New Skills in Auditing: Embracing Emerging Technology in the Audit Profession

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Abstract

The primary focus of this research is to better understand how cognitive technology is affecting the audit profession. Several technology-based tools currently used in audits are examined to demonstrate the progress made and future implications on the profession. The findings of this research can be used by students, practitioners, or anyone interested in the subject to gain awareness of the impact technology has on the profession and how the profession is changing.

Table of Contents

List of Tables

I: Introduction

Advances in IT and real-time approaches to business create real challenges for the auditing profession (AICPA, 2020, pg. 10). However, with challenge comes opportunity. These opportunities are possible through all the cognitive technologies that are now available from the emergence of artificial intelligence (AI). Cognitive technologies take automation to another level, adding perceptual and cognitive skills and giving computers a sense of human intelligence from identifying faces and recognizing handwriting to planning, learning, and reasoning from uncertain information (Schatsky et al., 2015). As a result, change is expected from every industry in one way or another, which means it has implications for the audit profession. These implications include new risks that come from audit clients implementing cognitive technology into their business processes (Lindsay, Doutt, and Ide, 2019) and from audit firms implementing these technologies themselves to analyze client information more efficiently and effectively. However, innovation in the audit profession must be done in a way that ensures relevant and reliable evidence (PCAOB, 2021a). There is not much room for error because the effects of having material misstatements going unnoticed can prove to cause widespread panic in our capital markets (Center for Audit Quality, 2021). Recently, audit-related technology has progressed in multiple directions, including process mining, robotic process automation, expert systems, machine learning, and other cognitive technologies. Moving beyond theoretical and into the development of pragmatic solutions requires strategic considerations involving introducing this technology's management, economic, technical, organizational, and governance (Naqvi, 2020).

This study aims to analyze how cognitive technologies are transforming the audit profession by providing a detailed analysis of how audit is moving from theoretical to pragmatic solutions toward improving audit quality and stakeholder relevance through technology-based tools. After a brief literature review and discussion, I provide an overview of the more common cognitive technologies currently used in audit, including robotic process automation, machine learning, process mining, and expert systems. Then, I look at the audit life cycle and break down wide-view audit processes into sub-processes, activities, and work tasks to identify the areas where these technologies can transform audit. Finally, based on this analysis, I recommend skills the modern audit professional needs.

II: Literature Review

The research in this section relates to how the audit profession is changing with the emergence of cognitive technology. Although the scope of this study is primarily focused on how audit firms are using emerging technology, I believe it is still relevant to mention how the audit profession can be affected by the increasing use of emerging technology in businesses where necessary, such as how the use of new technology can affect the risks that are associated with the financial reporting process for auditors. Additionally, audit firms are increasingly adopting emerging technologies and rethinking how they plan and execute audits as technology-based tools can provide a more efficient and effective service while improving the quality of audits. The trend eventually led the PCAOB to launch the Technology Innovation Alliance Working Group in 2020, and they have since released two statements regarding audit firm methodology changes from using technology-based tools. The following sections show that, at this point, the PCAOB believes the increasing use of technology-based tools by audit firms and the way they are being used are currently adaptable concerning compliance with the audit standards.

According to The Center for Audit Quality (2019), “it is important for auditors to have a strong understanding of how emerging technologies affect the financial reporting process; as the use of emerging technology in financial reporting grows, the ability for auditors to design traditional substantive tests to respond to identified assertion-level risks decrease.” Research from Lindsay et al. (2019) looks at the opportunities and risks of emerging technology as it relates to the financial reporting process. According to Lindsay et al. (2019), where appropriate, auditors should consider the risks that result from the implementation of emerging technology and how they differ from traditional systems by obtaining a sufficient understanding to assist in the risk assessment. These risks include emerging technology's effects on the client's internal controls and overall risk assessment of the client in general.

The use of emerging technology in business and as tools for auditors has prompted a stream of research from the Public Company Accounting Oversight Board (PCAOB) (2021a, p. 3) to assess "if there is a need for guidance, changes to PCAOB standards, or regulatory actions." This research speaks to the transparency of the PCAOB in furthering their understanding of how auditors are using new technology as tools for identifying and responding to inherent and control risk. The PCAOB states that their research results indicate "that PCAOB auditing standards do not preclude firms from using technology-based tools during an audit engagement" (PCAOB, 2021a, p. 4). They did acknowledge, however, that the standards do not specifically mention technology-based tools. They continue to monitor advancements in this area to make changes in the future if needed. However, as firms are currently using technology-based tools, the PCAOB (2020) believes that these tools are not changing the nature of the standard procedures being conducted but instead offering a more efficient or effective approach to conducting the same procedure, which may even provide more reliable information. Additionally, when it comes to responding to inherent and control risk and collecting audit evidence, the procedures that are in the standards and have traditionally been performed are still being performed. The only difference is that auditors are now using technology-based tools to perform them.

PCAOB's research project on technology investigated the expanded volume of external data that has affected the nature of the information available to auditors for gathering evidence during an audit (PCAOB, 2021b). The PCAOB stated,

> Advancements in technology have improved the accessibility and expanded the amount of information available to companies and auditors including traditional external sources like industry data providers and regulatory agencies, but also nontraditional external sources like social media platforms and web data aggregators (PCAOB, 2021b, p. 3-4)

The PCAOB states that auditors may use external information as audit evidence if the information has been evaluated and deemed relevant and reliable.

Additionally, the American Institute of Certified Public Accountants Auditing Standards Board (ASB), which issues auditing standards for audits of private companies, released a new standard in 2020. SAS 142 provides guidance on emerging technologies, the application of professional skepticism and expanding sources of external information for audit evidence (AICPA, 2020). According to Tysiac (2020), it recognizes the use of technology-based tools for obtaining audit evidence.

An article from the Journal of Accountancy talks about how many audit firms are adopting a digital mindset, which involves thinking about how technology can be used to help plan and execute audits (Tysiac, 2022). According to Tysiac (2022), a digital mindset is about asking questions that eventually lead to solutions using technology that add value to the audit process.

III: Discussion

Advances in cognitive technology have created an opportunity for auditors to better assess risk and collect more convincing evidence during an audit. Specific research is adamant about it being the only option for the audit profession to remain relevant (Lombardi et al., 2014; Bumgarner & Vasarhelyi, 2015). An audit's effectiveness relies on the ability to process the large amount of information that businesses are now producing (Srinivasan, 2016, p. 172), and this is where emerging technology can be helpful. Another stream of research speaks to the possibility of a continuous audit, which uses emerging technology, but has different characteristics, primarily used within an internal audit function. It may be hard to believe that a continuous automated audit solution can be achieved. However, current research believes it is possible (Srinivasan, 2016; Naqvi, 2020; Bizarro, Crum, & Nix, 2019; Chan et al., 2018). Despite the many advocates for continuous auditing, it appears that the main focus of audit firms and standard setters alike is to ensure that risk assessments and the collection and evaluation of audit evidence are occurring most efficiently and effectively, which includes using technology for automation, insight, or embedded into service offerings.

