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The Emergence of Artificial Intelligence: How Automation is Changing Auditing

Julia Kokina
Thomas H. Davenport
Babson College

ABSTRACT: This paper provides an overview of the emergence of artificial intelligence in accounting and auditing. We discuss the current capabilities of cognitive technologies and the implications these technologies will have on human auditors and the audit process itself. We also provide industry examples of artificial intelligence implementation by Big 4 accounting firms. Finally, we address some potential biases associated with the creation and use of artificial intelligence and discuss implications for future research.

Keywords: artificial intelligence; automation; auditing.

INTRODUCTION

Impact of Artificial Intelligence on Accounting and Auditing

The field of accounting in general and auditing in particular is undergoing a fundamental change due to advances in data analytics and artificial intelligence (AI) (Agnew 2016). This paper is motivated by the need to more deeply explore the use of artificial intelligence in accounting (Sutton, Holt, and Arnold 2016). The 2015 *Deep Shift: Technology Tipping Points and Societal Impact* survey of 816 executives from the information technology and communications sector reported that 75 percent of respondents agreed that a tipping point of 30 percent of corporate audits performed by AI will be achieved by 2025 (World Economic Forum 2015).

While the idea of employing artificial intelligence in accounting and audits is certainly not new (Keenoy 1958), there is reason to expect that its impact on the field will be more substantial in future years because of recent developments in information and technology. Artificial intelligence requires both substantial data and processing power, and both are available in large quantities today. In addition, both open source and proprietary versions of artificial intelligence software have proliferated over the past several years. Artificial intelligence has gone through several "winters" and "springs," but this spring is seeing a larger flowering of activity than ever before.

There are both demand and supply factors behind the latest upsurge in AI. On the demand side, there has not been much productivity improvement in advanced economies over the past several years (only 1.3 percent average annual growth from 2007 to 2015, and decreasing productivity in the first two quarters of 2016), and companies are anxious to learn whether cognitive technologies can finally spur productivity growth. There are also many situations today in which a traditional human approach to analytics and decision-making is simply impossible. These decisions need to be made with too much data and in too short a time for humans to be employed in the process. Digital advertising, medical diagnosis, predictive maintenance for industrial equipment, and a detailed audit of all company transactions fall into this category.

On the supply side, we now have both software and hardware that is well suited to performing cognitive tasks. Both proprietary and open source software is widely available to perform various types of machine cognition. Google, Microsoft, Facebook, and Yahoo! have all made available open source machine learning libraries. And some of the world's largest IT companies are providing proprietary offerings.

Data scientists, however, often comment that the supply-side factors that really make a difference for this generation of AI are data and processing power. Neural networks, for example, have been available since the 1950s. But current versions of them—some of which are called "deep learning" because they have multiple layers of features or variables to make a decision

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TABLE 1

Aggregate Task Structure
Adapted from Abdolmohammadi (1999)

Audit Phase	No. of Tasks	Task Structure: Structured	Semi-Structured	Unstructured
Orientation	45	7 (16%)	14 (31%)	24 (53%)
Control Structure	75	10 (13%)	58 (77%)	7 (10%)
Substantive Tests	171	114 (67%)	54 (32%)	3 (1%)
Forming an Opinion and Financial Statement Reporting	41	0 (0%)	9 (22%)	32 (78%)
Total	332	131 (39%)	135 (41%)	66 (20%)

about something—require massive amounts of data to learn on, and massive amounts of computing power to solve the complex problems they address. In many cases, there are data sources at the ready for training purposes. The ImageNet database, for example—a research database used for training cognitive technologies to recognize images—has over 14 million images from which a deep learning system can learn.

The availability of almost unlimited computing capability in the cloud means that researchers, application developers, and accountants can readily obtain the horsepower they need to crunch data with cognitive tools. And relatively new types of processors like graphics processing units (GPUs) are particularly well suited to addressing some cognitive problems. GPUs in the cloud provide virtually unlimited processing power for many cognitive applications.

Auditing is particularly suited for applications of data analytics and artificial intelligence because it has become challenging to incorporate the vast volumes of structured and unstructured data to gain insight regarding financial and nonfinancial performance of companies. Also, many audit tasks are structured and repetitive and, therefore, can be automated. In other words, accounting and auditing have not been left behind in this latest AI spring.

