern data-driven audit. The broad expanse of research regarding analytics in the engagement is now exposed, in juxtaposition to the very narrow range of analytics used by the external audit profession. What has been lacking to date is the execution in assurance practice of this rich research – however, with the challenges that auditors face in this modern business environment of analytics and big data, motivation for a shift in practice towards more complex analytics surely must be strengthening.

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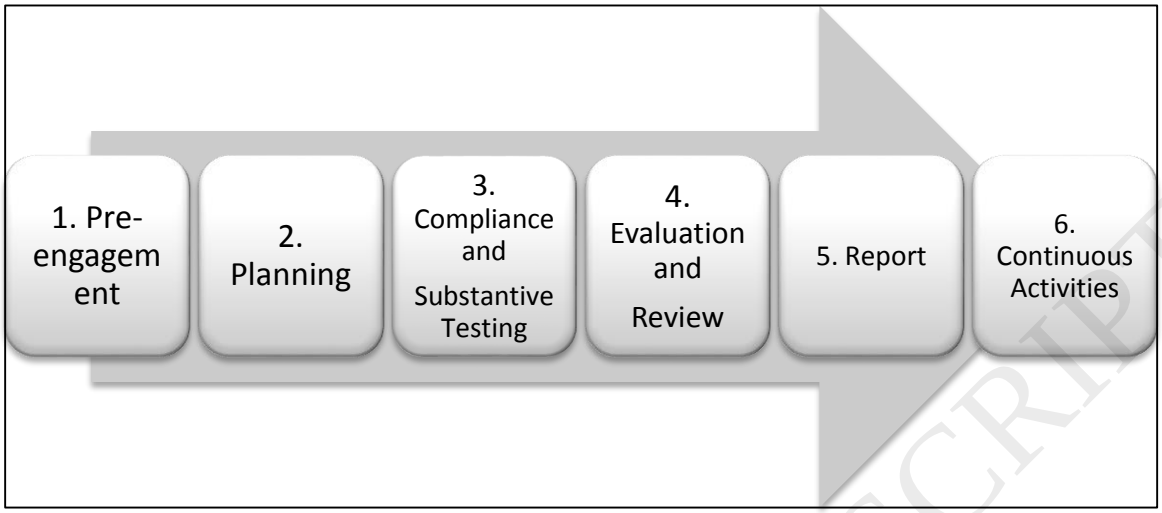


Figure 1: Model of Engagement Cycle based on Cushing and Loebbecke Model (1986) and modified to reflect the current standards and general practice and which provide context for understanding the use of Aps.