It is, however, usual to have excessive expectations when attempting to predict the future, as we sometimes paint it in terms of what we would like it to be rather than what it can be at the time (Naqvi, 2020, p. 103). An example is when expert systems were considered a definitive solution to many accounting problems (Meservy et al., 1992). However, that is not to say that automation is not becoming impactful in the audit profession because it is, and efforts are being made to implement automation where possible.

Perhaps the question should not be 'how much of the audit process will be automated moving forward?' Professional bodies and large public accounting firms promote technology as an enabler to practitioners (AICPA, 2020; Deloitte, 2022), and I believe this to be true because not all technology creates automation, and when it does, at least for the more unstructured tasks, the job will become to audit the technology. However, technology can sometimes be used to create insights that are used for further analysis. Whatever the change caused by technology, it creates challenges for the profession. It is not just about the profession adapting to new technology but also about ensuring accountants' and auditors' skill sets align with the changes brought about by new technology. For example, fewer structured tasks mean more value-added work, which entry-level auditors will need to be able to handle.

The good news is that the most efficient use of emerging technology is to implement it to work with humans, leveraging the strength of each (Schatsky, Muraskin, and Gurumurthy, 2015). There are several considerations for coming to that conclusion. However, it will suffice here to say that human labor still dominates over technology in occupations of service due to human labor’s flexibility, adaptability, and ability to empathize and show emotion (Fernandez & Bisello, 2022, p. 821). After all, auditing is not just a numerical but a behavioral exercise. For example, auditing standards require specific inquiries concerning the risk of fraud (PCAOB, 2020b), and this type of interrogative inquiry requires the auditor to use listening techniques and observe behavioral cues. Additionally, technology can contribute to increased audit quality, making audits more stakeholder relevant. For instance, the use of technology enabling an auditor to test a full population rather than just a sample can provide better assurance (Huang, No., and Vasarhelyi, 2022) to those that are invested in the company.

This study first discusses several types of technology commonly used in audits. This includes robotic process automation and artificial intelligence , including machine learning, natural language processing, and deep learning.

After gaining a basic understanding of how these technologies work, I analyze automation's impact on the audit lifecycle pragmatically by breaking processes into sub-processes, activities, and work tasks for careful analysis to determine how automation can materialize. Finally, I discuss the modern audit professional and recommend skills needed in an automated environment.

IV: Robotic Process Automation

Robotic process automation (RPA) is “the use of a computer program used to automate the input, processing, and or output of data across computer systems or applications” (Cooper, Holderness, Sorensen, and Wood, 2019, pp. 10-11). RPA can be used to automate tasks that are more repetitive in nature by breaking a task up into individual user actions such as clicking, selecting an item, typing text, or closing a window. Automating a series of individual user actions can result in a higher-level event, such as filling out a form.

According to (Fantina, Storozhuk, & Goyal, 2022), there are four traits to determine if RPA is suitable for a process: (1) Is the process repetitive? (2) Would the cost of automating the process exceed the cost of continuing to do it manually? (3) Is automation required for competitive value? (4) Would automating a process better enable the organization to fulfill government regulations? The first question must be answered with 'yes' to proceed. Additionally, the cost of automation exceeding its benefits may be justified if there are competitive or regulatory benefits beyond financial considerations.

RPA has recently emerged as an area of interest for public accounting firms and standard setters (PCAOB, 2017; KPMG, 2016; PwC, 2017). Research from Cooper et al. (2019) reveals an informative view of how the Big Four public accounting firms are implementing RPA into their firms. According to Cooper et al. (2019), although public accounting firms may focus on different service lines such as tax, advisory, and audit, just like any business, they, too, have internal operations, and these large public accounting firms began experimenting with RPA in their internal operations. Once the implementation of RPA in their internal operations showed successful results, they then focused on the firms’ value-added activities, such as their service lines. This lets the firm understand the technology and ensure its scalability before introducing it to their clients or using it for client services. Since RPA is generally inexpensive, the results are increased profits, quality improvement, and streamlined processes. One option for audit firms is to license RPA tools through companies like UiPath or Blue Prism. When licensing, firms can bypass the variety of tools that need to be used in conjunction with each other, as RPA vendor tools offer very similar capabilities without programming at the user-level interface.

In the audit profession, processes that can benefit from RPA include data collection and cleansing, controls testing, risk assessment, and reconciliation (Moffit, Rozario, and Vasarhelyi, 2018, pg. 4). Applying RPA to control testing can automate tasks such as segregation of duties, exception reporting, access related controls, change management controls among others. RPA can automate data collection and classification in risk assessment and identify trends during the annual risk assessment process. For reconciliations, RPA can automate data collection from various sources while reconciling data to preconfigured rules (Devarajan, 2018, p. 15). In light of RPA, auditors can focus more on complex areas such as estimates or investigating potential anomalies. Several studies have depicted actual processes that were implemented by RPA (Gotthardt et al., 2020; Moffitt et al., 2020; Huang & Vasarhelyi, 2019).

Tiberius and Hirth (2019) conducted a Delphi study to gather likely results of emerging audit trends over the next decade. The study reported that 93% of participants agreed that all routine audit tasks would involve RPA. This covers nearly 40% of all audit tasks (Kokina et al., 2017) and does not cover other technologies that could impact the auditing profession. RPA automation is predicted to have the most impact in the short term on audit and accounting (Gotthardt, Kolvulaakso, Paksoy, Saramo, Martikainen, and Lehner, 2020); however, more advanced cognitive technology will provide more impact over the long term. Although RPA and

Artificial Intelligence (AI) are not the same, they do not replace each other. They can be used together or separately.

Overall, companies of all types worldwide have found RPA implementation to be a success and plan on expanding their use in the short-term (Protiviti, 2019). This implementation of RPA by clients has directly affected external audits and can cause a need for changes in the timing and extent of the audit procedures (Deloitte, 2018). Public accounting efforts toward RPA are still in the early stages. However, results have also been positive as firms plan to continue expansion (Cooper et al., 2019). The long-term impact of RPA seems to be an organizational change where roles are reassembled since RPA focuses on individual processes. Thus, an auditor's position would change from collecting, processing, analyzing, and disseminating data to evaluating it (Moffitt et al., 2018, p. 5). RPA will be disruptive to all fields because deskilling jobs have been a trend for the last 100 years, but with RPA, people will reverse that trend to focus on more interesting work (Lhuer, 2020).