Each of the Big 4 accounting firms has invested heavily in technological innovation. KPMG has partnered with IBM's Watson AI to develop AI audit tools (Melendez 2016). PricewaterhouseCoopers (PwC) has developed Halo, an analytics platform that serves as a pipeline to AI and augmented reality products (M2 Presswire 2016). Deloitte has developed Argus for AI and Optix for data analytics. Traditionally, accounting firms have relied on recent graduates to fill the entry-level positions required to perform repetitive administrative tasks. Due to the emergence of AI, one Ernst & Young (EY) source estimates that the number of new hires each year could fall by half, which would substantially alter the industry's employment model (Agnew 2016).

LITERATURE REVIEW

Artificial Intelligence and Audit Procedures

The focus of AI capabilities in auditing is on the automation of labor-intensive tasks (Rapoport 2016). These are structured and repetitive tasks performed throughout the audit. The effects of AI are likely to be the most pronounced in audit tasks that were once performed manually, but have already been supported by some technology (Agnew 2016).

To identify audit areas that are likely to be impacted by AI to the greatest extent, it is important to decompose the audit into a series of tasks and identify those with the most structure. Abdolmohammadi (1999) provides empirical evidence of audit task structure based on 49 audit manager and partner evaluations of 332 audit tasks representing six audit phases and 50 subphases. He finds that the majority of audit work consists of structured tasks (39 percent, or 131 out of 332 tasks) and semi-structured tasks (41 percent, or 135 out of 332 tasks), with only a small portion of tasks classified as unstructured (20 percent, or 66 out of 332 tasks) (Table 1). Most structured tasks (67 percent, or 114 of 171 tasks) appear to be in the substantive test audit phase. Furthermore, Abdolmohammadi (1999) reports that the substantive test phase was judged to have the largest proportion of tasks suitable for decision-aid development.

An analysis of structured automated tasks that are presented in Abdolmohammadi (1999) reveals that automation assists with tasks that include verification, recomputation, footing, and vouching. Specific examples of several structured automated tasks performed during the substantive test audit phase are: the verification of mathematical accuracy of all relevant supporting schedules (Task No. 18); the footing of cash receipts journal and cash disbursement journal and tracing to general ledger postings and bank statements (Task No. 10); the recomputation of depreciation (amortization) book and tax basis (Task No. 109); the footing of voucher register, tracing to general ledger, inspection of supervisory review, and approval of summarization and posting (Task No. 76); the footing of purchases journal and tracing to accounts payable subsidiary ledger, and inspection of supervisory review and approval of summarization and posting (Task No. 77).

Srinivasan (2016) recently published a high-level model of external audit process activities, and argued that automation of them could lead to the extinction of human auditors, although it was only speculative. Even though there is no detailed model of which we are aware that identifies specific audit tasks suitable for AI-enabled technology applications, Baldwin, Brown, and Trinkle (2006) summarize earlier uses of AI in documenting the use of neural networks in the performance of analytical review procedures and risk assessment, and the use of genetic algorithms to assist with classification tasks (e.g., collectible debt or a bad debt). They also document the use of expert systems in materiality assessments, internal control evaluations, and going concern judgments. To more holistically conceptualize a modern-day AI-enabled audit, Issa, Sun, and Vasarhelyi (2016) envision it to be similar to an assembly line in which an output of one step turns into an input of the step that follows. They identify seven distinct audit phases from pre-planning to the audit report and present how AI could transform each of those phases of the audit process.

Currently, the impact of AI in audits is especially pronounced in the area of data acquisition (data extraction, comparison, and validation) (Brennan, Baccala, and Flynn 2017). This means that AI-enabled technology can locate relevant information, extract it from documents, and make it usable for the human auditor, who can devote more time to areas requiring higher-level judgment. For example, AI enables full automation of such time-consuming tasks as payment transaction testing, including extraction of any supporting data for further substantive testing (Brennan et al. 2017).