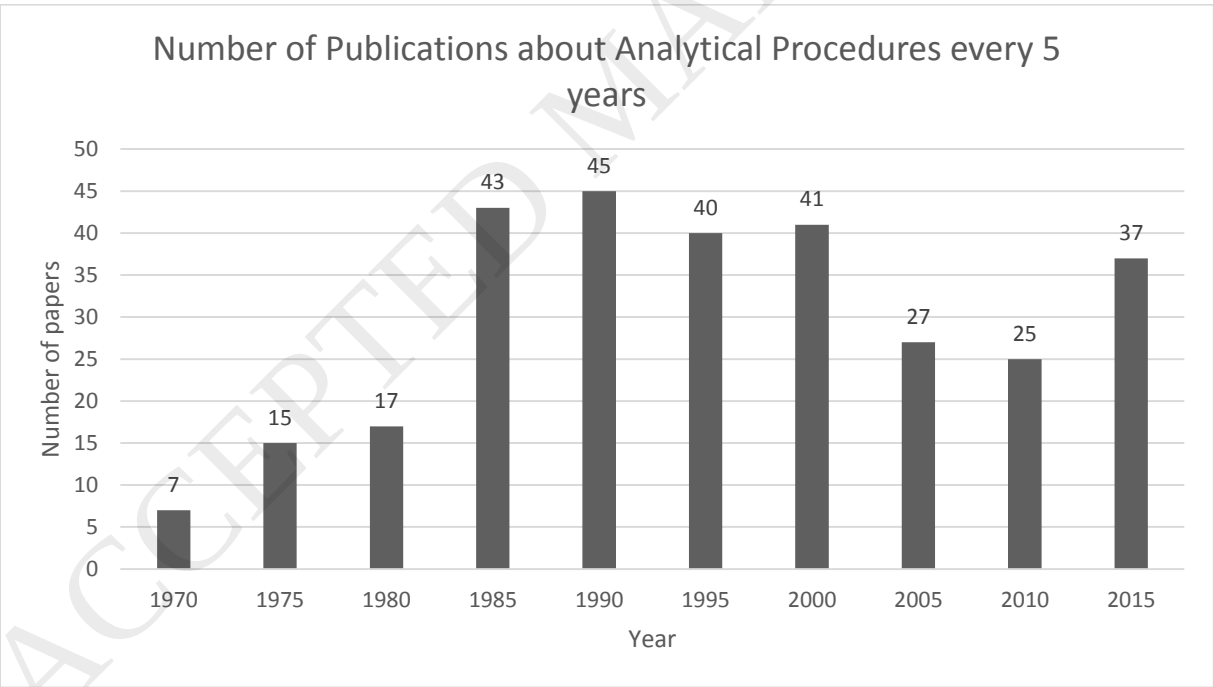


Figure 2: Number of Analytical Papers per year, from 1970 (aggregated for years prior to 1970) until 2015, in five year increments

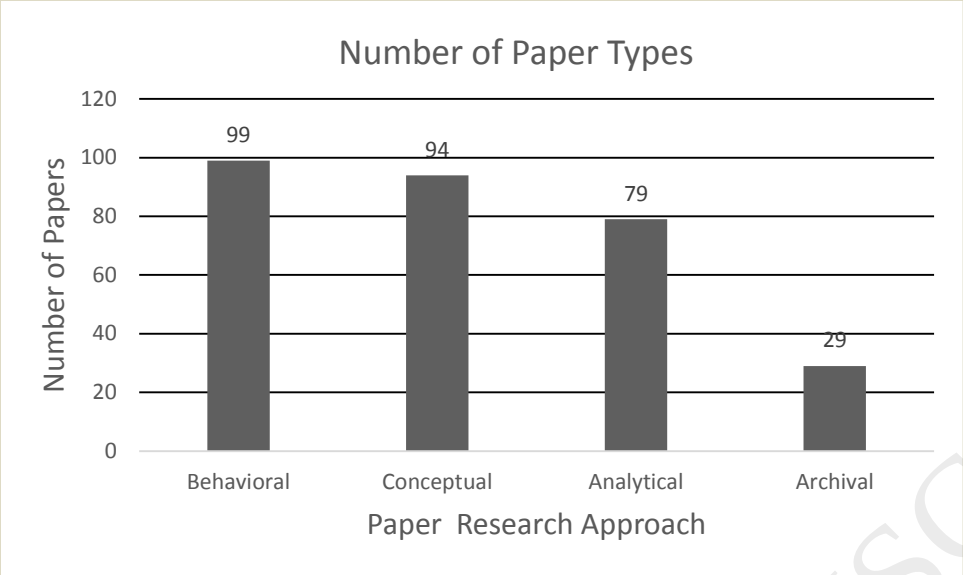


Figure 3: Display of the number and percentage of paper types/approaches that discuss analytics in the external audit