V: Artificial Intelligence

Artificial intelligence (AI) is "the theory and development of computer systems able to perform tasks that normally require human intelligence" (Schatsky et al., 2015). Cognitive technologies are AI products, which include machine learning, natural language processing, computer vision, and many others. AI is a crucial driver in enabling data analysis and continuous audits in the audit space, drastically changing the profession's future (AICPAa, 2020, p. 15). Since auditing is a complex activity, it can benefit from cognitive technologies, and some even believe it is essential to the business environment's complexity. When an environment becomes more complex, navigating it requires greater intelligence. Just as humans experience continuous learning and improvement while pursuing and achieving goals, the same can be said for AI.

Clark (2015) states that AI research focuses on computer teaching to create solutions to problems. What are the limitations of AI? Of course, there are perspectives on this topic. Many believe that although computers can show signs of intelligence, they will never be able to think for themselves (Makridakis, 2017, p. 7). Alternatively, others express little doubt that AI will eventually “imitate the way children learn through deep learning, rather than instructions by programs for specific applications based on logic, decision trees, and if-then rules” (Parloff, 2016).

The following sections break down AI into two broad sections: Machine Learning and Deep Learning. Each section is broken up into subsections to describe their characteristics.

V.1: Machine Learning

Machine learning (ML) is based upon one branch of AI derived from statistical learning methods, and it uses algorithms rather than a rules-based approach. The purpose of ML is to predict outputs and make inferences (AICPA, 2019, p. 10). In accounting terms, ML could determine whether a transaction is an expense or a capital expenditure and then identify the specific account to which the journal entry should be posted. However, the algorithm cannot be a set of detailed instructions for the machine to compute. It is not a step-by-step guide (rule-based approach); instead, it will learn to identify the recipe by giving it many ingredients with expectations. The concept of ML hinges on developing a statistical mindset. It is the difference between the rules-based approach, where a machine would likely need thousands or millions of lines of code for any given situation to cover all possibilities.

Machine learning focuses on either making predictions where the output is a real value or classifications where the output variable is a category (Chilakapati & Rochford, 2019). Since machine learning problems usually involve predicting outcomes using historical data, this technology is well suited for problems that require analysis of numerous quantitative factors to generate an output. For machine learning, "predict" means estimating some unknown value and not necessarily a future event. Machine learning is only relevant if the historical data represents the current environment. It requires proper interpretation from an experienced analyst to determine the validity of the prediction or classification since it cannot state the output with 100% precision. It can only predict with high reliability; thus, it uses inductive reasoning.

According to AICPA (2019, pp. 10-11), “There are three techniques used for the machine to learn the problem and become competent at providing the answer: Supervised, unsupervised, and reinforcement learning. *Supervised learning* is a method used to teach by example. The goal is to approximate the function so well that when new input data is available, it can predict the output variable for that data." Here, learning from the training dataset is synonymous with a student learning from a teacher. The correct answer is known from historical data, the algorithm predicts based on the data used for training, and correction comes from the teacher when it is wrong. Once an acceptable level of performance is achieved, the learning stops. The more data, the better because the more examples provided, the better the algorithm can learn.

For classification problems, ML uses each set of inputs to classify them as output, which can be binary, multiclass, or multilabel. Binary classification is where the input is classified between one of two classes. A multiclass classifier can choose one out of more than two classes from each data set, and a multilabel classifier can be classified into more than one class from each data set. Grover, Bauhoff, & Friedman (2019) provide an in-depth example of using a supervised learning classification technique for independent verification using Random Forest, Machine Support Vector, Linear Regression, and Naïve Bayes.

Referring to the accounting transaction classification example, a supervised learning technique, the transaction details (features or properties) are the inputs, and the transaction details' values help classify the transaction (output). Then, from the classified output class, it identifies the specific account to use when posting the journal entry (subclass). This problem is a multilabel classifier since each set of inputs can be assigned to more than one class (ex., capital expenditure, equipment), where capital expenditure is the class and equipment is a subclass. Also, it is supervised learning since we know the answer, and, in a sense, we act as the teacher to the machine, the student.

Hoogduin (2019) provides an example of a supervised learning regression analysis problem in an audit context using the relationship between a variable and a set of predictors. This can be efficient in identifying outliers to investigate further. Examples of relationships include analyzing salaries paid with the number of personnel. However, external data sources could also be used if they affect the model's effectiveness in locating outliers and obtaining evidence for concluding material misstatement of an account. Remember, the data needs to be directly related to your prediction and represent the current environment. The PCAOB (2021b) published staff guidance for auditors on determining if the external source provides relevant and reliable evidence.

Unsupervised learning aims to model the data structure to learn more about it and develop insights. Unlike supervised learning, unsupervised learning has no correct answers. Algorithms are asked to explore and relay interesting structures from the data. Unsupervised learning can benefit many business problems because if we have a lot of data, the objective here is to discover patterns within that data providing us with new knowledge. The algorithm groups the data based on similar characteristics without giving the input data labels to learn (IBM, n.d.). This kind of learning can help detect fraud or errors by discovering anomalies.

An example of unsupervised learning from Hoogduin (2019) is to classify journal entries. Hierarchical Agglomerative clustering provides a number of similar entry clusters using the accounts of the ledger and the debit/credit amounts. The clusters are located on a scatterplot to visualize several color-coded clusters. This can be useful in many ways. For instance, it locates the significant streams of transactions, such as revenues or expenses. It shows how complex the process is and, if controls were used; the timing of transfers to different accounts. The use of clustering can help with locating entries that may look unordinary. Finally, this technique will reveal common organizational structures that assist in locating relationships that can serve as a basis for other ML techniques.

Reinforcement learning is where a machine can learn by itself without needing trained data sets by making predictions while double checking them and continuously adjusting for better results. This is commonly referred to as reward-oriented algorithms. Supervised and reinforcement learning are typically used to solve regression problems. Depending on the specifics, all three can be used for classification problems (AICPA, 2019, p. 11). Reinforcement learning is a powerful and unique form of learning because, like humans, it learns significantly from its successes and failures. This learning maximizes its cumulative reward, making it a good tool for sustained strategic-making areas. It explores unknown territory and exploits the current knowledge while maximizing its reward.

