Consideration of the ethical implications of artificial intelligence in the audit profession

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CONSIDERATION OF THE ETHICAL IMPLICATIONS OF ARTIFICIAL INTELLIGENCE IN THE AUDIT PROFESSION

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INTRODUCTION

Artificial intelligence (AI) oriented applications are quickly becoming omnipresent in today's society as 81% of Americans own smartphones (Pew Research Center, 2019). For example, sometimes a simple Google search for a pair of shoes will translate into numerous advertisements on different websites or social media. This process is initiated by using recommendation engines powered by AI. By using AI and machine learning to filter information based on the user preferences, these recommendation engines create a custom list for the user. This is just one example of how AI technologies can be utilized to solve problems that are not possible with traditional approaches. AI technology is currently being utilized in many different facets of business and is expected to impact the future of the audit profession, therefore being able to understand how AI functions is crucial. (Kokina & Davenport, 2017).

This technology is rapidly evolving, and it will also be important for auditors to understand the capabilities of AI and how it impacts the audit decision-making processes. In addition, the ethical considerations related to the use of these technologies are an emerging issue in all aspects of society including the auditing profession. The overall goal of this research is to gain a better understanding of how these emerging technologies will potentially enhance audit quality and the ethical considerations that future auditors need to be mindful of when using these technologies.

Although the use of AI in the auditing profession is still in the early stages of development, AI is now widely utilized on social media platforms such as Instagram and Twitter via algorithms to provide the user with customized information. Social media is heavily used among many adults with the largest percentage of users between the ages of 18 and 29 (Pew Research Center, 2019). In 2019, there were 3.5 billion active social media users which equated to 45% of the world's population (Vojinovic, 2021). Social media is heavily used by the world and has a tremendous influence over humans. The incorporation of AI into these social media platforms influences the choices that consumers make. Vojinovic (2021) noted that 75% of users react to seeing an advertisement on Instagram by visiting a website or making a purchase. When a user engages with social media applications, the recommendation engine learns from that past activity. This activity is used to interpret the data and the results include predicting relevant social media accounts, recommending people the user may be interested in following, and identifying items to purchase that the user might also enjoy.

AI is not only prevalent in social media but in other large consumer-oriented companies such as Netflix. Netflix not only highlights the top ten most trending movies and shows in the United States, but also provides personalized recommendations. Netflix targets watchers of certain shows and recommends additional shows based on previous preferences. Netflix also uses AI to determine the cover image (thumbnail) shown on Netflix for each respective movie and television show on their platform. This technology uses thousands of video frames and an algorithm that ranks these images to determine which image will have the highest likelihood of being selected by a given user (Yu, 2019).

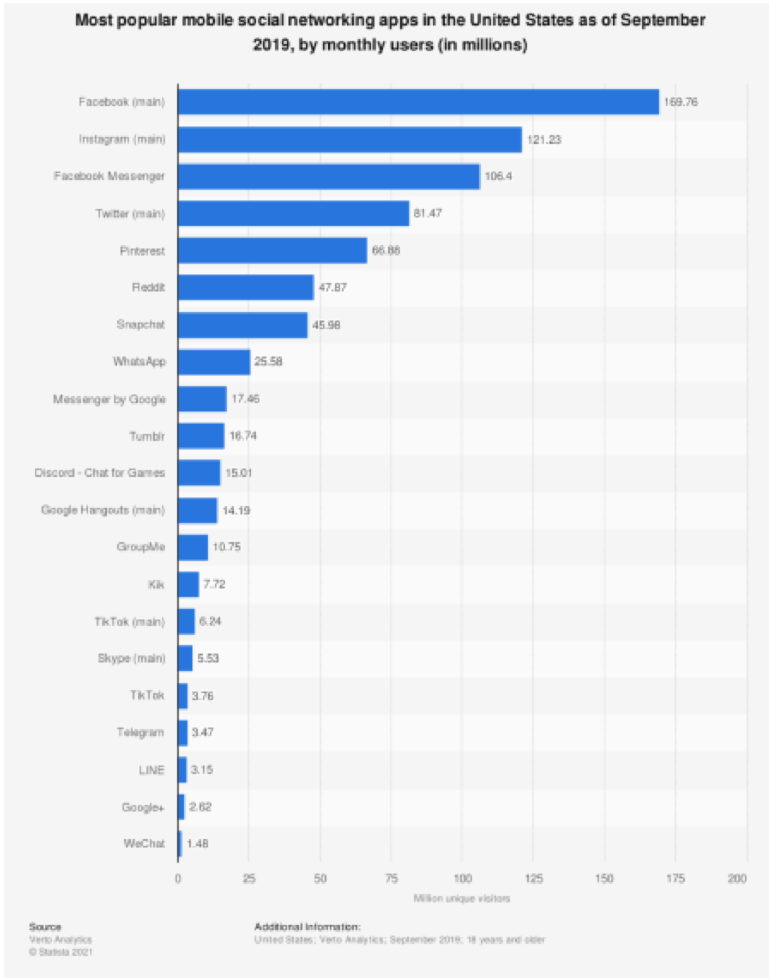

Figure 1: Social Media Platforms
(Statista, 2019)

AI provides a tool that organizations can use to turn user data into valuable information. For example, the recommendation engines use the information received from the consumer to provide targeted advertising. This form of advertising focuses on the preferences of a consumer. When a consumer opens a website such as Amazon to search for a product, Amazon will create a file called a cookie. A cookie file is a text file with data that can identify specifics and improve the web browsing experience (Kaspersky, n.d.). Certain websites have a pop-up window that explains their use of cookie files on their website and may ask the user to accept the use of cookie files on that website. When a user searches for a product on Amazon and the cookie file is created, automated advertisements read the cookie file to produce ads for similar products related to the Amazon product that will be presented to the user when they are on other websites.

Although targeted advertising may be beneficial to businesses, the use of cookie files can be viewed as an invasion of privacy to the consumer. By accepting the use of cookies on a website, the user is giving permission for the internet web browsers to track, save, and personalize a user's information (Kaspersky, n.d.). All the information submitted to the internet such as websites visited, search engine requests, and social media postings can be tracked. The more information readily available to advertisers can help to predict buying habits. Age, race, gender, income, and more can be used to produce targeted advertising. Targeted advertising does not just stop on a computer. With the ability to sync devices, a user may search for something on their smartphone and later see an advertisement for the related search on their tablet. AI technologies are heavily utilized by social media platforms to make the experience more enjoyable for users and to also help the social media companies retain users, yet the ethical implications surrounding the use of these technologies continue to be subject to significant debate.