Modern AI tools are increasingly able to scan for keywords and patterns in complex electronic documents to identify and extract relevant accounting information from various sources, such as sales, contracts, and invoices (Agnew 2016). For example, AI tools can spot if a company records unusually high sales figures just before the end of a reporting period, or disburses unusually high payments right after the end of the reporting period (Rapoport 2016). AI tools can also spot anomalies in the data, such as an unexpected order increase in a particular region, unusually high expense items posted by an individual, or exceptionally favorable equipment lease terms for a supplier (Brennan et al. 2017). Overall, "as audits become increasingly automated, there will be less emphasis on ticking and tying and vouching, and greater emphasis on understanding the overall picture painted by the data, better understanding inputs and assumptions, and identifying and evaluating trends, patterns, and outliers" (*Accounting Today* 2016).

DISCUSSION

Artificial Intelligence Capabilities in Accounting and Auditing

Artificial intelligence (also known as cognitive technology or cognitive computing, which we view as synonymous terms with AI) is a broad category, and not all aspects of it are relevant to accounting. In Exhibit 1, we describe a set of tasks that cognitive technologies perform, and the level of intelligence they have reached thus far (Davenport and Kirby 2016a).

Most of the task categories are relevant to accounting and auditing. Performing physical tasks is the traditional domain of robots, but it may have relevance to certain auditing tasks like counting inventory. Certainly, "analyze numbers" is the dominant task in accounting and auditing. This has traditionally meant algebraic analysis, but accountants and auditors are increasingly using business intelligence and visual analytics to communicate results (Schneider, Dai, Janvrin, Ajayi, and Raschke 2015). They are also employing hypothesis-based predictive analytics, as well, to predict the likelihood of financial events and malfeasance (Tschakert, Kokina, Kozlowski, and Vasarhelyi 2016).

When this type of analytics is done on a repetitive operational level, it qualifies as "repetitive task automation." Some accounting firms have begun to do this type of ongoing production work in the context of their auditing "platforms," although it is only in the early stages of application.

The next level of intelligence for analyzing numbers is machine learning, which is already being widely used outside of accounting to automate statistical and mathematical modeling. It is particularly relevant when organizations wish to dramatically increase the speed, granularity, and productivity of modeling. As we note below, it is just beginning to be used by large accounting firms to analyze data. In particular, it can be used for identifying anomalies in large datasets, which may be a basis for further forensic investigation.

EXHIBIT 1
Types of Cognitive Technology and Their Intelligence Level
Adapted from Davenport and Kirby (2016a)

Levels of Intelligence Task Type	Human Support	Repetitive Task Automation	Context Awareness and Learning	Self-Aware Intelligence	
Analyze Numbers	BI, data visualization, hypothesis-driven analytics	Operational analytics, scoring, model mgmt	Machine learning, neural networks	Not yet	
Digest Words, Images	Character and speech recognition	Image recognition, machine vision	Natural language processing, generation, deep learning	Not yet	The Great Convergence
Perform Digital Tasks	Business process management	Rules engines, robotic process automation	Not yet	Not yet	
Perform Physical Tasks	Remote operation	Industrial robotics, collaborative robotics	Fully autonomous robots, vehicles	Not yet	

In the task category of digesting words and images, the most common accounting and auditing application is analyzing contracts and other financially relevant documents. The first step in this process is the "human support" task of recognizing characters and translating documents into digital information. If this is done on a large scale, then it qualifies as repetitive task automation. But a higher level of intelligence is necessary to understand context within the document and extract relevant details from it. This "natural language processing" capability is available from external vendors and has been adopted by accounting and law firms. "Natural language generation," or the automated creation of meaningful text, is being used for accounting-oriented tasks such as creating "Suspicious Activity Reports" for anti-money-laundering processes in financial services (Davenport 2016). It could eventually also be used for the automated generation of other required audit reports. As yet, there are no current accounting-oriented uses of image recognition of which we are aware, but there might be a future use with regard to recognizing and counting certain types of inventory. As Cathy Engelbert, CEO of Deloitte LLC, put it in a speculative comment:

> This might sound a little sci-fi to you, but drones could do physical inventory observations. Maybe you wouldn't have to send people out to look at that kind of thing. Take it one step further. We could use imaging technology to look at things like storage tanks and grain silos. We could use it for a variety of things as you look at the industrial internet of big things. (Cohn 2016)

The task category of "perform digital tasks" typically involves orchestrating an online process, accessing data, and making changes in entries and records. This activity has distinct relevance to accounting and auditing processes, and has been widely adopted for many years by accounting firms to improve productivity in the management of audits (Banker, Chang, and Kao 2002). Current auditing "platforms" (Whitehouse 2015) are an industry-specific version of "business process management" technology that moves work through a process and keeps track of key data. The next level of capability for this task, "robotic process automation," automates structured tasks and draws from multiple information systems sources (Lacity and Willcocks

2016). This technology would appear to be quite useful for automating structured audit processes, but we are not aware of its actual adoption by accounting firms for external audits or by companies for internal audits.