V.2: Natural Language Processing (NLP)

Natural language processing (NLP) "is a branch of AI that helps machines understand, interpret, and manipulate human language" (IBM, n.d.). It strives to build machines that can understand and respond to voice and text data and respond with their own speech or text. According to the RSM (2019), there are four primary applications that auditors can consider using with NLP: "Text classification, information retrieval, natural language generation, and natural language understanding."

Text classification's ability lies in sentiment analysis. Sentiment analysis helps determine the expressed emotion in a piece of text. For instance, it can identify news sentiments, and accurate text classification models can achieve over 90% accuracy (Joulin, Grave, Bojanowski, and Mikolov, 2016). Text classification can be used in a financial statement audit during a standard procedure to verify client identity and potential risk, which means an auditor must understand the client's business. A part of understanding the client's business is performing due diligence for sentiments about the firm's management. Rather than manually utilizing search engines, text classification automates this process (Schmidt, Schnitzer, and Rensing, 2016). NLP can process text in any language and can be useful in global scenarios where an auditor may need something translated by reducing the cost of a professional translator.

NLP can retrieve important information from documents like invoices or contracts, and hard-copy documents can be converted to machine-readable format via optical character recognition (OCR). Vouching is examining documents to determine if a transaction is accurate and occurred, which can be time-consuming. Extracting hard-copy data into machine-readable format can improve the accuracy of data entry and boost audit efficiency.

The last two are extensions of NLP, natural language generation (NLG) and natural language understanding (NLU). NLG can produce understandable text in human languages and can be used in report generation. NLG can partially automate report generation, realizing efficiency and cost benefits. Another application with NLG is forming summary descriptions from charts or graphs, which is referred to as narrative generation for interactive dashboards. NLU is a sophisticated application of NLP and interprets what the text means, so it extracts all the data and filters what is unimportant to provide meaningful content (Sciforce, 2021).

NLP can be beneficial since about 80% of all data is unstructured (Grimes, 2008). Analyzing this unstructured data has been cited as a top challenge by respondents of a 2014 AICPA survey (Baysden, 2014). Unstructured data comes internally from a company in the form of emails, system logging, etc., and comes externally in the form of social media, online news media, etc. This kind of data must be extracted and cleaned, which involves converting the raw data into a format that is useable and prepares the data to be stored and analyzed. This is typically the most time-consuming step.

V.3: Deep Learning

Deep learning is "a subset of machine learning. It is an emerging and exciting form of AI that can identify relationships and linkages in vast volumes of data that would be impossible for humans to process and apply them to similar situations" (AICPA, 2019, pg. 13). Deep learning technology can classify features from unstructured data. As discussed earlier, the idea of AI has been around since the mid-1900s. However, deep learning needs certain elements to work correctly. These elements include computational power and data storage. This emerging technology is still evolving but represents using big data for audit evidence.

Deep learning is more advanced than machine learning because it can learn without human intervention and requires only a fraction of the data preprocessing. Earlier, we discussed how analyzing unstructured data was too big a task for humans to extract and clean for analysis. This hampers an auditor's ability to use unstructured data for audit evidence. However, deep learning can enable the use of unstructured data, which would enhance audit quality. Considering how effectiveness and efficiency have historically counteracted each other in auditing, this would be a win for the profession toward improving audit quality.

Deep learning can aid auditors in text analysis. Textual data that is useful for auditors include but is not limited to transcripts, press releases, regulatory filings, earnings calls, management discussion & analysis, contracts, messages from social media, and news articles. Therefore, reviewing all corporate documents would no longer be too costly since deep learning could automate textual analysis. Textual data can be classified on features, as I discussed earlier. Models can be trained based on sentiment, transforming qualitative information that requires significant effort from humans to analyze to be integrated for further analysis. This can be particularly useful in audit procedures such as inspection, analytical procedures, and confirmations (Sun, 2019).

Deep learning can also assist auditors in speech recognition and image and video parsing. Financial statement audits are just as much behavioral as they are numerical. Therefore, the language used during interviews and how subjects respond to questions can be just as important as their answers. Deep learning can analyze speech in real time for emotions, risk factors, and other insights. Several research papers (Pickard, Burns, and Moffit, 2013; Pickard, Schuetzier, Valacich, and Wood, 2017) have focused on embodied conversational agents (ECA) for audit interviews. "ECAs are autonomous interfaces capable of human-like interactions" (Pickard et al., 2013).

There are many unanswered questions regarding deep learning, especially in the audit profession. It becomes a problem in a standard and regulation-driven industry when the algorithm is so complex that it is unclear why or how the decision has been made. One objective of an audit is to aid in transparency, and if the audit evidence itself lacks transparency, it can damage the people's trust in the capital markets. For this reason, standard setters will likely need to issue updated guidance for deep learning.

VI: Process Mining

Process mining is a "technique making it possible to discover, analyze, and monitor processes by extracting readily available data from your underlying IT systems and tools" (Deloitte, 2022). The collection of event logs in real-time of processes across systems allows the construction of a visualization of business processes, which allows a simple relation between the actual and desired process state.

To better understand process mining, consider two types of data: Transactional data and metadata. Transactional data includes data from procurement, sales, and accounting databases. Metadata is the data about transactional data. This information is used to capture audit evidence to determine factors such as if the system was accessed by the people who were authorized to do so, if the system was accessed at odd times or near the closing period if the system was accessed with higher frequencies and certain time intervals if two or more systems were being accessed by a person whose responsibilities do not allow them to do so due to separation of duties, and if systems were accessed by a group of people whose hours of accessing the system matched, however, do not typically access the systems at the same time.

Process mining in audit was argued by Jans, Alles, & Vasarhelyi (2013), who made a strong case for value creation potential. They presented four attributes of process mining to benefit audit:

1. Process mining provides analysis of an entire data population and not a sample.
2. The data contains metadata that is entered without any action from the client.
3. It allows the practitioner ways of doing walk-throughs and performing other procedures.

4. It allows the practitioner to analyze what was not available with traditional tools, like visualizing how processes are conducted and identifying social relationships between individuals.

Process mining identifies processes from beginning to end, giving a comprehensive view of how a process moves through the company's systems and lays out the audit trail. Combining machine learning with process mining can produce continuous, automated, and integrated audits. The idea to add machine learning to process mining came from the fact that process mining creates many exceptions, which have to be interpreted by humans and marked as either "interest" or "no interest." A study from Jans & Hosseinpour (2019) mentioned how these exceptions provide a significant source of data to learn from to classify the output of process mining data. It turned out to be the perfect solution since human-classified data provides ideal examples for teaching the machine how to identify a good or unacceptable pattern. By using supervised learning classification, the machine can identify patterns and generalize its learning to recognize previously unknown anomalous patterns.