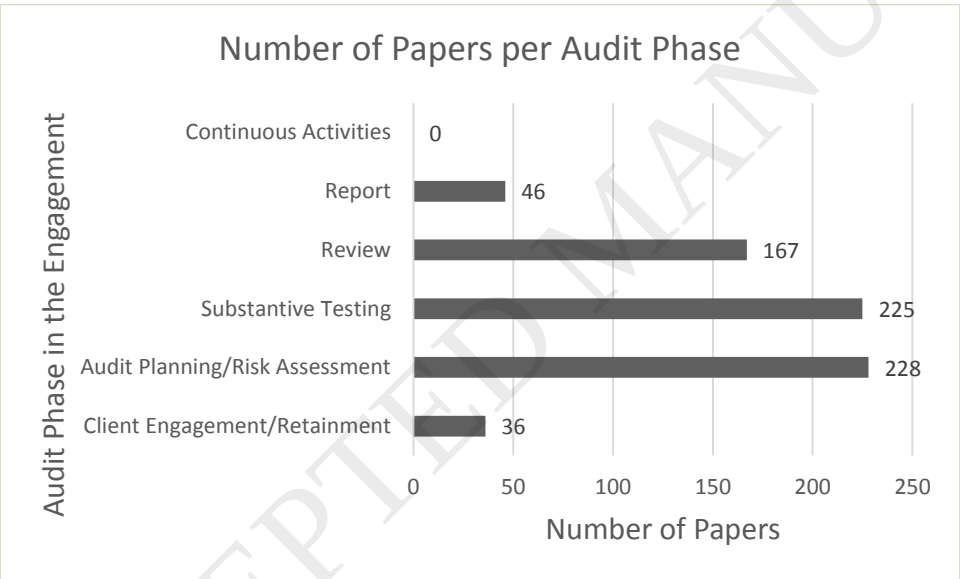


Figure 4: Total number of papers discussing the application of analytics per Audit Phase

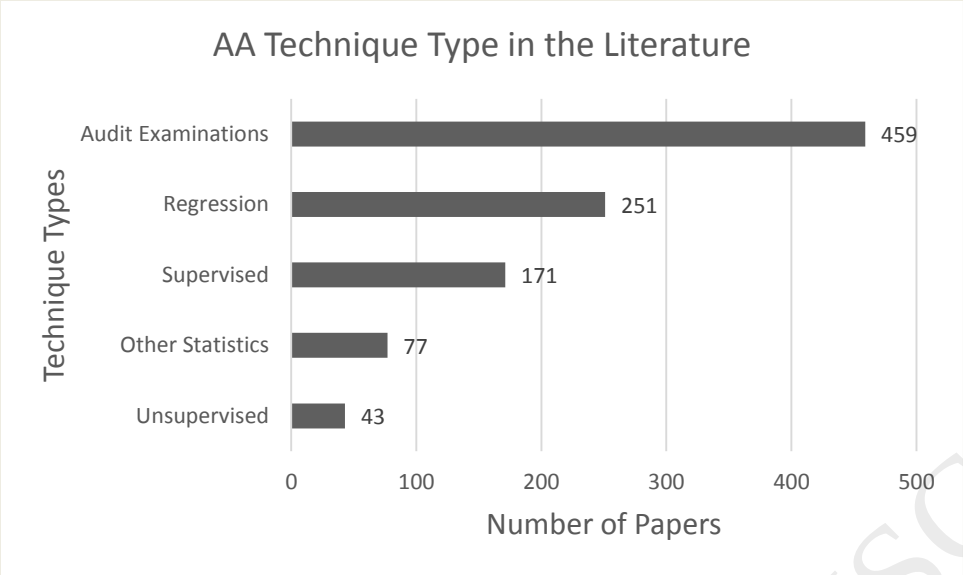


Figure 5: Number of papers using certain Audit Analytics techniques in the literature