The use of AI does not just include social media and streaming services. One of the most intensely debated emerging AI technologies is autonomous self-driving cars. Autonomous vehicles utilize AI algorithms rather than relying on a human to drive the vehicle. The use of a self-driving algorithm poses several potential ethical issues. For example, ethicists question whether or not an autonomous vehicle should be able to utilize its capabilities to it lock a criminal inside the car and drive them to a police station (Shaw, 2019). Further considerations include whether a blind person should be able to ride alone in an autonomous car or whether speeding should be allowed in cases of emergency (Shaw, 2019). Where does the blame lie if the driver instructs a car to speed and there is an accident: the driver or the automobile manufacturer (Shaw, 2019)? These potential issues cannot be answered by a simple yes or no, but by careful consideration of human behavior and ethics. Ethical issues such as transparency, privacy, and data completeness all have the potential to affect the implementation and use of AI.

Given its burgeoning development and powerful use of data interpretation and analyses, AI is important to the future of the auditing profession. These new and emerging tools are needed to increase the efficiency and effectiveness of tasks (Baldwin, Brown, & Trinkle, 2007). Firms that provide these auditing services are looking for ways to use AI to assess the risk of unstructured and semi-structured, repetitive, decisions. Although AI is currently playing a prominent role in various aspects of our modern society, the use of this technology is still in the earlier stages of development for the auditing profession. Therefore, this research is designed to answer the following research questions:

1. What are some of the emerging tools using artificial intelligence in auditing and how will they impact audit quality?
2. What are the ethical implications of these emerging artificial intelligence tools in auditing?

METHODOLOGY

Because AI is such a new and emerging issue in the auditing profession, the methodology used in this research is an extensive review of the existing literature on AI. This review of the existing literature is intended to provide insights into the origins and development of AI, how AI functions, and concrete examples of certain AI tools that possess the potential to impact the auditing profession. Determining the potential impact of AI on the auditing profession requires gaining an understanding of how these specific AI tools work and identifying possible ethical considerations that should be addressed before these tools become a fully implemented part of the decision-making processes.

The literature review begins by providing a background on the history of AI. Next, the seven patterns of AI are reviewed followed by the three types of AI. A brief introduction on the importance of considering the ethical implications follows. The literature review concludes by identifying two AI tools that have the potential to impact the audit profession and providing an overview of the functionality of these tools and highlighting certain ethical considerations associated with the incorporation of these tools in the auditing decision-making processes.

LITERATURE REVIEW

History of Artificial Intelligence

AI is a vast concept that combines aspects from statistics, psychology, and cognitive science. The original goal with the creation of AI was to make computers more capable of independent thinking. AI uses machines that can interpret and learn from external data. Although the history of AI is difficult to pinpoint, most historians agree that the birth of AI was in the 1940s when Alan Turing, a mathematician, created a test to measure a machine's ability to replicate human actions (Haenlein & Kaplan, 2019). The goal of this test was to make these actions indistinguishable from actual human behavior. The test was like the imitation game which considered if machines can think. Later named the Turing test, this test measured machine intelligence and tested the machine's ability to think as a human. The Turing test became the foundation of future AI testing because it considered machine ability and "intelligence."

The actual term "artificial intelligence" was officially coined after the 1956 Dartmouth Summer Research Project on Artificial Intelligence (DSRPAI) hosted by Marvin Minsky and John McCarthy (Haenlein & Kaplan, 2019). This eight-week conference would unite researchers from various fields to create new research focusing on a machine's ability to mimic human intelligence. Progressing through the years, AI has taken on many new forms. Many movies have been created to emulate some of the feats of AI while other inventions have been created such as the iRobot vacuum that uses machine learning to clean while avoiding obstacles.

A key subset of AI is machine learning, which was created with the idea that machines could be taught similar to the ways in which humans learn (Dickey, Blanke, & Seaton, 2020). The advancement of the internet and computers has made the concept of machine learning and AI a prevalent part of present-day society. Using machine learning algorithms allows computer programs to automatically improve through experience. Machine learning can leverage large amounts of data with corresponding statistics to make predictions and recommendations. For example, the music streaming service Spotify uses machine learning to match the audio statistics with other factors such as tempo, genre, and instrumentality to generate a recommender system. This recommender system is then able to suggest music to the listener based on their previous music selections.

Machine learning approaches are divided into three categories: supervised, unsupervised, and reinforcement learning. Supervised learning uses past information to predict future outcomes. The historical data used provides a basis of datasets for machine learning to use in predicting outcomes (Iriondo, 2018). Unsupervised learning uses different techniques than supervised learning. Unsupervised learning is autonomously done by the machine by figuring out the individual data patterns on its own. Unlike supervised learning, the unsupervised learning algorithms do not have specific output categories or labels for the data. Reinforcement learning, the third most popular type of machine learning uses observations collected from the interaction of the machine with its environment to maximize reward or reduce risk. Reinforcement learning is named as such because of the machine's ability to continuously learn from the environment. Examples of reinforcement learning include computer games like chess where the computer is continuously understanding how the user of the game is playing (Iriondo, 2018). Reinforcement learning is utilized in day to day lives, continuing to provide a more interactive experience.

Seven Patterns of Artificial Intelligence

There are seven patterns used in different combinations of every project involving AI (Walch, 2019). First is the pattern of *hyperpersonalization*, which uses machine learning to develop a profile unique to each individual. This profile will adapt over time and is used to provide the personalized content unique to each user instead of grouping users into categories. Hyperpersonalization is used in targeted advertising to create profiles for individual users and display relevant content and products based on the user's previous preferences. The second pattern of AI is *autonomous systems*. An autonomous system can complete a task, goal, and interact with its surroundings with minimal or no human involvement (The Seven Patterns of AI, 2019). This autonomous system can have both hardware and software components, but the overall goal is to minimize human labor. Autonomous systems are used in cars, airplanes, boats, and more which provide information with minimal human involvement.

The third pattern is predictive *analytics and decision support*. This process involves using cognitive approaches and machine learning to determine patterns that can help predict future outcomes (Walch, 2019). Predictive analytics is used in projection methods such as forecasting to help humans make better decisions. The fourth AI pattern is *conversation and human interaction*. This pattern is a crucial part of AI because although artificial intelligence is technologically advanced, there is still a need to interact with humans. The objective of conversation and human interaction is to enable machines to interact with humans the way that humans interact with each other (The Seven Patterns of AI, 2019). The ability for machines to communicate with humans includes voice assistants, chatbots, and the generation of text, images, and audio.