The benefits of process mining include process visualization, optimization, automation, and compliance. Process visualization can aid in developing detailed process maps to simplify complex processes. Process optimization can identify inefficiencies to correct issues before they disrupt operations or customer experience. By analyzing processes, process mining creates opportunities to benchmark and standardize performance. Process automation helps identify opportunities for automation using detailed insights into repetitive and less competitive tasks by analyzing the impact of automation and a potential return on investment. Process compliance helps identify deviations from desired paths that could lead to non-compliance.

The challenges with process mining for auditing are highly dependent on the availability of relevant data. This data is mainly stored in enterprise resources planning systems which could be more process-oriented. Since the data related to any given process is typically scattered over dozens of tables, extracting the data for audit use is significant. Traditional audit practices. which are based on sampling, mean that auditors examine a small sample of data and do not continue the examination in the case of no deviations. Full population testing would increase audit quality and, consequently, the audit's time and cost unless it was automated.

The larger audit firms have begun developing proprietary software tools to introduce process mining to audit approaches because of the observed benefits. However, more guidance is needed on how process mining can be implemented into external audits to meet the standards requirements. Because all audit results are reviewed with either mandatory peer reviews for private company audits or PCAOB reviews for public companies, using less-than-common techniques can have detrimental consequences. Nevertheless, with the struggles that the audit profession has historically faced with major corporate scandals, process mining could be a justifiable route. Accounting methodologies would need to change for process mining to become an accepted auditing approach, and so would auditors' skill sets. Auditors would need better IT and analytical skills.

VII: Expert Systems

Expert systems (ES) "are computer programs that store an expert's knowledge and simulate the expert's reasoning processes when solving problems in a particular topic" (Tomas, 1998). This field addresses the solutions to complex problems as they mimic human experts in a particular field, such as tax or auditing. Early attempts at expert systems collected knowledge in rules form and used algorithms for decision systems. When applied to audits, Expert systems provides benefits, such as an instant knowledge of processes (Omoteso, 2012). The application of ES in accounting started around the 1980s (Dungan, 1983). Public accounting firms invested in building ES to support planning of audits, testing compliance, risk, and decision-making (Brown, 1991).

Much went into developing more sophisticated systems between 1986-1998; however, expert systems have continued to disappear from the literature since 1999. Research shifted to artificial neural networks (ANN), which is deep learning. The traditional artificial neural network is simplistic and only feasible with supervised learning making it applicable only in limited areas such as forecasting fraudulent financial reporting, predicting going concern, assessing management fraud, and support for issuing qualified opinions. According to Issa, Sun, and Vasarhelyi (2016), "Combining ES and ANNs may facilitate the introduction of deep learning. Just as ES has an extensive knowledge base, a DL model using a deep neural network with a deeper hierarchical structure than a traditional ANN has its training dataset and extracts features from those samples."

VIII: Analyzing How Automation Can be Used in Audit

Successfully implementing emerging technology requires planning. My planning methodology includes six degrees of planning that I will briefly review and go deeper into specific areas throughout the section. It begins by analyzing the business model and the related work processes. It breaks down processes into subprocesses and activities. Each activity is broken down into a work task, and one or more agents are identified to automate the task. A method is used to determine the agent's internal structure, and we expand further if it has a machine learning component. Now, let us review the audit lifecycle and break it up to envision how emerging technologies can transform the audit process.

First, I analyze how a firm creates value for its clients by identifying the business model and the audit processes. In an audit context, I could use five wide-view processes: pre-audit management, risk assessment, procedures, reporting, and post-audit matters. Next, I map out subprocesses and activities, as shown in Table 1. The goal is to break the processes down into eventual work tasks. Doing this allows us to analyze how the previously discussed technologies can contribute to the audit process. It will become apparent how deep each process can go, which will give us at least two important insights: (1) the audit process can be extremely time-consuming, requiring a lot of resources, and (2) the level of difficulty and multi-disciplinary expertise it takes to automate the audit process. Abdolmohammadi (1999) estimated that the audit process had a total of 332 tasks.

Process	Sub-Process	Activity	Work Task
Pre-Audit Management	Preliminary Engagement (AS 2101.06)	Client Continuance (AS 1001) (AS 2101.06.a)	Management background Client financial background Culture assessment Client conflict patterns Relationship assessment Extraordinary business risks Fraud index
		Independence & Ethics (AS 1005) (AS 2101.06.b)	Independence in form evaluation Independence in appearance evaluation Ethics
		Contractual Terms (AS 1301) (AS 2101.06.c)	Special requirements Cost assessment

Table 1: Pre-Audit Management Sub-Processes, Activities, and Work-Tasks

The preliminary engagement can generally be divided into three activities: client continuance, independence and ethics, and contractual terms. About half of the tasks in the preliminary engagement process are unstructured (Abdolmohammadi, 1999), making parts of this task significantly difficult to automate; however, the goal of intelligent audit automation is to automate even unstructured tasks. The way to identify if a work task is structured, semi-structured, or unstructured is to observe the task and determine the input requirements. For instance, any given task will be composed of at least one or a combination of the following: Doing, Thinking, or Creating.

Doing needs to be done and has no variability and high repeatability. An example is being asked to pick apples. There is no thought involved. Thinking has variability and requires the processing of information with multiple possibilities as to what could happen. An example is a task requiring a telephone call to make a reservation. The person on the other end could give several different answers, determining how you may need to respond. However, making reservations involves doing and thinking because making the telephone call is simply doing, but having a brief conversation will require thinking. Finally, creating has unlimited possibilities, unlimited paths, and no repeatability. An example of creating is identifying a new target market for customers or developing a new product. There is an infinite amount of unknowns involved with these tasks. We can use this "Do, Think, Create" model to determine if a task is structured, semi-structured, or unstructured depending on the combination of these elements. When a work task involves multiple steps, each step must be isolated to identify its structure for automation purposes. This tells us what kind of technology can be used for automation. For instance, RPA can only be used if the work task or parts of the work-task is structured, meaning the task has elements of "doing."

Whether an audit firm accepts new business as a first-time or repeat client, the firm makes routine preliminary engagement efforts. Typically, repeat clients are less extensive of a review; however, this part varies widely depending on the firm's size, as larger audit firms usually perform background checks on management key members (Srinivasan, 2017). Ultimately, the standards leave it up to the auditor whether they decide to accept the client beyond the legal and ethical requirements and require that audit firms establish policies and procedures for accepting or continuing client relationships. The standards recommend that the audit firm consider if it has the "capabilities to perform the engagement and has considered the integrity of the client" (PCAOB, 2020c). Beyond that, it is up to the audit firm to perform due diligence as it sees fit, though common sources of information include communicating with the predecessor auditor upon obtaining permission from the prospective client, inquiries of firm personnel and third parties such as bankers, industry peers, or legal counsel, and background searches of relevant databases (Messier, Glover, and Prawitt, 2021). The firm may look for significant client changes to analyze potential independence issues or general business risks such as entering a risky business, an overly complex business model, legal or regulatory issues, and new management with a faulty record. For a new client, the audit firm must make an additional effort to determine if they are willing to accept the client, as prior due diligence from the audit firm has yet to be established. In the case of client continuance, firms should periodically evaluate the continuance based on their developed policies and procedures.