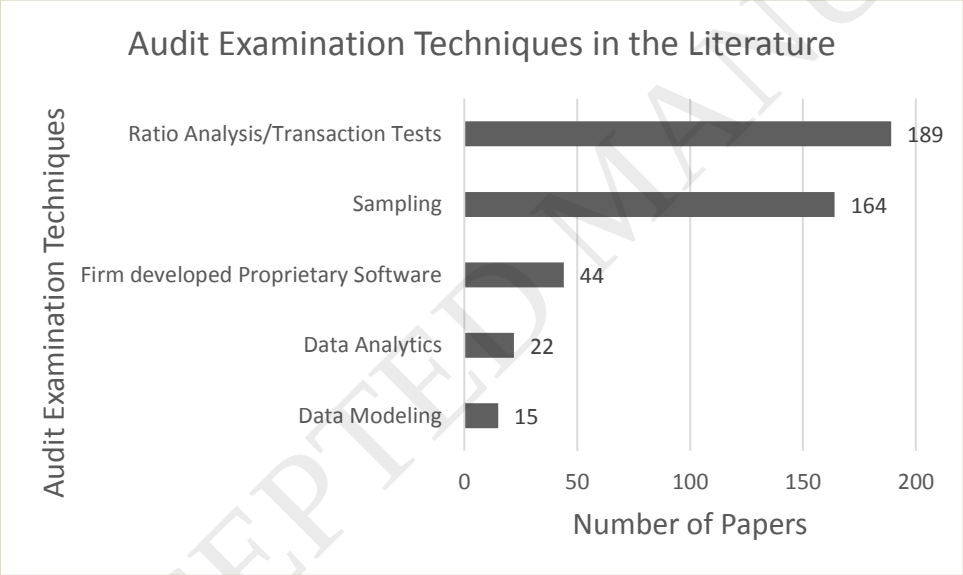


Figure 6: Total number of papers that discuss the various Audit Examination techniques