Fifth is *anomaly and pattern detection*, whereby machine learning is used to find patterns within the data. Anomaly and pattern detection is used to determine connections between the information and can determine if the data fits into a pattern or if it is an outlier. This pattern is primarily used to decide which data is similar to other information and which data is different. Discovering anomalies using intelligent monitoring can make a significant difference to businesses such as fraud detection. Pattern detection also works in predictive text to determine the next string of words or phrases the user might choose. The sixth pattern of AI is *recognition*. The recognition pattern uses machine learning to specifically identify desired information within unstructured data. Unstructured data is data not easily identifiable such as audio and video. Structured data is data with clearly defined data types that makes it easily identifiable. This desired information could be text, audio, visuals, or other data that needs to be segmented and can be categorized. The primary objective of the recognition pattern uses machine learning to identify and understand desired things from unstructured content. Finally, *goal-driven systems* are the seventh pattern of AI. These are defined as "using machine learning to give people the ability to determine the best solution to a problem" (Walch, 2019). An example of a goal-driven system is in a business that needs to find the optimal way to achieve a goal. Using this pattern will allow the business to have the best solutions to possible problems.

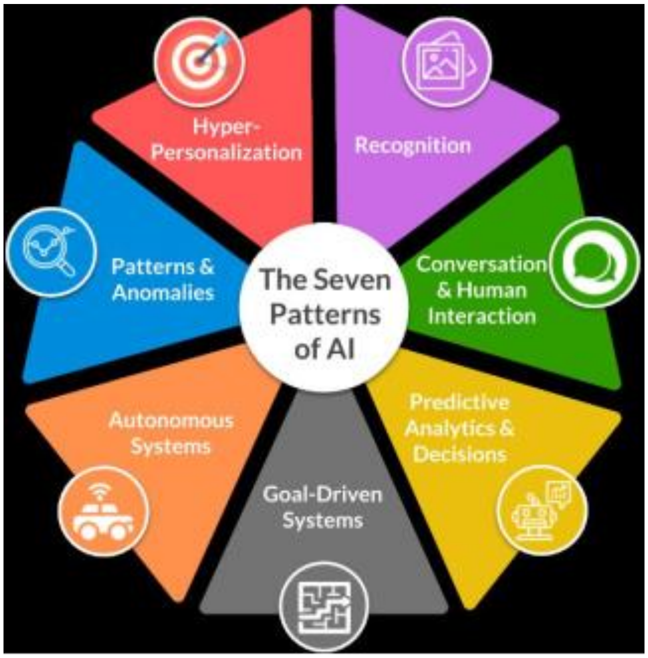

Figure 2: Seven Patterns of Artificial Intelligence
(Walch, 2019)

Three Types of Artificial Intelligence

There are three types of AI that each pose different ethical implications in the auditing profession: Assisted AI, Augmented AI, and Autonomous AI. Rice (2020) defined *Assisted AI* as "a means of automating simple processes and tasks by harnessing the combined power of Big Data, cloud and data science to aid in decision-making." Assisted AI is to support humans in making decisions (Munoko, Brown-Liburd, Vasarhelyi, 2020). The users of Assisted AI need to have trust that the AI will perform its intended role. Assisted AI has the benefit of being used to complete basic tasks, thus freeing up the user to perform more complex tasks.

Augmented AI allows organizations and people to do things they could not otherwise do by supporting human decisions, not by simulating independent intelligence (Rice, 2020). Augmented AI is more advanced than Assisted AI because Augmented AI can make some decisions on its own but is not completely independent of the user. Overall, Augmented AI "suggests new solutions rather than simply identifying patterns and applying predetermined solutions" (Rice, 2020). Decisions made by Augmented AI are not solely relied upon, as the user of this technology will still be responsible for evaluating the decisions made by Augmented AI. Augmented AI poses an ethical risk of the autonomy of the user (Munoko et al., 2020, p. 219). If there is a novice user working with an Augmented AI system, the user may not have appropriate experience to interact appropriately with the system.

Finally, *Autonomous AI* is the third type of AI. The most advanced form of AI is Autonomous AI, "in which processes are automated to generate the intelligence that allows machines, bots and systems to act on their own, independent of human intervention" (Rice, 2020). Autonomous AI is the most sophisticated type and has the capability to operate without any user interference. Autonomous AI is able to "adapt to their environments and perform tasks that would have been previously unsafe or impossible for a human to do (e.g., the use of drones to perform inventory inspections autonomously of assets in remote locations auditors do not have access to)" (Munoko et al., 2020, p. 219). However, the challenge of ethics with Autonomous AI is if these systems operate independently, humans will not be able to see how this system makes decisions.

The intelligence capability of AI sets it apart from other software that have coded rules, such as Robotic Process Automation (RPA). RPA is a useful tool in performing many administrative tasks. Gotthardt, Koivulaakso, Paksoy, Cornelius, Martikainen, and Lehner (2020, p. 91) defined RPA as "a technology that automates standardized and rule-based activities using scripts." The difference between RPA and AI, is RPA is a highly process-driven system. For example, RPA automates rule-based tasks and are constrained by technical capabilities and the judgement needed to operate them. RPA uses software robots to automate processes that are easy to configure and will be deployed to automate manual tasks. Traditional RPA has limitations because of its ability to only process information in digital form. For example, RPA can copy, paste, and cross-reference data between applications but does not have the ability to check information over the phone or through human interaction. Because RPA is rule-based and task focused, it does not have the learning capabilities that are seen in the other forms of AI previously discussed. Neither the RPA nor AI technologies are fully developed and adopted by accounting firms. Currently only five percent of companies consider themselves to be mature in their use of AI and 15 percent in their use of RPA (Gotthardt et al., 2020). Although these technologies are currently being developed, the use of these AI and RPA tools in the accounting and auditing industry are still in the early stages with such a small percentage of firms considered to be mature in their use of AI and RPA.

Ethical Implications of Artificial Intelligence in Auditing

Ethics is defined as "the part of practical philosophy concerned with all things normative (moral philosophy, answering the fundamental question of how to live one's life) permeates all aspects of human action" (Leidner & Plachouras, 2017, p. 30). The concept of ethics are moral principles that affect people and how they make decisions. Because AI relies on programmed algorithms designed by humans to make decisions, consideration of the ethical implications of using these tools is imperative.