The specific activity I will focus on from the preliminary engagement is performing background checks on the management team using public information. The goal here is to build a profile on an individual to gain insight into their credibility about their position and responsibility. Based on the individual's responsibility, the audit firm may also want to know which areas they are most likely to fail--unintentionally due to being incompetent, negligent, unskilled, or intentionally due to moral weakness, etc. Development of this profile will allow the auditor to understand the client's executives' personality, behavior, and motivations, which can act as warnings for possible misconduct. For this task, the use of publicly available information will need to be obtained. Our attributes or inputs are limited only to our creativity if the data we select is relevant to the insights we wish to gain, and since the bearing of this task contributes to the assessment of whether to accept the client, the audit firms primary focus is on avoiding a potential lawsuit in the future, otherwise known as engagement risk. No evidence relating to this task will be documented in the actual audit. We can use apparent choices like criminal, legal, and credit. However, given how everyone leaves activity trails online, we can pull data from speeches, articles, social media updates, photos, comments, likes or dislikes, reviews, etc.

Using AI to assist with background checks can add tremendous value as audit firms still use a significant number of staff to investigate individual backgrounds manually (Vilner, 2022). Let us focus on developing the structure of the agent for performing background checks on the client’s management team. Table 2 shows an automated background check analysis on individual members of the client’s management.

Agent	Sensors (Data Input)	Analyze	Decision	(Output)	Learn

Background check	Criminal and legal data Publicly disclosed sale/purchase of equity Employment data LinkedIn and Social Media data Articles and Interviews data	Look for criminal behavior or activity. Identify signs of deceptive personality traits. Identify fraud-related personality traits.	Decision to accept client or not. Recommendation to investigate further.	Provide ongoing feedback.	Learn to perform the background checks. Learn to classify each candidate on various output dimensions of deception or fraud traits.

Table 2: Automation Analysis for Background Checks

This type of analysis can be done using natural language processing (NLP) which was discussed earlier. The text or communications is analyzed for language patterns and then classified based on previously known usage of certain words, styles of speaking, and vocal features. Text mining is used, an AI technology that uses NLP to transform unstructured data from publicly available information in documents and databases into normalized, structured data that is suitable for driving machine learning algorithms. Once the data is cleaned, we can use the machine learning techniques discussed earlier, such as supervised, unsupervised, or reinforcement learning and classification or regression problems. However, a supervised learning classification technique would work best for this situation.

The risk assessment process contains two sub-processes: evaluating inherent and internal control risks, which make up the risk of material misstatement. Inherent risks are the risks that are from the nature of the business. This includes rapid changes in technology, regulatory changes, new business entry, and other factors. Assessing the entity's inherent risks is done by performing risk assessment procedures. Risk assessment procedures include "inquiries of management or other entity personnel, analytical procedures using audit data analytics or automation tools for analysis, recalculations, reperformance, or reconciliations on large volumes of data, and observation and inspection" (Messier, Glover, Prawatt, 2021).

Process	**Sub-Process**	**Activity**
Risk Assessment (AS 2110)	Evaluating Inherent Risk (AS 2110.59-71)	Risk identification Risk assessment Risk evaluation Management problem
	Evaluating Internal Control Risk (AS 2110.18-40; 72-73A)	Environment evaluation Risk assessment Control activities assessment Monitoring assessment Information and communications evaluation

Table 3: Risk Assessment Sub-Processes, Activities, and Work-Tasks

Automating the inherent risk evaluation will require multiple agents to analyze and measure the inherent risk. There are several possible ways to automate the evaluation of inherent risk. It may depend on factors such as whether the system is being developed for internal or external audits, the time and investment available for the firm, and the level of automation the firm hopes to achieve. Inherent risk is embodied in the nature of the account and comes from factors like form, size, frequency, transactions, training, incentives, and business model. For instance, cash can be considered inherently risky since it can easily be stolen. Cash is riskier than other assets, such as a building. A building has inherent risks; however, the risks differ from cash risks. While an account will exhibit a high or low inherent risk, a business's circumstances can also impact the inherent risk. The nature of inherent risk will vary for each account based on the type of industry, firm, accounting systems, business model, and processes. As business experiences change, the inherent risk can also change. For instance, a business that has always accepted cash but switches to not accepting cash has lowered its inherent risk of cash.

Since experienced auditors are familiar with the risk characteristics of specific industries and can recognize the areas where firms have a greater risk, this knowledge can have tremendous value in developing the automation process. The cognitive work that auditors perform involves understanding the nature of transactions in an industry and then evaluating the likelihood of error or fraud associated with each transaction. The inherent characteristics of transactions can be determined by factors like the nature of the account, account balance size, transaction estimation, business model, transaction volume, transaction complexity, transaction treatment, and past history. As these risks reach an account level, it manifests in an invalid or fictitious recording of transactions or failure to record factual transactions. It can happen by incorrectly posting or accounting for the transactions, from classifying transactions in the wrong accounts, transactions being posted in the wrong period, and misleading disclosures. These can occur as errors or frauds. Automating the measurement of inherent risk implies modeling the auditors' thought process.

We can approach the identification and measuring of inherent risk in terms of a risk identification, assessment, evaluation, and management problem. The auditor processes information about the industry, firm, and management team and practices, which is then translated into a risk estimate. This risk estimate can be viewed as the cumulative measurement of values of risk drivers. Risk drivers are individual risks that collectively will lead to the measurement of the total audit risk. Since the auditor maps the financial statements to accounts and accounts to risk factors, we can conclude that risk factors are based on the economic and operating environment, industry dynamics, and management's decision-making.

For automation purposes, I first develop a stationary model of inherent risk composed of identifying the relationship between assertions and accounts in terms of risk. Each assertion contributes to the risk of an account in different ways. Some may have less contribution than others. I can identify four assertion risk factors for each assertion and assign a risk contribution weight to each risk factor. I can then rate each risk factor in magnitude (high, medium, low). Separately, drivers of assertion risks are identified. External and internal variables drive the assertion risk higher in a dynamic risk assessment model.