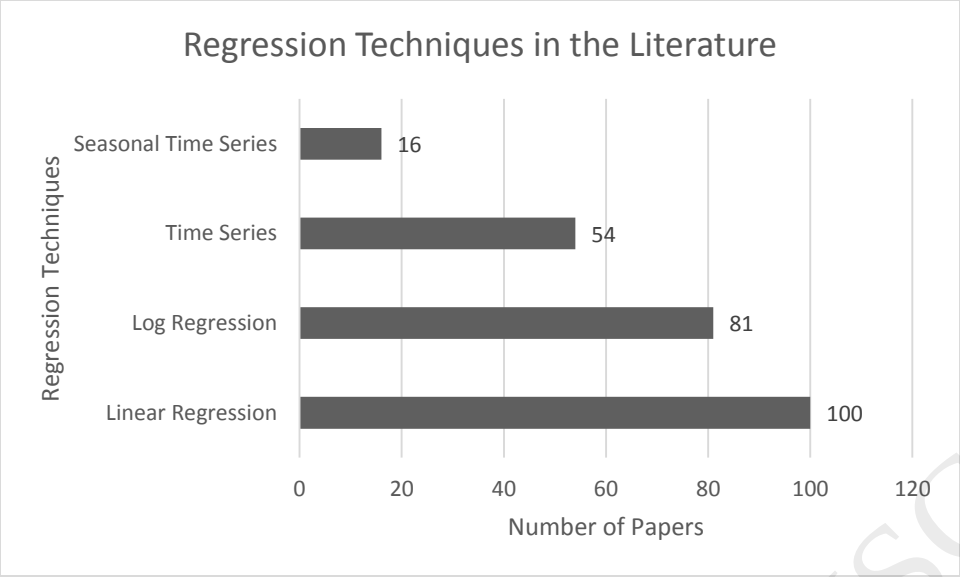


Figure 7: Total number of papers discussing Regression Methods

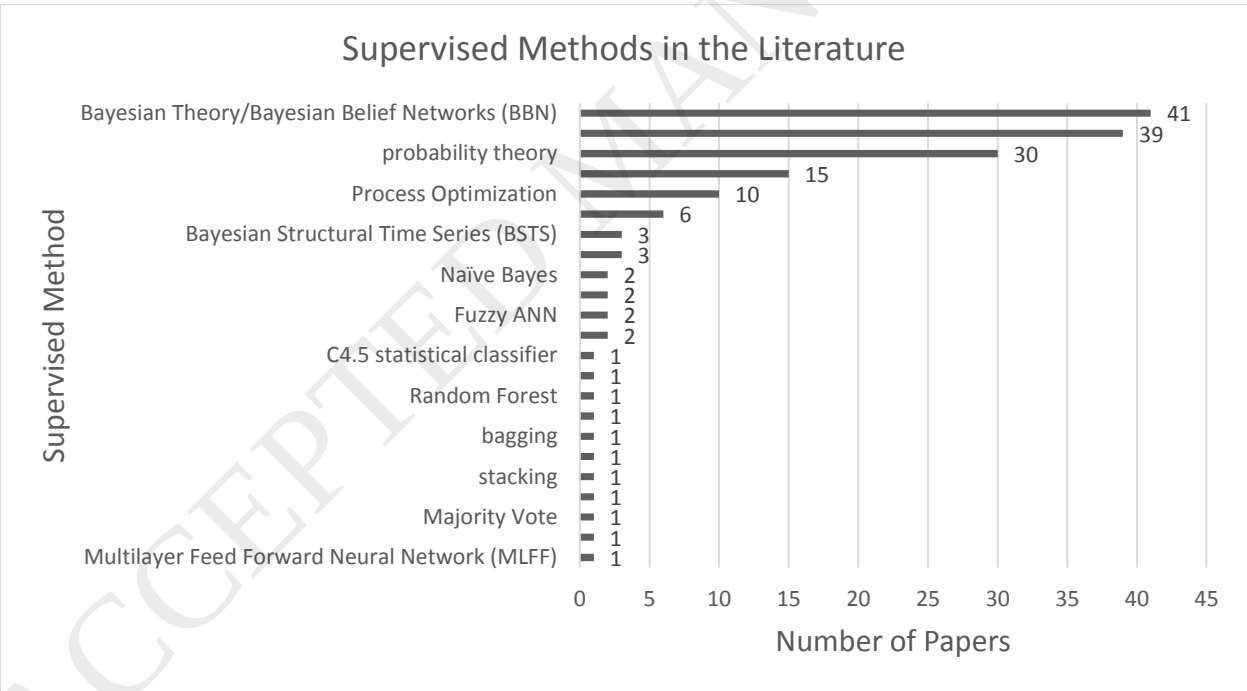


Figure 8: Breakdown of Supervised Methods by technique and the total number of times each is discussed