The use of machine learning technologies provides a relevant example of the necessary considerations that should be given to ethics when incorporating a new technology into the audit decision-making process. For example, one potential application for using machine learning-based predictive models in an audit is to predict which transactions may be fraudulent. This poses ethical considerations because previous systems were pre-populated by humans, whereas new autonomous AI systems do not require human interaction and instead use the data provided to make interpretations and predictions (Munoko et al., 2020).

Machine learning tools use outcomes from previously used data populations, which is called "training data" and then apply the rules learned from the training data to new data populations. This machine learning algorithm allows the auditor to identify population anomalies without human involvement. An ethical issue arises when an autonomous system makes decisions that may not be directly evident to humans due to the complexity of the decision. The code of ethics requires that "in complying with the principle of professional competence and due care, a professional accountant shall take reasonable steps to ensure that those working in a professional capacity under the accountant's authority have appropriate training and supervision" (IESBA, 2018, p. 20). AI works to find relationships between different elements of data. While this may have predictive accuracy, this also can yield false positives. For example, if the algorithm reaches a conclusion that happens to be a false positive, and the person reviewing the algorithm's results does not understand the process that led to that decision, the user will not be able to take the appropriate steps to fix the problem. This also leads to an ethical issue if the auditor does not have the proper training, then they are not able to properly interact with the system.

The following sections highlight two emerging AI technologies that could impact the audit decision-making processes: Facial Processing Technologies and Natural Language Processing. Each section provides an extensive overview of how the technologies function, how they might be used in an audit, and the relevant ethical considerations to be considered before these technologies are fully implemented.

Facial Processing Technologies

Facial processing technology (FPT) is becoming an increasingly expansive term that encompasses face detection. Facial analysis and recognition are used within FPT to find specific key points on the face (Raji et al., 2020). FPT can be adopted for a variety of uses in areas such as law enforcement (e.g., to identify missing persons), smartphone and laptop applications (e.g., as more secure passcodes), airports, and shopping venues.

FPT has the capability to improve the recognition of facial features. According to Ouanan, Ouanan, and Aksasse (2016), “facial expressions form a visual channel for emotions and nonverbal messages, and they have a role in supporting the spoken communication” (p. 488). Identifying facial expressions gives humans another form of communication that is not naturally spoken. Humans are automatically able to identify facial features and expressions, but a machine does not have that initial capability. Machines face challenges such as the background lighting, the scale of the facial image, and facial expressions (Hemalatha & Sumathi, 2014). If the background lighting is different in multiple images, the machine has a hard time identifying the face in the images, since they all have different backgrounds. The goals of facial feature extraction are to reduce the time of machine training. To achieve this reduced training time, facial features are selected that contain the most relevant features to the original input data (Sufyanu, Mohamad, Yusuf, Musa, & Abdulkadir, 2016). There are two overall methods to extract facial features: geometric features based (GFB) methods and appearance-based methods (Sufyanu et al., 2016).

__Geometric Features Based Methods__

The GFB method consists largely of facial localization and landmarking. Facial landmarking is using detection and localization to find specific key points on the face. These key points of the face are used as identifying marks to determine facial expressions. Some commonly used landmarks on the face include the tip of the nose, corners of the eyes, nostrils, corners of the mouth, ear lobes, arcs of the eyebrows, and the chin (Ouanan et al., 2016). Facial landmarks are separated into two categories: the primary landmarks, known as the fiducial landmarks and the secondary landmarks. The primary landmarks are the corners of the mouth and eyes, the tip of the nose, and the eyebrows. These landmarks such as the tip of the nose or eye corners are affected little by facial expression, making them more reliable landmarks, and are referred to as fiducial points or fiducial landmarks (Ouanan et al., 2016). The secondary landmarks are the chin, the cheek contours, midpoints of the eyebrows and lips, and the non-extremity points.

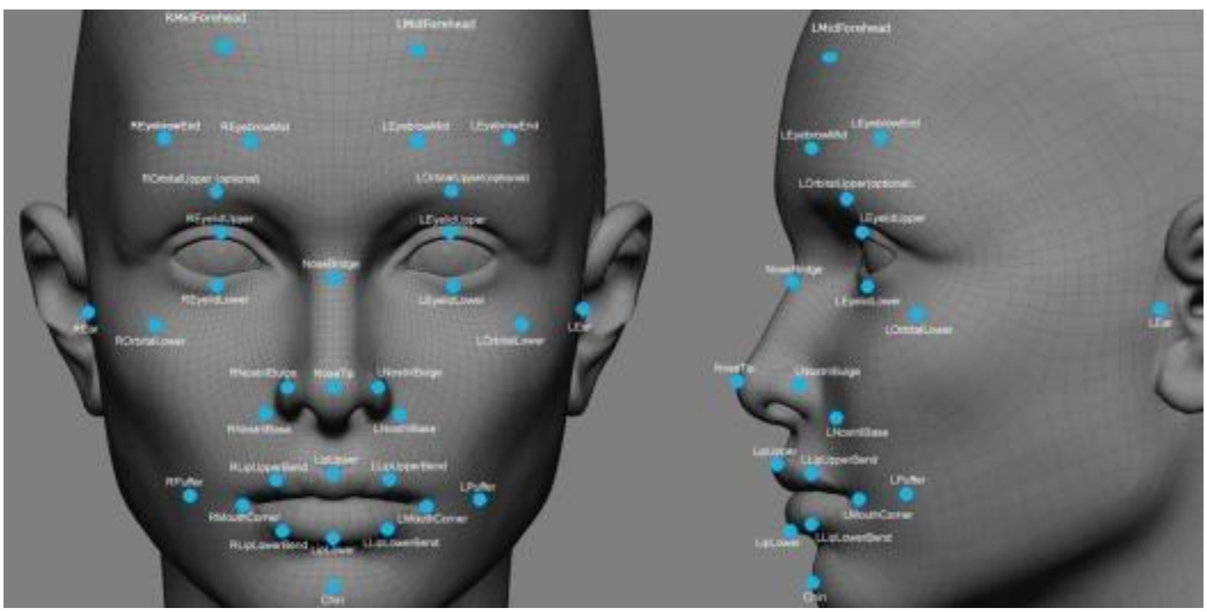

Figure 3: Facial Landmarks
(Dormehl, 2014)