Note in Exhibit 1 that there are no cognitive technologies that are yet capable of self-aware intelligence, although that level of artificial general intelligence is widely predicted to arrive at some point in the future (Bostrom 2014). That degree of reason and sentience, sometimes called "the singularity" (Kurzweil 2006), is seen often in fictional depictions of machines and robots, and includes such attributes as formulating goals and objectives, using imagination, having broad general intelligence, and being critical of others' and one's own performance. Such machines would be able of accomplishing not just a single task better than humans, but a broad range of tasks. Most researchers do not predict the arrival of self-aware intelligence in less than 20 years from now, and some speculate that it will take as long as 100 years to arrive (Goertzel 2007).

It also seems likely that these technologies will converge in the future as they achieve greater levels of intelligence. For example, the ability to digest text and images may well be incorporated into the performance of digital tasks. As another example, the power of server-based machine learning and natural language processing (for example, IBM's Watson) are already being incorporated into physical robots (Wang 2016). All of these developments would be likely to have dramatic effects on accounting and auditing processes in that technologies would then be able to perform virtually all tasks that humans do today.

Industry Examples of Artificial Intelligence Usage

The most important evidence of AI's relevance to accounting is adoption of the technology by practicing accountants and auditors. Although it is still early in the process, several leading firms have adopted cognitive technology already. Some are still in development, while others have applied it to production audit processes. Some firms are employing predictive and other forms of analytics to, for example, examine and summarize entire populations of auditable entities like inventories, rather than samples. While this technology is an important precursor of cognitive technology, we do not consider it to be cognitive or AI unless it is autonomous and learns over time.

There appear to be two key strategies that accounting firms are employing to add AI or cognitive capabilities to their businesses. One involves adoption of a broad set of AI capabilities from one vendor—specifically, IBM's Watson. KPMG is the most public proponent of this approach, signing a broad agreement with IBM in March 2016 that is intended to apply Watson to a variety of audit processes (Lee 2016). The specific audit processes being addressed by the system are not clear, but Watson has a wide variety of application program interfaces (APIs) that do everything from document entity extraction to facial recognition. KPMG is also making use of advanced predictive analytics technology from the auto racing firm McLaren Applied Technologies (Sinclair 2015), although this does not appear to be a cognitive application. Its primary purpose is to examine financial statement risk.

The other primary approach is to assemble a variety of cognitive capabilities from diverse vendors and integrate them as required into an audit process and platform. This is the primary approach taken by Deloitte, for example. According to Jon Raphael (2016), the firm's Chief Innovation Officer, Deloitte has focused on several specific audit subprocesses and tasks, including:

- document review
- confirmations
- inventory counts
- disclosure research
- predictive risk analytics
- client request lists

Some of these activities are more exploratory, and others are already in production. For example, Deloitte partnered with the vendor Kira Systems to do document review and extract the relevant terms from contracts, leases, employment agreements, invoices, and other legal documents. The system learns from human interaction and improves its ability to extract important and relevant information over time (Whitehouse 2015). By March of 2016, the Kira-based solution (which Deloitte calls "Argus") had been applied to over 100,000 documents (Kepes 2016).

Raphael (2016) also suggests that additional tasks are forthcoming, and that the most challenging aspect of applying AI to audits is getting the data in a structured and consistent format across clients. Deloitte is exploring the use of machine learning technology for the integration and structuring of data.