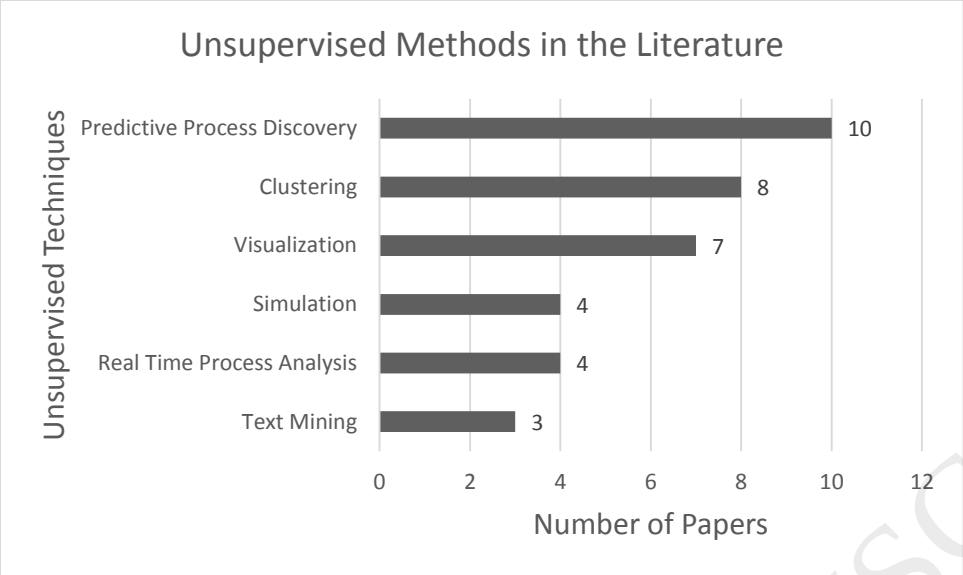


Figure 9: The total number of papers discussing each Unsupervised Method

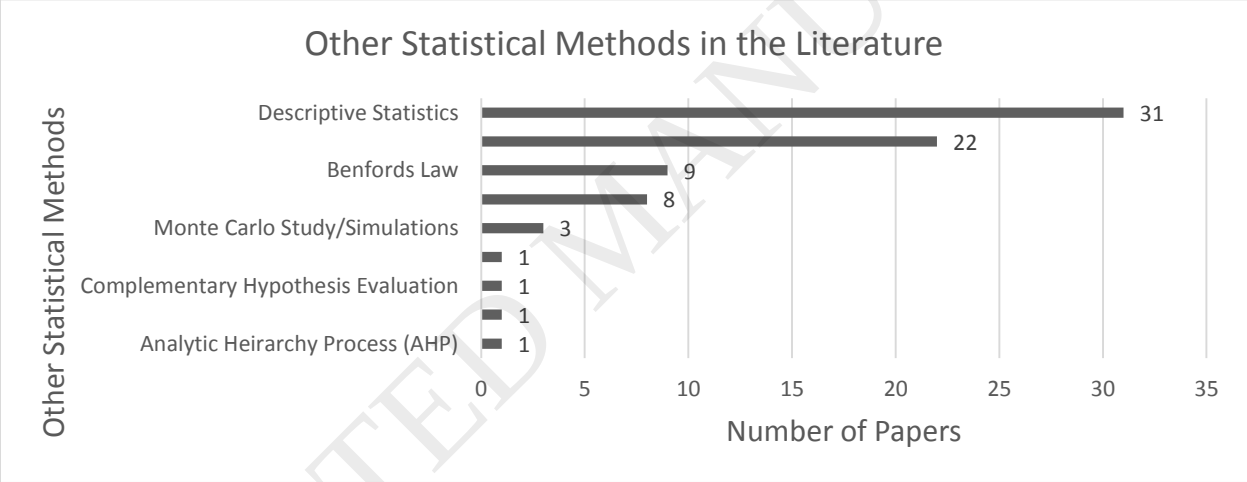


Figure 10: The total number of times that Other Statistical Methods are discussed

**Engagement**

| Orientation: | Audit Examinations | Unsupervised | Supervised | Regression | Other Statistics |
|---|---|---|---|---|---|
| Descriptive | √ | √ | | | √ |
| Predictive | | | √ | √ | √ |
| Prescriptive | | | | | |

**Planning/Risk Assessment**

| Orientation: | Audit Examinations | Unsupervised | Supervised | Regression | Other Statistics |
|---|---|---|---|---|---|
| Descriptive | √ | √ | | | √ |
| Predictive | | | √ | √ | √ |
| Prescriptive | | | | | |

**Substantive & Compliance Testing**

| Orientation: | Audit Examinations | Unsupervised | Supervised | Regression | Other Statistics |
|---|---|---|---|---|---|
| Descriptive | √ | √ | | | √ |
| Predictive | | | √ | √ | √ |
| Prescriptive | | | | | |

**Review**

| Orientation: | Audit Examinations | Unsupervised | Supervised | Regression | Other Statistics |
|---|---|---|---|---|---|
| Descriptive | √ | √ | | | √ |
| Predictive | | | √ | √ | √ |
| Prescriptive | | | | | |

**Opinion Formulation and Reporting**

| Orientation: | Audit Examinations | Unsupervised | Supervised | Regression | Other Statistics |
|---|---|---|---|---|---|
| Descriptive | √ | √ | | | √ |
| Predictive | | | √ | √ | √ |
| Prescriptive | | | | | |

**Continuous Activities**

| Orientation: | Audit Examinations | Unsupervised | Supervised | Regression | Other Statistics |
|---|---|---|---|---|---|
| Descriptive | | | | | |
| Predictive | | | | | |
| Prescriptive | | | | | |

Figure 11: Conceptual External Audit Analytics (EAA) Framework, where the shaded areas indicate suggested areas of great potential for continued or additional research, based on the extant research of Aps.. The checked marked areas indicate where research has already occurred. The shaded cells indicate where research is sorely needed, based on potential scope of EAA.

| **Analytical Procedures** | **Sources of Information** |
|---|---|
| Comparison of current year account balances to same account balances of other periods | Financial account information/reports |
| Comparison of current account balances to the anticipated results found in the client's budgets and forecasts | Client budgets and forecasts |
| Evaluation of the relationships of current year account balances to other current year balances for conformity with predictable patterns based on the client's experience | Financial relationships among accounts in the current period |
| Comparison of current year account balances and financial relationships (ratios) with similar information for the client's industry | Industry statistics |
| Study of the relationships of current year account balances with relevant nonfinancial information | Pertinent nonfinancial information |