There are multiple methods within GFB methods to detect facial landmarks: knowledge based, feature invariant, and template matching (Hemalatha & Sumathi, 2014). The first method of *knowledge based* uses human knowledge of what makes up a typical face. This method was designed to use face localization to pinpoint identifying facial features (Rizvi, Agarwal, & Beg, 2011). The information used in the knowledge-based method is derived entirely from the input rules from the user. There are simple rules such as a face has two eyes, a nose, and a mouth. Other rules are not as easily distinguishable and are more difficult to translate into a well-defined rule. If the rule is too general, it may yield many false positives, but if it is too specific, the computer will not be able to identify all the facial expressions that should fit the rule. This has ethical implications because if the person inputting the rules has an attentional bias towards specific emotions, it could impact the accuracy of the output data. In a study done on people from two different types of cultures, one group from Germany and the other from Namibia, it was found there was a longer time spent staring at images with negative facial expressions (fear, anger) as opposed to positive (happy) or neutral facial expressions by both Germans and those from Namibia (Mühlenbeck, Pritsch, Wartenburger, Telkemeyer, & Liebal, 2020). Attentional bias was shown toward the negative facial expression of fear over any other facial expression, however, and that fear rather than anger was what created the attentional bias towards negative facial expressions. Overall, if the person inputting the rules for the knowledge-based method has a preexisting bias, the output data will not be accurate.

The second method of *feature invariant* considers multiple factors. Facial features, texture, and skin color are all part of this method (Hemalatha & Sumathi, 2014; see also Rizvi et al., 2011). Facial localization is used to detect the size and location of the face from a background and can determine where the facial features should be on the face. Human faces have a specific texture that is unique from the background making the face easier to separate. Skin color has proven to be an effective identifiable feature in face detection. Not all humans have the same skin color, but the difference in skin color lies not in the hue of the color but in the intensity. The images used are transformed into a grayscale image and skin color is identified by intensity.

The third method used to identify facial landmarks is *template matching* (Rizvi et al., 2011). Standard patterns of a face are stored to either describe the overall face or specific facial features. Template matching compares the templates to facial images and identifies the facial landmarks. This method is relatively simple to implement but has the disadvantage of not being able to identify if there are differences from the template. Utilizing these methods to extract facial features and landmarks enables this technology to construct an image of a human face.

Appearance Based Methods

The appearance-based method is identifying the facial features using what was learned from example images (Rizvi et al., 2011). The appearance-based method relies on machine learning to find similarity between facial features without a template or the guidance of a model (Ouanan, et al., 2016). The appearance-based method is easier to implement since there is no detection of the geometric facial features required. This method relies on techniques from statistical analysis and machine learning to find the relevant characteristics.

Utilizing Facial Processing Technologies in Fraud Interviews

FPT have already been implemented in a variety of uses and has the potential to be utilized in auditing. Financial statement and fraud audits may use these FPT as part of the fraud interview process. Fraud is defined as "an intentional act that results in a material misstatement in financial statements that are the subject of an audit" (AICPA, 2002). FPT can be utilized in these interviews to identify facial patterns that may suggest nervousness or deceit (Dickey et al., 2020).

Required by the AICPA's Statements on Auditing Standards (SAS) No. 99, *Consideration of Fraud in a Financial Statement Audit*, the auditor should inquire of management about:

- Whether management has knowledge of any fraud or suspected fraud affecting the entity.
- Whether management is aware of allegations of fraud or suspected fraud affecting the entity, for example, received in communications from employees, former employees, analysts, regulators, short sellers, or others.
- Management's understanding about the risks of fraud in the entity, including any specific fraud risks the entity has identified or account balances or classes of transactions for which a risk of fraud may be likely to exist.
- Programs and controls the entity has established to mitigate specific fraud risks the entity has identified, or that otherwise help to prevent, deter, and detect fraud, and how management monitors those programs and controls.
- For an entity with multiple locations, (a) the nature and extent of monitoring of operating locations or business segments, and (b) whether there are operating locations or business segments for which a risk of fraud may be more likely to exist.
- Whether and how management communicates to employees its view on business practices and ethical behavior (AICPA, 2002, p. 1725).

The auditing standards indicate auditors need to conduct inquiries with management through fraud interviews. Utilizing FPT to identify facial patterns in fraud interviews can aid auditors and indicate when management's response may require further investigation. Since firms’ train auditors to conduct fraud interviews, the auditor should already have a sufficient understanding of behavioral patterns and facial expressions to indicate if fraud is taking place. However, humans make mistakes, and it can be difficult for a human to detect specific facial expressions during the fraud interview in real time.

The use of FPT in fraud interviews can assist and alert auditors if there is potential of high risk of fraud in a company based on the facial expressions of management in a fraud interview. This evidence of potential fraud obtained from an interview could impact the quality of the audit. Auditors are already obtaining evidence by inquiring with management about potential fraud. FPT would provide auditors with additional evidence. FPT can be used to provide evidence to auditors, but not without potential ethical considerations.

Other Uses of Facial Processing Technologies for Auditing Firms

There are other current uses of FPT by accounting firms that go beyond the audit process. One example is the COVID-19 pandemic has caused many companies to move to working remotely as opposed to the office. PwC has a facial recognition tool that enables their clients to track finance workers’ absences from their computer screens while working remotely (Sweet, 2020). This technology uses the employees’ webcams to monitor when they are away from their desk and will potentially have the option to have employees provide an explanation for the unauthorized time away from their screen (Sweet, 2020). This technology is intended to be used by finance services employees that are subjected to strict regulations. For example, traders are not allowed to have personal mobile phones and their calls are recorded (Sweet, 2020). Working remotely hinders these regulations as there is currently not a suitable way to monitor these regulations from employees’ homes.

Ethical Considerations of Facial Processing Technologies

There are many ethical concerns over FPT privacy, including both how the data used to train FPT is obtained and the accuracy of FPT. One of the main overarching ethical concerns is the lack of federal regulations and standards surrounding FPT (Martin, 2019). With any new technology, comes the lack of existing knowledge and thus the lack of regulations surrounding that technology. As aforementioned, FPT can be utilized by law enforcement. However, in December 2015, Denver police used FPT and falsely arrested a person simply because his face matched in their system and did not check to see if he had an alibi (Wesson, 2020). The police's technology falsely identified another man's face and did not consider an alibi before arresting him. Both of these cases relied erroneously on FPT instead of considering all of the facts. While facial recognition can be a beneficial tool, it should not be the epitome of all cases - "It's meant to serve as an investigative tool not evidence" (Wesson, 2020).

There are also ethical considerations surrounding the use of FPT if there is no serious crime being committed, or in the case of auditing, there is no indication of fraud. With no concrete regulations established, FPT could be utilized for virtually anything. However, FPT's were implemented to assist the users in making decisions and not an everyday use. In a country founded on free speech and social equality, it begs the question on how FPT can be deployed in our society. Washington and California have implemented laws that forbid the use of FPT on any individual participating in "a particular noncriminal organization or lawful event" (Wesson, 2020). These laws are moving towards the right to protect people's privacy to "walk down the street anonymously" (Wesson, 2020).