PwC and EY, the other two members of the Big 4 accounting firms, appear to be making increasing use of audit platforms and predictive analytics, but not the higher levels of intelligence and cognitive capability, as described in Exhibit 1. PwC, for example, employs "Halo" for analyzing accounting journals. Most of the analysis is traditional human support-based business intelligence, but there are some automated algorithms, as well (PwC 2016). EY is focused primarily on Big Data and analytics

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in audits (EY 2016), with a focus on "delivering audit analytics by processing large client datasets within our environment, integrating analytics into our audit approach and getting companies comfortable with the future of audit."

Likely Implications for Human Accountants

Senior accountants in large firms uniformly argue that the need for human accountants will not go away anytime soon (Agnew 2016). But many argue that the skills for successful accounting and auditing are likely to be different in the future, and some admit that they will need substantially fewer entry-level accountants in coming years.

At least over the next couple of decades, accounting is one of the many business fields that is likely to be augmented by technology rather than fully automated (Davenport and Kirby 2016a). Since AI technologies replace specific tasks rather than entire jobs, loss of employment in the short term is likely to be relatively slow and to be marginal rather than dramatic.

Remaining jobs in accounting are likely to involve some of the following types of activities:

- Working alongside intelligent accounting machines to monitor their performance and results, and (if possible) to improve their performance;
- Overseeing the use of intelligent machines in external and internal audit processes, and determining whether more, less, or different automation tools are necessary;
- Working with accounting firms and vendors to develop new AI-based technologies, and to support existing ones;
- Carrying out tasks that are now impossible with AI-based computers, including cultivating internal and external clients, interpreting audit and financial results for senior managers and boards of directors, and so forth;
- Addressing types of accounting tasks that are so narrow and uncommon that it would be uneconomical to build systems to automate them.

These five types of remaining jobs for human accounts correspond to five augmentation roles described in the augmentation literature (Davenport and Kirby 2016b).

It has already been noted (Tschakert et al. 2016) that many accounting programs do not currently prepare students for such roles. In addition, since many of the remaining tasks will require an understanding of the client's business and the ability to communicate effectively with clients, job roles that persist will probably be held by those accountants with substantial experience. Since the tasks performed by entry-level accountants are relatively structured today, they are the most likely ones to be automated. As in other professions, such as law and architecture, entry-level students will probably bear the brunt of automation's impact on the accounting labor market. This also raises the issue of how accountants will accumulate experience if there are substantially fewer recruits entering firms just out of school.

IMPLICATIONS FOR FUTURE RESEARCH

It is important for future research to examine bias in AI and whether humans using AI applications can engage in appropriate judgment and decision-making. Hammond (2016) points to the lack of objectivity and cautions that when intelligent machines are deployed, they tend to reflect the biases of humans who create or interact with them. The first bias is data-driven bias, which is associated with the systems generating biased outcomes because of the flaws or skewness in the underlying data. Another bias is bias through interaction that occurs when machines learn the biases of the people who train them. Emergent bias is the "algorithmic version of 'confirmation bias.'" It takes place when machines shield humans from conflicting points of view while providing them with information that confirms their preferences or beliefs (i.e., personalization bubble). Finally, a conflicting-goals bias is an unforeseen bias that occurs as a result of a stereotype-driven human interaction with the system.

Another direction for future research could address the role of transparency, or the lack thereof, in AI-based accounting and auditing decisions. Earlier versions of AI (for example, rule-based expert systems) and analytics (linear regression analysis) made it relatively easy for human observers to understand the relationships between inputs, transformations, and outputs of models. However, machine learning and deep learning neural networks, for example, are often "black boxes" that are difficult or impossible to understand and interpret, even for technical experts. Until such technologies are made more transparent, it may be difficult for regulatory bodies, accounting firms, and audited organizations to turn over decisions and judgments to them. Research on the challenges this poses and some possible solutions to it would be helpful to the field.

Future research should examine how these bias and transparency issues are addressed on behalf of both intelligent system creators and users in the context of accounting and auditing. Will the benefits of AI auditing systems outweigh the unintended consequences of the potential biases and uninterpretability? To what extent will human auditors rely on the results of tasks completed by intelligent systems? What benefits and problematic issues will be uncovered as this capability matures?

There is plenty of evidence that the role of AI in accounting and auditing is proceeding rapidly. This development has major potential implications for both the quality and process of accounting and auditing work. Accounting researchers and practitioners will need to collaborate closely in the coming years to shed more light on this transition and provide guidance to firms and regulators.

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