Table 1: Typical AP Engagement Tasks, adopted from Louwers et al (2015) page 99

| **Selection Step:** | |
|---|---|
| **Step 1** | Apply keywords and strings to all sources and follow up with source references, gathering results until additional papers cannot be extracted |
| **Step 2** | Exclude any invalid papers |
| **Step 3** | Apply inclusion/exclusion criteria to titles, keywords, and abstracts |
| **Step 4** | Apply criteria to introductions and conclusions |
| **Step 5** | Review the entire text, applying exclusion/inclusion criteria |

Table2: Format of literature selection process in a literature review (Keele 2007)

| **Exclusion Reason** | **Number of Publications Excluded** | **Running Total Number of Included Publications** |
|---|---|---|
| Total Number of Papers | | 572 |
| No mention of EXTERNAL or PUBLIC Audit/phase | (103) | 469 |
| Not available online (usually these are references from earlier publications) | (47) | 422 |
| APs are not mentioned | (21) | 401 |
| All other exclusion reasons | (100) | 301 |
| **Total Exclusions** | **(271)** | **301 (Total of Inclusions)** |

Table 3: Reasons for Literature Reduction from the total of 572 surveyed papers to 301 papers

| Focus of Research | Number of Papers |
|---|---|
| AP use in different phases, internal controls, sampling, and evidence | 177 |
| AP as secondary emphasis to primary topics such as judgment, independence, bias, and experience | 60 |
| APs to detect earnings misstatements and management fraud | 28 |
| Fraud detection (employee and financial statement) | 14 |
| Going Concern/Bankruptcy Assessments | 18 |
| APs for Valuations | 4 |

Table 4: Research Focus of the papers that mention Analytical Procedures in the External Audit

| **Techniques:** | **Audit Examination** | **Unsupervised** | **Supervised** | **Regression** | **Other Statistics** |
|---|---|---|---|---|---|
| **Audit Phase:** | | | | | |
| **Engagement:** | Ratio Analysis (21) | Visualizations (3) | Expert Systems/ Decision Aids (7) | Log Regression (15) | Multi-criteria Decision Aid (3) |
| | | Text Mining (4) | | Linear Regression (7) | Structural Models (1) |
| | | Process Mining (1) | | Time Series (2) | Descriptive Statistics (11) |
| | | | | Univariate and Multivariate (6) | |
| **Planning:** | Transaction Tests (20) | Clustering (6) | Process Optimization (4) | Log Regression (65) | Multi-criteria Decision Aid (15) |
| | Ratio Analysis (159) | Text Mining (6) | Expert Systems/ Decision Aids (33) | Linear Regression (36) | Descriptive Statistics (27) |
| | CAATS (19) | Visualizations (7) | BBN (22) | Time Series (33) | Structural Models (7) |
| | | | Probability Model (19) | ARIMA (9) | |
| | | | | Univariate and Multivariate (25) | |
| **Substantive & Compliance Testing:** | Ratio Analysis (139) | Visualizations (8) | SVM (1) | Linear Regression (50) | Benford's Law (7) |
| | Sampling (145) | Text mining (5) | ANN (8) | Time Series (36) | Descriptive Statistics (24) |
| | CAATS (21) | Process Mining (4) | Genetic Algorithms (1) | ARIMA (12) | Structural Models (7) |
| | | | Expert Systems/ Decision Aids (26) | Univariate and Multivariate (22) | AHP (1) |
| | | | Bagging, Boosting (4) | | Monte Carlo Study (3) |
| | | | BBN (29) | | |
| | | | Probability Models (17) | | |
| **Techniques:** | **Audit Examination** | **Unsupervised** | **Supervised** | **Regression** | **Other Statistics** |
| **Review:** | Ratio Analysis (115) | Visualizations (8) | Expert Systems/ Decision Aids (24) | Linear Regression (36) | Multi-criteria Decision Aid (16) |
| | CAATS (14) | Process Mining (2) | BBN (4) | Time Series (28) | Descriptive Statistics (23) |
| | | | Probability Models (16) | ARIMA (10) | Structural Models (7) |
| | | | | Univariate and Multivariate | Hypothesis Evaluation |

| | | | | | |
|---|---|---|---|---|---|
| | | | | (26) | (1) |
| **Opinion:** | Ratio Analysis (35) | Visualizations (3) | Expert Systems/ Decision Aids (7) | Log Regression (22) | Multi-criteria Decision Aid (3) |
| | | Process Mining (1) | | Linear Regression (11) | Descriptive Statistics (10) |
| **Continuous Activities:** | | | | | |
| | | | | | |