Auditors are bound by ethical standards that need to be considered when using FPT. Since the appearance-based method to extract facial features is constructed from machine learning using example images, this poses a question of ethics about how the images that are being used to train the machine are obtained. Audit firms can obtain these FPT directly from third party companies or they can develop, customize, and train their own FPT themselves. Audit firms face challenges in developing good training data sets as these firms do not have as much access to training data compared to large companies such as Google or Facebook (Issa, Sun, & Vasarhelyi, 2016). Although there are some publicly available datasets used to train assisted AI, many different types of data are not available (Munoko et al., 2020). There is also an ethical consideration over the datasets used to train AI. If the FPT is not trained with representative, diverse datasets of the entire population, the technology may develop problems or have a racial or gender bias. Aside from biases, there is also the issue of taking what these algorithms produce at face value and that can lead to inequities produced by the algorithm. There is an opportunity for firms to buy training datasets from clients with their consent, but this could result in confidentiality breaches as there is not a fully defined criteria for auditors to use when buying training datasets. There is also a legal obligation of the auditors to maintain the confidentiality of the client information and are prohibited from disclosing confidential client information without client consent. Ethical standards are also placed on auditors, making it highly unlikely that these FPT or images should be taken from client audit interviews without client consent.

FPT need humans to input data to be trained through machine learning and eventually be able to make decisions. A fundamental quality of AI is that this technology was created in our current society, which means that the data and information used to teach AI already includes preexisting biases, prejudices, and presumptions. Biases can be developed either purposefully or accidentally by the algorithm, depending on the input data used to train the FPT. Auditors need to be conscious of these biases and discrimination when inputting data into FPT. Google searches already demonstrate the significance of these learned biases. For example, when searching “professor style” Google Images produces mostly middle-aged white men (Manokha, 2019). When searching “housekeeping,” Google Images yields mostly of images of women. These AI algorithms have learned which images to produce based upon the initial information and images used to train them.

Further considerations of the ethics surrounding FPT indicate a possibility of yielding false positives. When facial expressions that may indicate deceit, such as darting of the eyes or pursing of the lips occur during a fraud interview, the algorithm may indicate there is a potential concern. This information will be used by the auditors to determine if further fraud investigation would need to occur. False positives are a very real possibility with facial recognition software. In other uses such as facial recognition for law enforcement, a false positive could lead to the wrongful arrest on an innocent person. If the auditor or the user of the FPT does not understand the process that led to the conclusion of the false positive, the user will not be able to fix the problem.

Contrary to false positives, there is also the potential for false negatives from FPT. If a person can control some of the facial expressions that may indicate deceit, the algorithm may not detect that there is fraud. If auditors become too reliant on the use of FPT during fraud interviews, this can pose a risk of becoming too reliant on the technology rather than using basic human intuition to detect if there is fraud. This risk can pose a threat of ethics if these interviews are not properly detecting fraud, that the auditor is not doing their job correctly.

Both false positives and negatives reflect the overall accuracy of FPT. Since FPT has not been fully developed, this leaves room for error. As an emerging technology, with no concrete regulations yet established, it is hard to distinguish if this technology is accurate. Identifying a person from a passport image or a mugshot is much easier than identifying a face from a traffic camera. If the FPT was trained using standardized images such as a passport photo, but used to identify images from a traffic camera, the data produced will not be accurate. Also identifying different genders and ethnicities affects the accuracy of FPT. A 2019 review of two facial recognition algorithms, a United Kingdom academic algorithm and a Chinese commercial algorithm, showed the highest error rate of false positives was women of color (Castelvecchi, 2020). This review indicated that the algorithms had false positives and were not entirely accurate. Given the many potential issues with FPT, considerations need to be made by the audit profession over utilizing FPT in a fraud interview of a client with no suspected fraud. The risk of false positives may outweigh the benefits of FPT when using the technology in instances where there is no reason to believe that fraud exists within the company being audited.

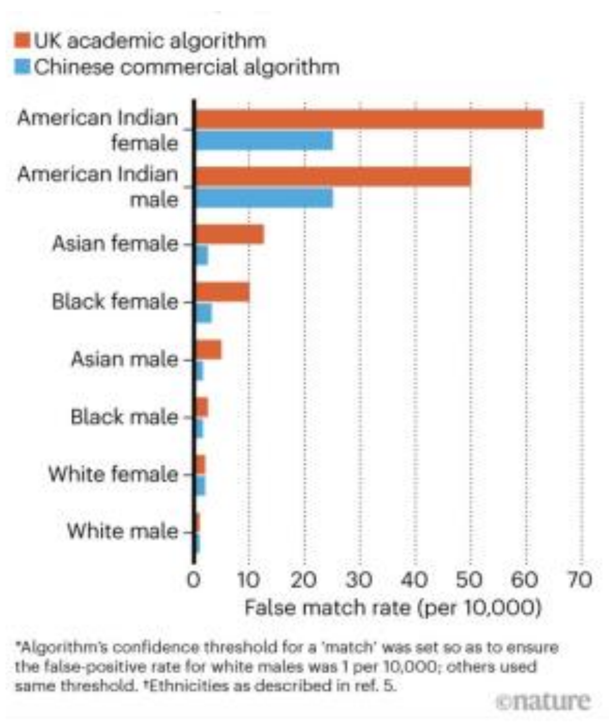

Figure 4: False Positives Among Algorithms
(Castelvecchi, 2020)

FPT can provide additional information during fraud interviews. This emerging technology has the potential to impact audit quality and could reduce some risks associated with fraud. With all new technology comes new potentials for abuse or ethical violations. It is also important to consider the regulations and standards surrounding these new technologies. Currently there are not a lot of regulations covering FPT. Before utilizing FPT in fraud interviews and in the accounting industry in general, the current and foreseeable risks need to be adequately vetted. Ethical concerns over FPT privacy, accuracy, and the way data is obtained to train this AI, are all key considerations current and future auditors need to be cognizant about when utilizing FPT. Finally, privacy concerns associated with FPT should be considered such as when using FPT through webcams to monitor employees who are working from home. Additional controls and safeguards will need to be considered over new FPT before it is implemented.