I can approach automating the inherent risk evaluation by developing an automated learning system that can track, identify, and measure the inherent risk in a firm's audit environment. I will use accounts receivable as an example to develop a model of intelligent automation to measure inherent risk based on identifying assertions to the account and developing risk factors, drivers, and values for the assertions.

Features	Drivers	Assertions	Impact	Accounts
Firm Industry Management Processes Strategies Accounts Others	Regulation changes Management team Proxies Frequency Size	Existence Rights and Obligations Completeness Cutoff Valuation Presentation & disclosure	Does it exist? Did transactions occur? Are assets owned by the firm? Were all transactions captured? Were transactions captured in the right period? Are accounts valued properly? Were proper methods used?	Accounts Receivable

Table 4: Accounts Receivable

The model will link accounts with assertions. Each assertion can be measured by factors such as likelihood, velocity, impact, and vulnerability. Likelihood measures how likely the assertion is to impact the account; velocity is how rapidly a situation can turn into a big problem; impact assesses the potential dollar impact; and vulnerability is the susceptibility of an account to be impacted by special situations. I will assign weights to each of the four risk measurements to signify the importance of risk for each account on a scale of 0% to 100%. If velocity was deemed the least important, it contributed only 10% versus likelihood and impact, which may be the most important and are labeled 100%. Additionally, each assertion risk will be valued at low, medium, or high with a scale of 1, 2, and 3.

Assertion	Likelihood	Velocity	Impact	Vulnerability
Weights	100%	100%	10%	20%
Existence	3	3	2	1
Cutoff	3	2	1	1
Valuation	3	3	1	1
Rights & Obligations	1	1	1	1
Presentation & Disclosure	1	2	1	1
Completeness	3	3	1	1

Table 5: Measuring Risk and Scale Assignments

Once each assertion is assigned a degree of risk to each factor, the total score for each assertion risk will be calculated by multiplying each of the entries by the risk importance (e.g., 3 x 100% = 3; 3 x 100% = 3; 2 x 10% = 0.2; 1 x 20% = 0.2) and then adding them up (e.g., 3 + 3 + 0.2 + 0.2 = 6.4). The highest possible risk is done using all 3 when multiplying with each percentage (e.g., 3 x 100% = 3; 3 x 100% = 3; 3 x 10% = 0.3; 3 x 20% = 0.6). We then divide the calculated risk by the total risk to get our value for our assertion.

Assertion	Likelihood	Velocity	Impact	Vulnerability	Sum Risk	Total Risk	Risk
Existence	3	3	0.2	0.2	6.4	6.9	93%
Cutoff	3	2	0.1	0.2	5.3	6.9	77%
Valuation	3	3	0.1	0.2	6.3	6.9	91%
Rights & Obligations	1	1	0.1	0.2	2.3	6.9	33%
Presentation & Disclosure	1	2	0.1	0.2	3.3	6.9	48%
Completeness	3	3	0.1	0.2	6.3	6.9	91%

Table 6: Risk Calculation

Doing this with each significant account allows us to analyze each account to understand which has higher inherent risks and why. A dynamic model is needed to study the changes in risk as changes to the business occur. Next, we should identify a set of drivers for assertions. Each risk factor of each assertion can change based on various internal and external factors. Since developments can add or subtract the values of the four risk factors and even change the importance weights, we need to identify those drivers that can raise or lower the assertion risk. Developments include obsolescence of inventory, client operational risk, conflict of interest, litigation, earnings management, profit smoothing, management credibility, or incentives.

The automation aspect comes from these internal and external factors an agent monitors. The agent learns to study the environment to predict if developments will increase or decrease the risk of an assertion. The design may be simple or complicated, depending on the situation. An agent's design would be simple if the agent looked at the number of transactions in an account to assess if the transaction frequency is increasing more than expected. A more complicated design would be to assess what conditions will impact which assertions. For example, an agent may use regression to predict the impact of sales forecast on the overall risk.

Suppose the agent determines by analyzing sales that sales volatility is high by analyzing social media data about the products sold by the firm. In that case, it could imply that the existence assertion risk for sales is higher. If the sales are made on credit, this implies that the accounts receivable existence assertion risk may also be higher. The automation chain here predicts sales volatility using features from social media, determining the assertion risk it impacts and by how much, adjusting the assertion risk factor values, and recalculating the inherent risk for an account.

A more sophisticated agent would use a multilabel classification problem where the input features will be used to perform classification into multiple risk drivers. This means the agent will use the features to learn to classify the output into one or more classes. There are many possibilities in terms of automating the inherent risk process. We can use the feature data to model inherent risk. Unlike using agents for each assertion risk driver, feature vectors are fed into a neural network to understand the inherent risk in various firms. This involves breaking the problem into multiple sections, each evaluating the related risk. The problem can be viewed as a classification problem, and based on the various inputs, the algorithm gives a classification output of high risk versus low risk. There can be several different versions where data from different areas are used at the input, or ideally, the data is used collectively and represented as separate calculations that are mathematically linked or as one large deep learning implementation where numerous features are represented.

Audit procedures involve the tests that are performed during an audit for evidence. There are two broad categories of tests: test of internal controls and tests related to the transactions and accounts. Test of controls can help us identify whether there are material weaknesses in internal controls, which we then need to do substantive procedures to understand the risk better. When we find no apparent internal controls violations, written policies and procedures do not imply they are actually being followed. These policies can also be overridden.

Automating audit procedures can help to think about technologies that can help with inquiries, observations, document testing, and reperformance. Inquiries generally consist of questionnaires and interviews. Questionnaires are created by generating relevant questions and then analyzing the responses. Since audit firms already have a set of context-driven questionnaires, it may be better to focus our efforts on deploying machine learning solutions to automate the analysis of responses that are obtained from the client.

Observations refer to obtaining evidence by observing various employees processes, functions, and job performance. AI can be deployed to understand processes better and evaluate the interaction and roles in processes. Machine learning and process mining are effective tools for evaluating and identifying segregation of duties. Automation is necessary for this area since these insights consist of millions, perhaps even billions, of machine-readable data, which is simply impossible for humans to examine efficiently. Observation is a function of how many and what kinds of inputs the client uses. Auditors should study the business model of a client so they can suggest the use of sensors that can help strengthen the client's internal controls.

Document testing is inspecting documents related to transactions. These documents are usually traced according to processes and provide an audit trail. Computer vision is a considerably promising technology for audits. It gives computers the ability to analyze digital images and videos. Computer vision is classified in a way that real-world objects can be named, their relationships and actions can be identified, and decisions can be made about them. Optical character recognition is one type of computer vision, and its goal is to analyze text from images and documents. Pictures and pdf files can be scanned, and the content can be categorized. With the diversity of documents encountered in business, this technology can be invaluable to the audit process. Automating the document reading and inspection allows auditors to check for important details that auditors check for in the documents.