Table 5: Summary listing/draft framework of the techniques occurring at least once in the various Audit Phases in the literature, where the numbers of papers containing that technique type per phase are indicated in parentheses.

| ***Descriptive*** | *Engagement* | *Planning* | *Testing* | *Review* | *Opinion* | *Continuous activities* |
|---|---|---|---|---|---|---|
| *Clustering Models* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| *Descriptive Statistics* | | | | | | ✓ |
| *Process Mining: Process Discovery Models* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| *Ratio Analysis* | | | | | | ✓ |
| *Spearman Rank Correlation Measurement* | | ✓ | ✓ | ✓ | | ✓ |
| *Text Mining Models* | | | ✓ | ✓ | ✓ | ✓ |
| *Visualization* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| ***Predictive*** | *Engagement* | *Planning* | *Testing* | *Review* | *Opinion* | *Continuous activities* |
| *Analytical Hierarchy Processes (AHP)* | ✓ | ✓ | | ✓ | ✓ | ✓ |
| *Artificial Neural Networks (ANN)* | ✓ | ✓ | | ✓ | ✓ | ✓ |
| *Auto Regressive Integrated Moving Average (ARIMA)* | | | | | ✓ | ✓ |
| *Bagging and Boosting models* | ✓ | ✓ | | ✓ | ✓ | ✓ |
| *Bayesian Theory/Bayesian Belief Networks (BBN)* | ✓ | | | | ✓ | ✓ |
| *Benford's Law* | ✓ | ✓ | | ✓ | ✓ | ✓ |
| *C4.5 Statistical Classifiers* | | ✓ | ✓ | ✓ | ✓ | ✓ |
| *Dempster-Shafer Theory Models* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| *Expert Systems/Decision Aids* | ✓ | | | | | ✓ |
| *Genetic Algorithms* | ✓ | ✓ | | ✓ | ✓ | ✓ |
| *Hypothesis Evaluations* | ✓ | ✓ | ✓ | | ✓ | ✓ |
| *Linear Regression* | ✓ | ✓ | | | | ✓ |
| *Log Regression* | | ✓ | | ✓ | | ✓ |
| *Monte Carlo Study/Simulation* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| *Multi-criteria Decision Aid* | | | | ✓ | | ✓ |
| *Probability Theory Models* | ✓ | | | | ✓ | ✓ |
| *Process Mining: Process Optimizations* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| *Structural Models* | | | | | ✓ | ✓ |
| *Support Vector Machines (SVM)* | ✓ | ✓ | | ✓ | ✓ | ✓ |
| *Time Series Regression* | | | | | ✓ | ✓ |
| *Univariate and Multivariate Regression Analysis* | | | | | ✓ | ✓ |

| ***Prescriptive*** | *Engagement* | *Planning* | *Testing* | *Review* | *Opinion* | *Continuous activities* |
|---|---|---|---|---|---|---|
| *Artificial Neural Networks (ANN)* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| *Auto Regressive Integrated Moving Average (ARIMA)* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| *Expert Systems/Decision Aids* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| *Genetic Algorithms* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| *Linear Regression* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| *Log Regression* | | ✓ | ✓ | ✓ | ✓ | ✓ |
| *Monte Carlo Study/Simulation* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| *Time Series Regression* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| *Univariate and Multivariate Regression Analysis* | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Table 6: Gaps and Areas of Scant Research in the APs literature in the EAA context are checked – these are techniques that should be explored with more depth in future academic research (adapted from Appelbaum et al 2016)