Natural Language Processing

Another aspect of AI that has a potential impact on future auditing quality is natural language processing (NLP). NLP is the technology used to aid computers in understanding the human's natural language (Garbade, 2018). This was developed to help ease the user's work and to communicate with a computer in natural language. Multiple disciplines are combined in NLP such as computer science and computational linguistics to fill the gap between computer understanding and human connection (Statistical Analytics System, n.d.). NLP uses multiple methods to interpret language including statistical and machine learning methods, or rules and algorithmic based approaches.

NLP dates to 1949 when Roberto Busa, an Italian Jesuit priest analyzed the works of St. Thomas Aquinas (Eggers, Malik, & Gracie, 2019). In 1949, Busa met with IBM founder Thomas

Watson, and Watson agreed to sponsor the *Index Thomisticus,* which created a readable version of Aquinas' work on a computer. After this, NLP received recognition in the 1950s when the development of machines to automate language translation became more prominent. Guided by AI and deep learning methods, today NLP can be seen in multiple different facets like health care, defense and national security, business, and energy.

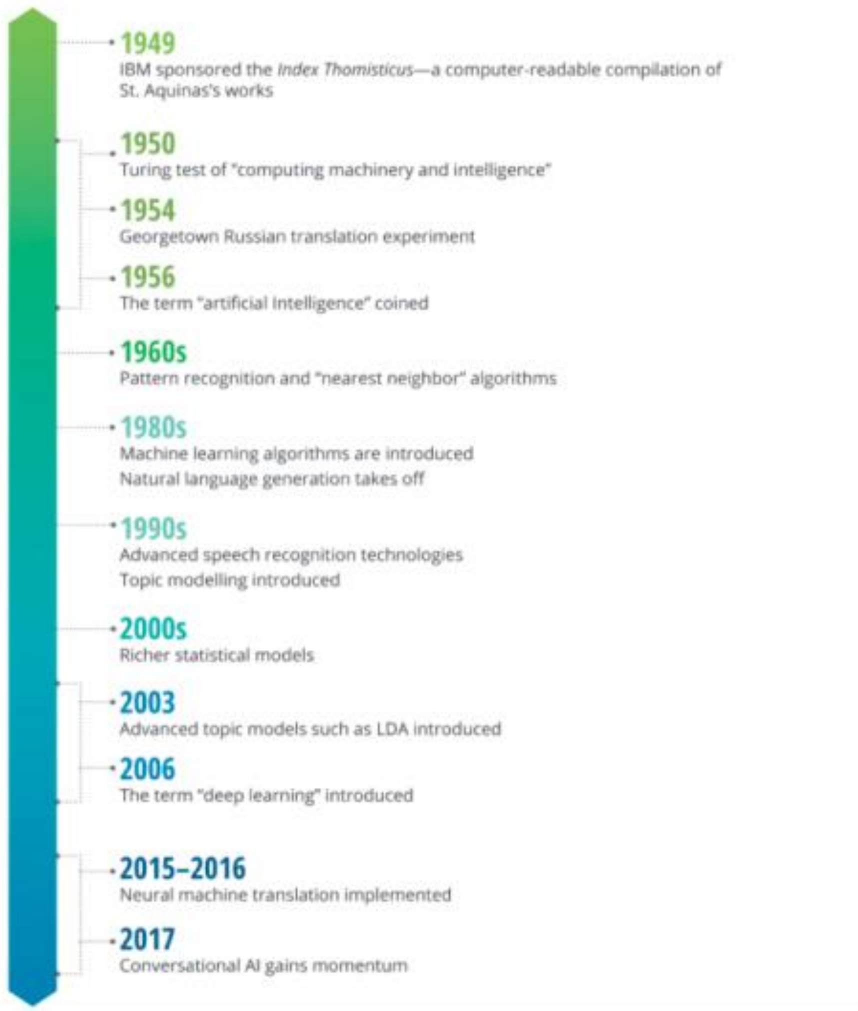

Figure 5: Evolution of NLP
(Eggers, Malik, & Gracie, 2019)

NLP breaks down complex language into shorter, more identifiable pieces and identifies the relationship between them. Machine code used to create algorithms and configure machines is not understood as widely by humans as other languages like English. NLP bridges the gap between languages spoken like English and machine language. Previously, code was required to be entered to program a computer. Now, with NLP, there are many voice-activated personal assistant applications such as Alexa. Instead of writing code for a machine to produce today's weather forecast, a user can say "Alexa, what is the weather," and a device will read in a humanlike voice today's weather forecast. Personal assistance applications like Alexa are only a part of NLP. NLP can be used in language translation such as Google Translate or in email spam filters. In smartphones, if there is a voicemail left for a missed call, there will be a transcript of the voicemail message displayed because of a speech to text NLP conversation (Statistical Analytics System, n.d.). The use of NLP eliminates the simpler tasks and allows humans to focus on more complex tasks.

Seven Key Capabilities of Natural Language Processing

There are seven key capabilities of NLP. The first capability is *topic modeling*, which is based on statistical algorithms to find hidden patterns among large collections of documents (Eggers et al., 2019). Topic modeling is identifying patterns in unstructured data and converting it to structured readable data for the user. The second capability is *text categorization*. This method classifies text into different categories. The junk or spam folder in an email inbox utilizes text categorization based on the wording used in the emails. Third is *text clustering*, which is employed to group text or documents based on similarities in context (Eggers et al., 2019). Text clustering differs from text categorization because clustering is allowing the AI to decide the similarity between the data, and text categorization is classifying the data into pre-existing categories. PwC utilizes text clustering with their Lease Fix algorithm that extracts relevant financial information from leases (PwC, n.d.). This allows the user to upload an individual lease, or a batch of leases and the text will be extracted to auto-populate different lease input data fields based on the analysis outcome.

The fourth capability is *information extraction*. This is used automatically to find critical information in unstructured text (Eggers et al., 2019). NLP technology has potential future uses in audit to identify crucial information from any written document provided by the client. Instead of auditors identifying handwritten text, NLP technology can use information extraction to pull the important information from the document. The fifth capability of NLP is *named entity resolution*. This method can derive the names of people, locations, and companies and arrange them into predefined labels. For example, the text may include the word "Georgia" which is both a state and a nation (Eggers et al., 2019). Using named entity resolution, the correct use of "Georgia" can be categorized in the respective category. Sixth is *relationship extraction*, which helps create semantic relationships between entities. For example, if a document were to mention the University of Northern Iowa (UNI) and the College of Business Administration, relationship extraction would identify the correlation between UNI and the College of Business Administration. Finally, the seventh capability of NLP is *sentiment analysis*. Sentiment analysis interprets the meaning behind the human language. There are many applications for the sentiment analysis. For example, this can be utilized in social media platforms, websites, and other applications for feedback (Eggers et al., 2019).