Reperformance is the reconstruction of a process such that the auditor performs the steps done by the client to arrive at a particular account balance, number, or estimate. This is a manual process to compute and compare the numbers as reported by the management. Process mining can be used for reperformance testing to better understand processes, map the process steps, and conduct the testing. The testing can be based upon preconfigured routines based upon ranges of values for transactions or account balances. The threshold or range-centric testing can be achieved with RPA or an expert system. The limitation of this model is that it can only work with known test areas and under known conditions. Any new patterns, transactions, or creative accounting may go undetected.

This section aimed to provide an idea for the automation process as a part of the external audit. While I only covered a few areas of the audit, this process can be used on any part of the audit, potentially using one or more emerging technologies discussed earlier. Large accounting firms have invested heavily in technology to eventually reach a level of audit automation that can keep up with the rapidly evolving business environment. However, it takes time to implement due to the numerous factors in building a sustainable business model built around new technology. This is true for the audit profession, where specific standards and regulations must be considered.

VIII.1: Are Small Firms with Less Resources at Risk?

The large public accounting firms invest millions of dollars on AI, leaving a sense of uncertainty as to how these technological changes will affect smaller firms down the road. History has shown us that technological developments in business have no concern for layoffs and displaced workers; therefore, the fear is validated (Makridakis, 2017). Smaller firms may lack the resources to invest in an AI infrastructure like the larger firms can, but that does not mean they do not have options. It does, however, require a strong dedication to change management. Garbelman Winslow CPAs in Marlboro, Maryland provides an example. A partner with the firm, Samantha Bowling, talks about how a small firm with just a few CPAs and employees is using AI as a part of its audit process despite its firm size.

According to Bowling (2019), she realized a fear of losing her audit business when AICPA President, Barry Melancon, mentioned the Big Four's large investment in AI while serving on the AICPA governing Council. Bowling has retained her firm’s competitive advantage by keeping up with technology, from computers to distributed computing to cloud computing, over the years. Considering recent developments with AI, Bowling searched for two years to find a suitable AI platform; however, many were too expensive. She found a company in 2017 called MindBridge Analytics Inc. that offered cloud-based platforms for firms of all sizes based on the number of users and clients. She reached out to MindBridge with a proposition, and she told them she would work with their AI and give feedback as a small audit firm.

MindBridge was intrigued and gave the firm an initial discounted price, and they were given access in return for feedback from the audit firm. Bowling states, "The great thing about working with a small software company is they are willing to listen and make changes." The audit firm worked with the AI company for about half a year and provided feedback on recommendations for changes, and as a result, both firms were able to improve their respective service offerings. Additionally, the CPA firm's exposure to many businesses gives the software company an affiliate for promotion because they offer services that should appeal to controllers and internal audit departments. Bowling says "Small accounting firms can acquire this technology for less than $10,000, but the price will ultimately depend on the size of the firm" (Bowling, 2019). Garbelman Winslow CPAs are now using AI to review full populations of transactions instead of using the traditional statistical sampling methods and can assess potential new clients with their AI capabilities to instantly determine the risk involved and how much they should charge. This provides the CPA firm with a competitive advantage.

XI: The Modern Audit Professional

Just as humans have skill sets that will make it difficult for a computer to accomplish, such as the ability to lead and empathize, computers also have skill sets that a human will never be able to achieve. This is why a mix of humans and computers will always be the key to maximizing effectiveness and efficiency in the audit profession.

Accountants have a solid understanding of the financial reporting process and can speak the language of business. Becoming an accountant is not of little value or importance. The ability to depict business activities into accounting frameworks requires years of sophisticated training. It involves understanding the business context, observing the activity, determining if it is accounting-worthy, abstracting the critical features of the transaction, picking out the recordable elements, and then recording the transaction in the correct place.

The future auditor will be a combination of an IT and finance specialist. It is hard to see a scenario where the demand for competencies stays the same. The Audit Chief Innovation Officer at Deloitte, Jon Raphael, believes that the future audit will leverage external data to predict outcomes, challenge assumptions, and provide insights that differ from the current state of audit which is limited to preliminary, final, and substantive analytics (Davenport, 2016, p. 10). Changes of this magnitude will add additional value to external audits. However, the information will always need to be verified, even if auditors verify the algorithms conducting the procedures.

We are currently at a critical point where the skills demanded of CPAs are changing; therefore, the nature of the profession must change with it. This is because the business environment constantly changes and becomes more complex while producing more information. The audit profession needs technology-based tools to keep up with this increasing amount of information to provide better assurance.

As technology becomes more capable, assurance responsibilities will continue to broaden. Also, beyond the understanding of technology being used, auditors should know how it works, its risks, and how organizations address those risks. It calls for an increase in demand and provides an opportunity for practitioners to specialize in specific areas relating to risk and fraud.

The AICPA (2020, p. 13) speculates on new opportunities for auditors as they understand that the profession is bound to change. These opportunities include assurance reporting on AI tools. For instance, the tools themselves, the controls and processes, and if the client is using them appropriately. “An auditor's job includes evaluating risks, governance, and processes relevant to the selected subject matter. An auditor's independent mindset and focus on risk assessment are underlying concepts for evaluating the oversight and effectiveness of AI models” (Deloitte, 2022). In other words, the human aspect of AI is in the guidance and observation that is required for an AI system to operate successfully.

Overall, future auditors should be excited for what is to come as technology-based tools pave the way for auditing professionals to gain more meaningful work experience earlier in their careers by utilizing professional judgment and skepticism.

XII: Conclusion

The opportunities brought by cognitive technologies that are now available through the emergence of artificial intelligence have started to change how financial statement audits are being approached and conducted. Using emerging technology-based tools allows auditors to be more effective and efficient in managing their processes, supporting their audit planning, and informing their decision-making by analyzing larger amounts of client information quicker. Through advanced technology, auditors can access and analyze non-traditional sources of information, and if relevant, they can be used as audit evidence for forming an audit opinion. This is all made possible with cognitive technology, robotic process automation, process mining, and advanced data analytics. In an audit context, technology-based tools are used to review documents, test full populations, detect subtle patterns and anomalies, classify images, and better understand a business's risks and control environment. The benefits of better assurance through financial statement audits are widespread. It increases trust in the capital markets, gives businesses with better insights into their operations or issues with their information systems and potentially a less costly service, and gives shareholders better assurance.

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