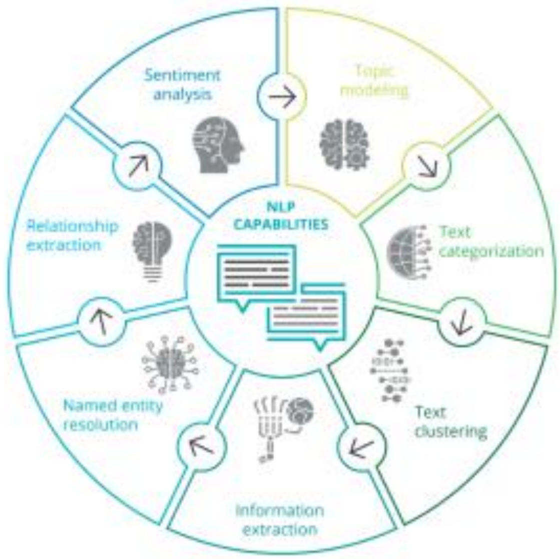

Figure 6: Seven Key Natural Language Processing Capabilities
(Eggers, Malik, & Gracie, 2019)

Utilizing Natural Language Processing in Auditing

NLP has the potential to significantly impact audit quality. NLP's have been used in auditing to detect fraud, bankruptcy, and restatements by analyzing the Securities and Exchange Commission's Accounting and Auditing Enforcement Releases and corporate form 10-K's (Fisher, Garnsey, & Hughes, 2016). NLP's have also been used to analyze emails to detect deception, exclusive words, and negative emotions (Keila & Skillicorn, 2005). Using a dataset from the Enron fraud, these NLP procedures found that deception emails had less frequent use of first-person pronouns, exclusive words, and a greater than normal frequency of negative emotion words.

NLP's have also been used to evaluate financial outcomes related to "news-based trading" and used to predict coming changes in financial status based on changes in linguistic patterns in a company's form 10-Q filing and Management, Discussion, and Analysis section of a company's form 10-K (Fisher et al., 2016). NLP has been proposed as a powerful tool for auditors to use to identify risks as part of an audit using a company's press releases, financial statement disclosures, and company filings. Brown, Wong, & Baldwin (2007) note that auditors may benefit from NLP algorithms that are enhanced by machine learning technologies in the same way that banks and credit card companies use machine learning to screen transactions for potential fraud. Tom Davenport and John Raphael (2017) of Deloitte note that NLPs are expected to play an important role in creating a "cognitive audit" where cognitive technologies are used to bring value to the audit process.

NLP utilized as speech-to-text translation in combination with FPT during fraud interviews would help auditors be able to identify if there were risks that required further investigation. This is made possible, by not only looking at facial expressions, but also considering the word choice used in the fraud interview. Now with NLP, audits would be able to become deeper and further reaching than before. There will also be a large decrease in the amount of time it takes to process documents. Something that used to occupy auditors for months, can be condensed down tremendously leaving more time for auditors to focus on other aspects of the audit.

Ethical Considerations of Natural Language Processing

Similar to FPT and any new developing technology, NLP also has ethical concerns. Data used to train NLP technology also have the possibility to include preexisting biases, prejudices, and presumptions. For example, the Enron dataset used by Keila and Skillcorn (2005) which identified first-person pronouns and negative emotions as indicators of fraud consisted of a known fraud where data was analyzed in hindsight. There may be other contexts where less frequent use of first-person pronouns and negative emotions do not convey fraud or instances where fraud has occurred but without indicators such as less frequent first-person pronouns and neutral emotional language. These contexts should be heavily contemplated to avoid potential false positives or negatives. Although the NLP technology has been used for certain audit-related issues in the past, the technology is still in the early phases of being an extensively used part of the audit decision-making processes. Understanding that these technologies are not immune to error will be critical if these emerging technologies become significantly integrated into the financial statement auditing processes. The use of these technologies as risk identification tools will likely be more appropriate than subordinating auditor judgment to the outcomes that these technologies generate.

Privacy and accuracy are also ethical implications for NLP technology. Protecting the confidentiality of client information is a fundamental responsibility of auditors. With any software or algorithm that interacts with humans, there is an inherent risk of the accuracy of the information provided to the user. Training the NLP technology to interpret language as humans do poses some challenges. The datasets used to train NLP provide the foundation for its decision making. Using representative and diverse datasets can help to prevent biases.

The issue of transparency arises within NLP technology. It is important for auditors to ensure transparency to the users of financial statements and one issue of NLP is the lack of transparency into AI to perform adequate oversight. It is the responsibility of the auditor to provide oversight and monitor the use of this AI technology. Also, transparency may come at the cost of privacy. Developers of AI technology provide explanations of how decisions are made. While this can provide more transparency, privacy may be violated. Current data laws are created to protect people's privacy but are not protecting the data subjects from the risk of inferential analytics (Munoko et al., 2020). With no concrete regulations established surrounding these new technologies, auditors need to be aware of the ethical implications surrounding NLP.

CONCLUSION

There are numerous current and potential uses for AI in auditing. Emerging technologies such as FPT and NLP are highly promising for the audit profession. AI technologies can be utilized to solve problems that would not be possible with traditional approaches. Utilizing these technologies as part of the risk assessment process or in aspects of the auditing decision-making processes such as fraud interviews can assist auditors and improve the overall quality of the audit. There are some ethical concerns that could obstruct the benefits of these AI technologies if not carefully considered, however. The implementation of these technologies poses a significant risk for the profession if the ethical implications are not fully considered. For future research purposes, it is important for these technologies to be monitored by multiple different sources to ensure there are no pre-existing biases already programmed into the technology.

Ethical considerations such as privacy, accuracy, confidentiality, data protection, transparency, and biases all need to be considered. Auditors also need to be conscious of these ethical implications when developing and implementing AI. To maintain the public's trust, auditors need to understand the ethical issues surrounding these emerging technologies before implementing them in client work. This is a continuous process to uphold the ethics defined for auditors and to protect client information. It is important for auditors to be adaptable as this technology is rapidly evolving. It is impossible to completely foresee how AI will impact the future of auditing, but auditors and professionals need to be cognizant of the potential impact. With the appropriate consideration prior to full-scale implementation, these AI technologies will become more viable and the risk of the unintended consequences that can potentially harm the profession will be mitigated.

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